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EVS37

International Electric Vehicle Symposium
and Exhibition (Seoul, Republic of Korea)

Edited by
Joeri Van Mierlo, Myoungcho Sunwoo and Namwook Kim

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**EVS37—International Electric Vehicle
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Guest Editors

Joeri Van Mierlo

Myoungho Sunwoo

Namwook Kim



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Hanyang University
Seoul
Republic of Korea

Namwook Kim
Department of Mechanical
Engineering
Hanyang University
Ansan
Republic of Korea

Editorial Office

MDPI AG
Grosspeteranlage 5
4052 Basel, Switzerland

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Article

A Flexible Assembly and Gripping Process of Hairpin Baskets [†]

Felix Fraider *, Peter Dreher, Josette Lindner, Dominik Reichl, Florian Kößler and Jürgen Fleischer

WBK Institute of Production Science, Karlsruhe Institute of Technology, Kaiserstraße 12, 76131 Karlsruhe, Germany; florian.koessler@kit.edu (F.K.); juergen.fleischer@kit.edu (J.F.)

* Correspondence: felix.fraider@kit.edu

[†] This article is a revised and expanded version of a paper entitled “Collaborative Assembly of Hairpin Coils”, which was presented at EVS37 Symposium, Seoul, Republic of Korea, 23–26 April 2024.

Abstract

Established hairpin stators for electric traction motors are made up of a large number of so-called hairpins. To produce these stators, the individual hairpins must first be pre-assembled into an auxiliary device in order to achieve the desired winding scheme. The resulting hairpin basket must then be picked up and transported to the lamination stack. Automated solutions for both processes are characterized by a high degree of complexity and low flexibility. Manual assembly, however, is prone to errors. The new approach presented in this paper is therefore based on the collaborative assembly of the hairpins and a flexible hairpin basket gripper. A cobot hands the hairpins in the correct sequence to the operator. The correct positioning of the hairpins in the auxiliary device is ensured by the use of a monitor located under it. The creation of the correct assembly sequence is partly automated by a collision detection program. In addition, a new and flexible hairpin basket gripping concept is presented. Tests show that the cycle times of both new processes are slow due to hardware limitations. This restricts their use to specific applications, such as complex winding patterns or very small quantities.

Keywords: hairpin technology; stator production; pre-assembly; collaborative assembly; hairpin insertion; hairpin basket gripper

1. Introduction

Hairpin technology has become the predominant technology for stators in electric traction motors in recent years due to its advantages in terms of product and production. By using flat wires, higher slot fill factors can be achieved compared to round wire windings, which is reflected in a higher motor efficiency [1]. Furthermore, the production of hairpin stators is characterized by a high degree of automatability [2].

The winding of a hairpin stator consists of a large number of so-called hairpin coils (referred to simply as hairpins in the following), which are first bent into their typical U-shape from a wire coil and then assembled manually or automatically into the desired winding pattern. The assembled winding made up of all the hairpins is called the hairpin basket. This assembly process (also called pre-assembly) is particularly error-prone when performed manually, as it may lead to hairpins being damaged or incorrectly positioned. Due to high tolerance requirements and the complex structure of the hairpin basket, which consists of hundreds of hairpins, the assembly process can only be automated using highly specialized machinery. For this reason, a collaborative hairpin assembly process is presented below, which uses flexible, manual assembly, but makes it safer through the

use of a cobot and visual support for the worker. The process was first presented and introduced in [3].

After the hairpin basket has been assembled, it must be gripped, lifted out of the auxiliary device, and threaded into the lamination stack. To do this, the hairpins in the gripper must be aligned very precisely. State-of-the-art grippers are complex and inflexible, which is why a new approach for gripping and aligning hairpin baskets in a more flexible way is being introduced.

2. Basics and State of the Art

2.1. Hairpin Technology

An example of a hairpin stator can be seen in Figure 1a. The winding can be divided into the part located in the lamination stack and the two winding heads. These can in turn be divided into the bending side and the twisting side, whose names derive from the production process explained later. Section view A-A (Figure 1b) can be used to explain the properties of the stator that are relevant for the subsequent pre-assembly process. In this example, there are 36 slots (slot number N) and 4 layers (number of layers L), which means that there are 4 hairpin legs in each slot. Two layers each form a so-called hairpin ring. With the exception of special hairpins, each regular hairpin has two legs in two different layers of one hairpin ring. The number of slots and layers results in a total hairpin number n with $n \geq N \cdot L / 2$ for a typical hairpin stator. Typical values for the number of slots are 36 or 48, but significantly larger numbers such as 72 or 96 are also possible, depending on the electromagnetic design. The number of layers is typically between 4 and 10, which can result in a hairpin number of several hundred for stators. The connection of the stator is either on the bending or twisting side. Either the bending or twisting process is accordingly complex. In the stator shown, the connections are located on the bending side in the form of I-Pins, which are explained in more detail in Section 2.3.

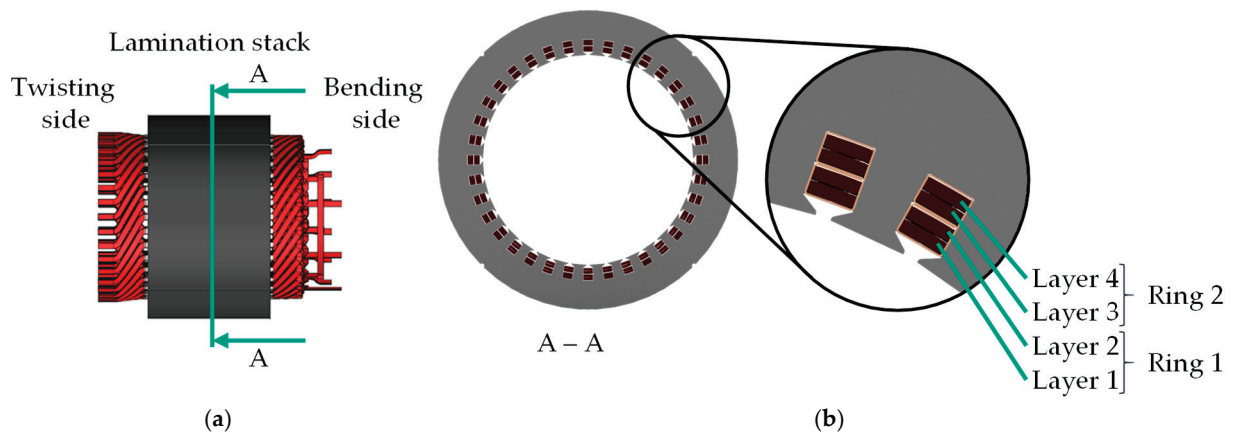


Figure 1. (a) Typical hairpin stator design; (b) Section view showing the different layers and rings.

2.2. Process Chain of Hairpin Technology

The process chain for manufacturing hairpin stators has already been described extensively in previous works, such as [4,5]. The basic process steps shown in Figure 2 can be derived from this. Starting from a coil, the wire is unwound, straightened, stripped at defined points and finally bent into the desired three-dimensional shape. Due to mutual overlaps, it is usually not possible to insert the individual hairpins directly into the lamination stack, which is why they are first pre-assembled into an auxiliary device outside the lamination stack. The entirety of these hairpins is referred to as a hairpin basket. The hairpin basket is then gripped, transported over the lamination stack and inserted axially

into it. To achieve the desired winding scheme, the hairpin legs protruding from the lamination stack are twisted and two of the previously stripped ends are contacted using a laser welding process. To improve the stator's heat dissipation and robustness against external influences, it is often impregnated as a final step.

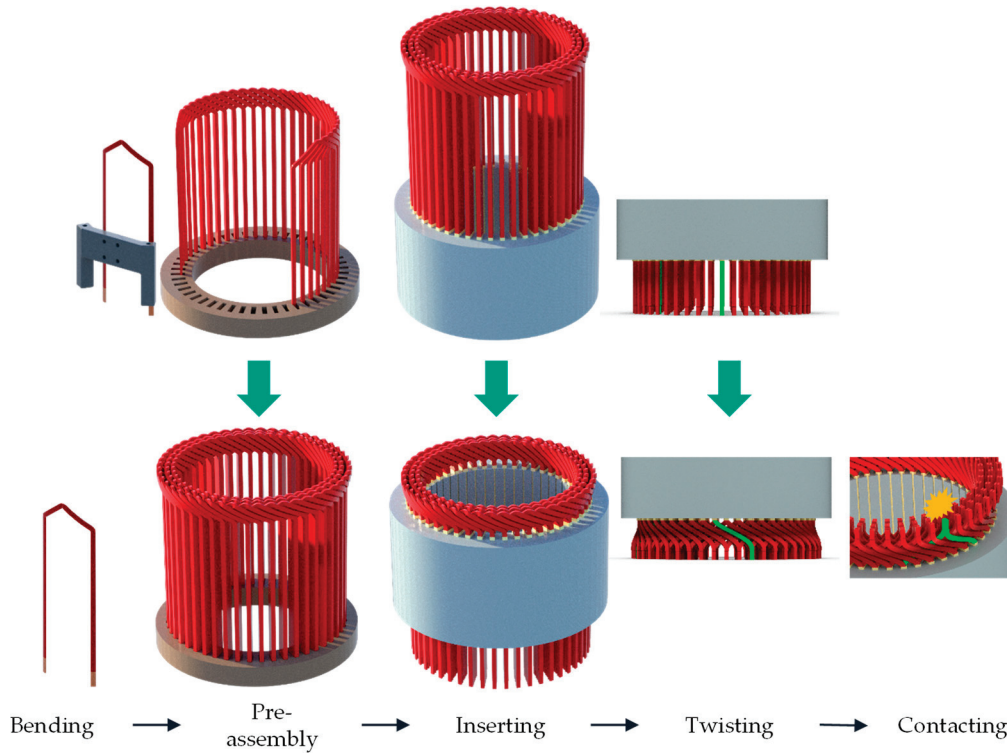


Figure 2. Process chain for manufacturing of hairpin stators.

2.3. Classification of Hairpin Shapes, Types and Topologies

In order to better understand the pre-assembly process, existing hairpin shapes, hairpin types and topologies should first be analyzed. Due to the large number of different stator and winding designs, no claim is made to completeness of the hairpin types and topologies. For example, there are certainly stators whose winding scheme cannot be completely described with the help of the classification presented. Nevertheless, it helps to understand the influence of the winding scheme on the pre-assembly process.

The typical shape of a hairpin is shown in Figure 3. Important geometric properties to describe the shape of a hairpin are its leg length and pitch span. Furthermore, the radius of both legs and the angle between them can be used to describe the shape, which is particularly important for the gripper design in the pre-assembly process. The three-dimensional, complex shape of the hairpin crown will not be discussed in detail here, as hairpins are usually gripped by the legs.

In addition to the geometric description of their shape, hairpins can also be divided into hairpin types according to their function in the winding scheme. There are different hairpin types within a stator, which result from the electromagnetic stator design respectively the winding scheme. Each hairpin type results in a different shape. The design of hairpin windings and rules for their design have already been published in detail, for example in [6–10]. Without claiming to be exhaustive, the most important types of hairpins are as follows.

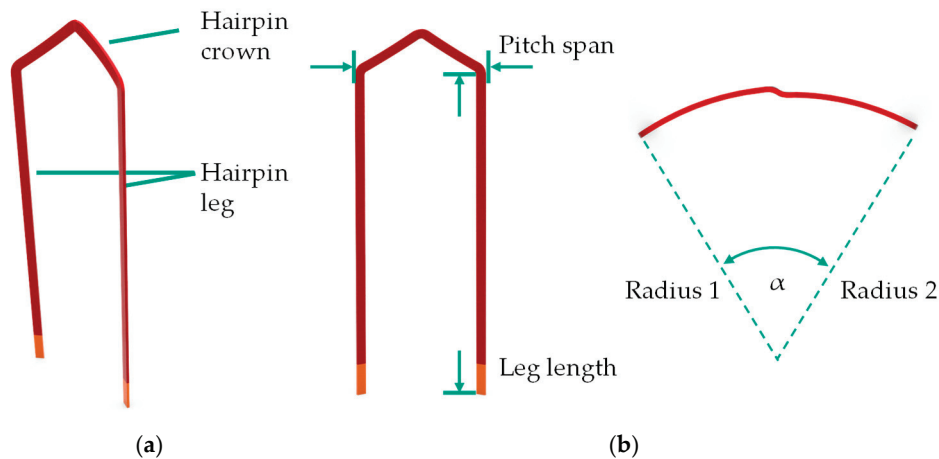


Figure 3. (a) Typical hairpin shape; (b) Basic geometric parameters to describe a hairpin.

First, there are the already mentioned regular hairpins, whose legs are in two different layers of one hairpin ring. These regular hairpins make up the majority of hairpins in a stator. As will be explained later, the number of regular hairpins with different shapes per hairpin ring is not limited to one. In certain winding schemes, two or more regular hairpins with different pitch spans can also occur within one hairpin ring. Due to the different diameters of each hairpin ring, regular hairpins of different hairpin rings also have different radii of their legs, see Figure 3b. The number of different regular hairpin shapes is therefore at least equal to the number of hairpin rings, but can also be greater. Since the regular hairpins are only arranged in one ring, additional hairpin types are required to connect the rings to each other. Accordingly, the legs of these so-called jumpers are located in different rings. For example, the legs are located in layers 2 and 3 to connect rings 1 and 2. Another type of hairpin is the so-called I-pin. These only have one leg and are used for subsequent interconnection. In addition, hairpins can be installed with both legs in the same layer (single-layer hairpins) or in layers that are not adjacent to each other. The number of special hairpins is usually significantly smaller than the number of regular hairpins. It is not always possible to distinguish hairpin shapes with the naked eye due to the slight geometric deviations between two shapes, which increases the susceptibility to errors in the pre-assembly process.

In addition to the shape respectively the geometric properties of an individual hairpin and its assignment to one of the hairpin types mentioned above, its location in relation to its neighbors is important for the pre-assembly process. This arrangement of two or more hairpins is referred to as topology in the following. To illustrate the topology of hairpins more clearly, the stator is mentally unwound as shown in Figure 4. The examples show a stator section with four layers and eight slots. The positions of the first and second legs of the hairpins in the stator are color-coded. Figure 4a,b show the most common topology, which is why it is referred to below as the standard topology. Here, both hairpins have the same span. Accordingly, both legs of the second hairpin are offset by one slot from those of the first hairpin. In the case of the standard topology combined with regular hairpins, the legs are in adjacent layers; in the case of single-layer hairpins, they are in the same layer. It is clear from this illustration that the standard topology with regular hairpins can be used to form an entire hairpin ring with—in the case of a stator with 36 slots—36 hairpins. This is not possible with single-layer hairpins because the second legs occupy the slots of the same layer. In the example shown, no further hairpin could be inserted in slot 7, as this slot is already occupied by the second leg of the hairpin with its first leg inserted in slot 1. For this reason, the standard topology with single-layer hairpins is only used for a certain number of hairpins, referred to below as a hairpin group. Such a hairpin

group often consists of two or three hairpins, for example. Another common topology is the tangentially-stacked topology shown in Figure 4c,d. Again, it can consist of regular hairpins (c) or single-layer hairpins (d). In this case, both legs of one or more hairpins lie tangentially between the legs of an outer hairpin. The tangentially-stacked topology with regular hairpins is an example for two regular hairpins with different shapes within one hairpin ring. Finally, the radially-stacked topology is introduced in Figure 4e, which describes the position of two radially adjacent hairpins. Here, both legs of one or more hairpins lie radially between the legs of an outer hairpin. According to the hairpin types introduced above, this topology is only possible with special hairpins whose legs are in non-adjacent layers.

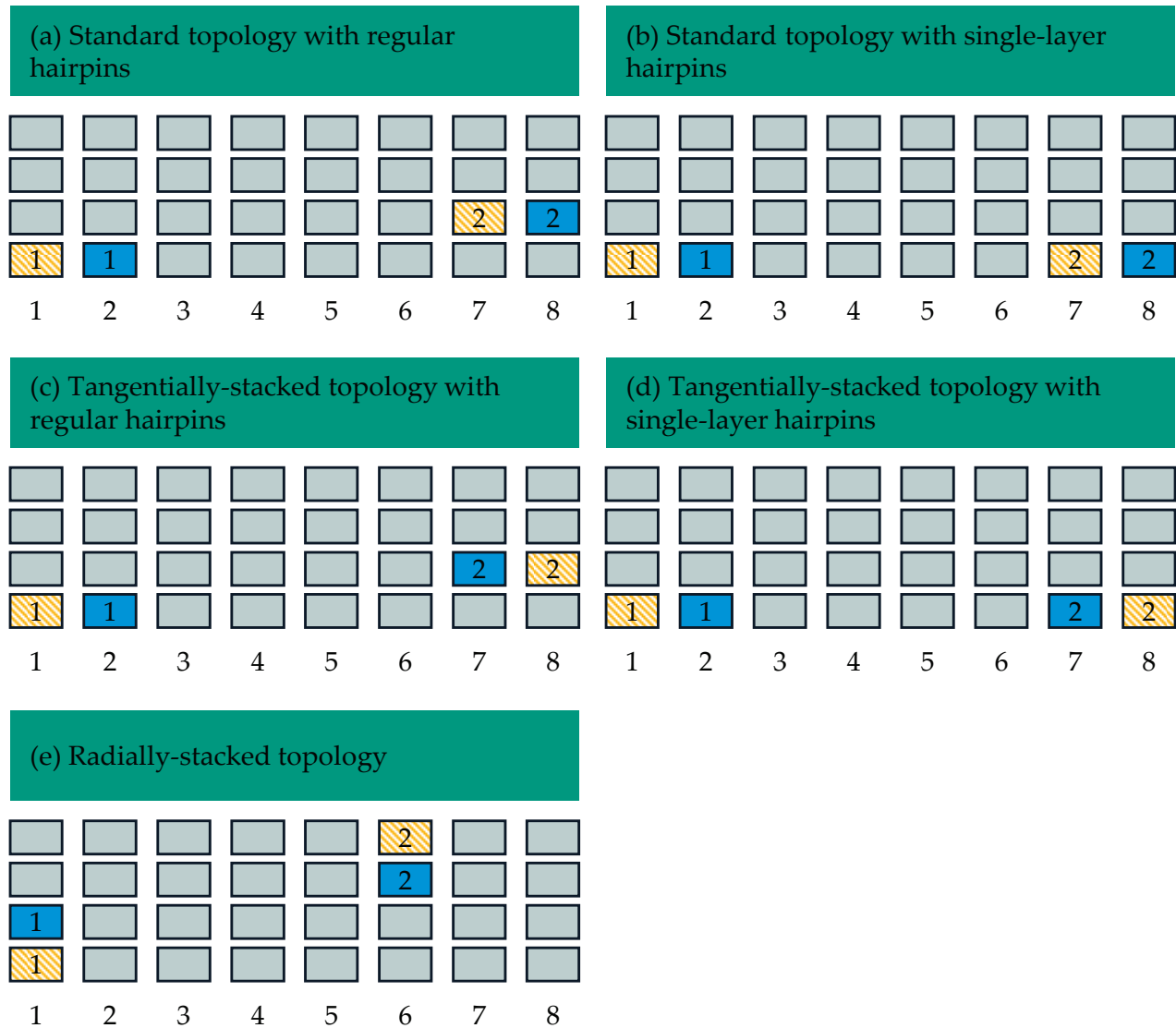


Figure 4. Different topologies of hairpins. The positions of both legs of two hairpins relative to each other are shown in each subfigure. The two legs of a hairpin are the same color and are numbered 1 and 2.

Different topologies can be combined within a hairpin group. Two examples are given in Figure 5, each consisting of three hairpins. Within the group, the standard topology is combined with the tangentially-stacked topology with single-layer hairpins.

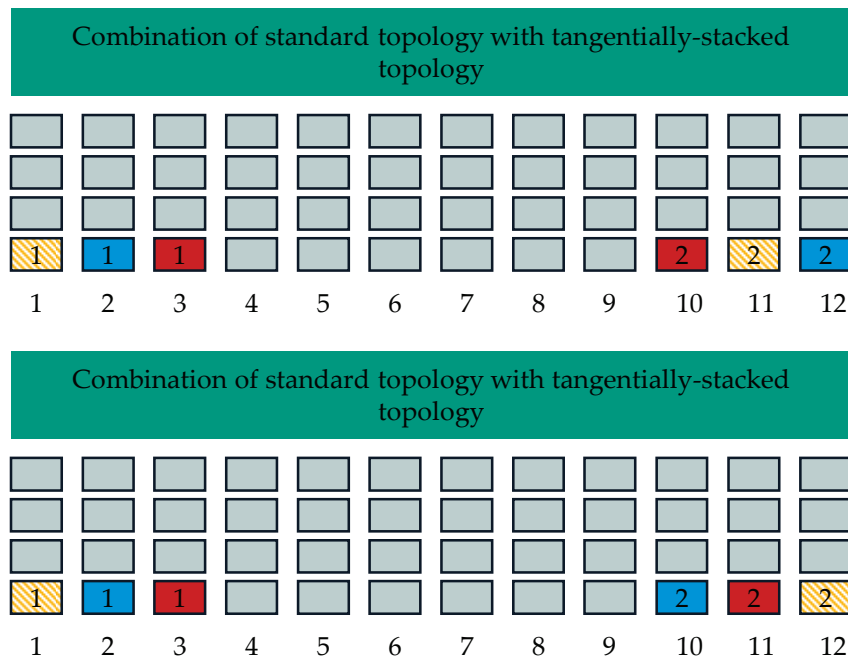


Figure 5. Two examples for the combination of different topologies in a hairpin group of three hairpins. The positions of both legs of three hairpins relative to each other are shown in each subfigure. The two legs of a hairpin are the same color and are numbered 1 and 2.

2.4. Pre-Assembly of Hairpin Baskets

The hairpin types and topologies described in Section 2.3 generally result in mutually overlapping hairpins. For example, the standard topology with regular hairpins results in the overlapping shown in Figure 6a. It can be seen that the legs of the first hairpin lie above and below one leg of the second hairpin. This results in the problem that the hairpins cannot be pre-assembled purely axially in z-direction. Possible movements that allow the collision-free pre-assembly of two regular hairpins in theory are shown in Figure 6b, although no auxiliary devices that could further restrict the possible movements are yet included in these considerations. In practice, it is almost impossible to insert all hairpins directly into the lamination stack automatically, as the joining gap in the slot is too small to perform the required movement of the hairpin. Even though direct insertion by manual assembly may be possible by carefully bending already assembled hairpins to the side in order to assemble further hairpins, it is common practice to first pre-assemble the hairpins in an auxiliary device, both manually and automatically. Even in this case, however, it is essential to adhere to a winding design-specific assembly sequence that allows collision-free assembly.

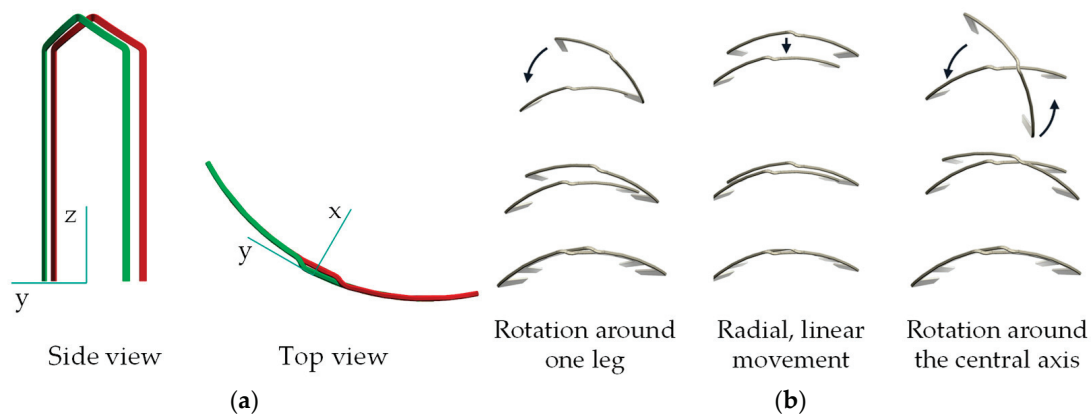


Figure 6. (a) Overlapping of two hairpins; (b) Possible movements for collision-free pre-assembly.

During manual assembly, the hairpins in the auxiliary device generally have more play than in the stator slots, which means that hairpins that have already been assembled can be pushed to the side slightly in order to set the next hairpin. Care must be taken not to apply any plastic deformation to the hairpins. Due to the large number of hairpins and different hairpin shapes, long process times and a high susceptibility to errors are to be expected during manual assembly. For this reason, lookup-tables are required that specify the assembly sequence. Nevertheless, the risk of setting wrong hairpins or placing correct hairpins in the wrong positions is high.

Automated assembly is often robot-based (for scientific approaches, see [2,11]), whereby not all hairpins are necessarily placed directly into a single assembly device to form the entire hairpin basket. Instead, the hairpin basket respectively the assembly device is often separated into individual rings or segments, which are then joined together in further steps to form the entire hairpin basket. It may also be necessary to set individual special hairpins at a later stage. Separating the hairpin basket greatly reduces the complexity of the individual process steps to be carried out by a robot. Examples of the segmentation of the hairpin basket can be found in [12,13]. The pre-assembly of single rings is often implemented by first setting the hairpins into the auxiliary device in a spread-out position and then screwing in the hairpins. A schematic representation of the separation of the hairpin basket into rings or segments can be seen in Figure 7. In order to achieve satisfying cycle times in the automated assembly of hairpins, the corresponding systems are usually optimized for a defined winding design and are correspondingly complex and inflexible.

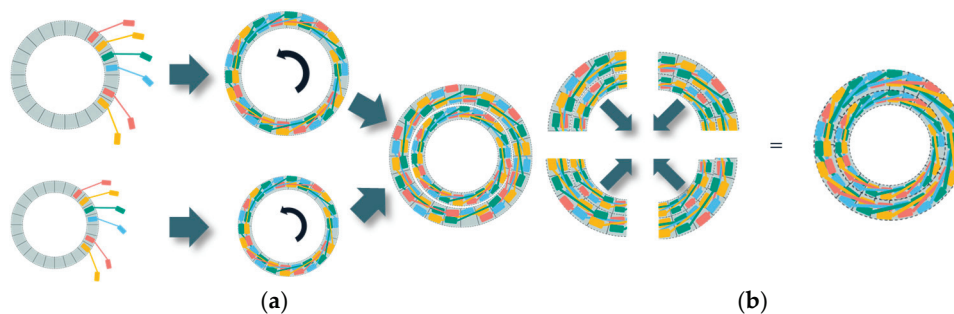


Figure 7. Schematic representation of an automated assembly of hairpin baskets; (a) Pre-assembly of single hairpin rings; (b) Separation of the hairpin basket into several segments.

Regardless of the pre-assembly method and degree of automation, it is essential to follow the correct assembly sequence, as this is the only way to ensure simple assembly that is gentle on the hairpins. Improper handling of the hairpins may result in damage to their shape or insulation. The former primarily results in problems or errors in subsequent processes (assembly, insertion, twisting, and welding) or incorrect dimensions, e.g., of the winding head. The latter can lead to defective motors. Incorrect assembly, either due to an incorrect assembly sequence or incorrect positioning of the hairpins, also usually results in electrically incorrect and non-functional windings.

Figure 6 shows that when gripping the hairpins from the outside and using an assembly movement radially inwards (in x-direction), the red hairpin must be set first and the green hairpin second. For manual assembly, the correct assembly-sequence and hairpin position usually offer enough information for the worker to assemble the hairpin basket. In the case of automated assembly, however, the assembly sequence as well as the gripper movement must be coordinated in the form of an assembly instruction. For stators with several hundred hairpins, these assembly instructions can become complex and ex-

tensive depending on the complexity of the winding—especially the number of special hairpins—and require a great deal of experience on the part of the worker or work planner.

2.5. Hairpin Grippers

The options shown in Figure 6b for pre-assembling hairpins without collision often result in radial assembly movements from the outside inwards. This in turn results in grippers that can grip the hairpins from the outside, e.g., using electric or pneumatic parallel jaw grippers. Both legs are gripped to ensure a secure hold even at high speeds. Due to the different shapes of hairpins, different configurations of the gripper are required, which is why it can be equipped with several pneumatic or electric actuators that allow the parallel jaw grippers to be positioned flexibly in relation to each other. Such flexible grippers are on the one hand complex, expensive and time-consuming to manufacture. On the other hand, they are heavy due to the actuators installed, which makes relatively large robots necessary to handle the hairpins weighing only around 50 g.

2.6. Gripping and Insertion of the Hairpin Basket

Once all the hairpins have been assembled in the auxiliary device, the hairpin basket must be gripped and guided into the slots of the stator lamination stack. Due to the small joining gap between the slot and the hairpins, this process requires great precision. On the one hand, this can be achieved using an auxiliary device that is fed in radially over the front of the lamination stack before the joining process. This device has insertion chamfers that guide the legs of the hairpins safely into the slots. An additional function is to protect the slot insulation paper from damage or being drawn into the slot. On the other hand, the hairpins should be aligned as precisely as possible by the hairpin basket gripper itself so that the play in the auxiliary device is eliminated. A detailed description of the process can be found in [14]. A schematic representation of the hairpins in the auxiliary device with play can be seen in Figure 8a. The hairpins have no defined orientation and position. Figure 8b shows the aligned hairpins as they should be in the hairpin gripper. How this alignment is implemented technically can vary greatly.

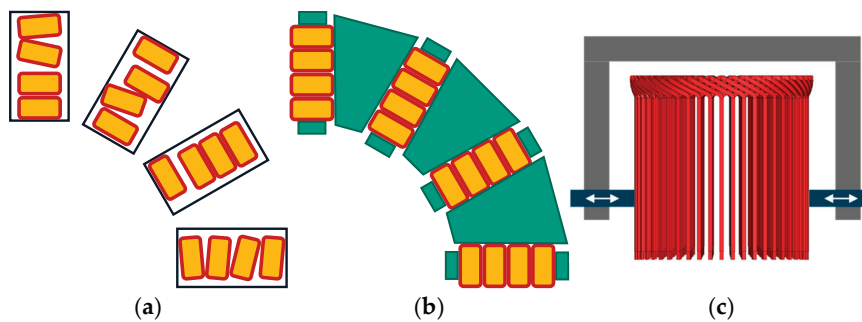


Figure 8. Schematic representation of the alignment process of hairpin baskets; (a) Pre-assembled, non-aligned hairpins in an auxiliary device with play; (b) Aligned hairpins fixed in the hairpin basket gripper; (c) Basic structure of a hairpin basket gripper with adjustable fingers (blue color).

2.7. Hairpin Basket Grippers

Hairpin basket grippers usually have complex mechanical components to ensure both exact positioning and secure fixation of the hairpins. Radially feedable fingers, which move between the rows of hairpins, are often used to realize these functions. The number of fingers corresponds to the number of stator slots, which means that the mechanics can be extremely versatile. In addition, the gripper design is highly inflexible with regard to the stator design. As a result, extensive set-up work or new gripper designs are usually necessary if stator properties such as diameter, number of slots, number of layers or wire

cross-section change. The basic structure of a hairpin basket gripper with adjustable fingers is shown in Figure 8c. The gripper is usually mounted on a gantry to lift the hairpin basket out of the auxiliary device and transport it to the lamination stack.

3. New Approaches for the Assembly and Gripping of Hairpin Baskets

In order to address the described disadvantages of manual and automated hairpin assembly as well as hairpin basket gripping, an approach for collaborative hairpin assembly and a new hairpin basket gripper design will be presented below. The collaborative hairpin assembly offers better support for the worker through the use of a cobot and visual representations, thus reducing the susceptibility to errors in the process while retaining the flexibility of manual assembly as much as possible. The new hairpin basket gripper design with a sequential alignment process provides greater flexibility in terms of stator design and significantly reduced mechanical set-up work. Both approaches have standard interfaces with upstream and downstream processes and could therefore be integrated into existing lines.

3.1. Vacuum Hairpin Gripper

In order to keep both the complexity and weight of the hairpin gripper low, an additively manufactured vacuum gripper is used for collaborative hairpin assembly (for more information see [15]). The 3D-printed base body has threaded inserts into which the suction cups can be screwed. The grippers presented here were made from PETG (polyethylene terephthalate glycol) on a standard FFF-printer (Fused Filament Fabrication). Alternatively, they can also be produced using a laser sintering process [15]. This provides even greater design freedom. For example, it enables an additively manufactured Venturi nozzle for vacuum generation to be printed directly into the gripper, or fibres to be integrated for reinforcement. For reasons of performance in terms of vacuum quality and simplicity, the laser sintering process was not used in this paper.

Vacuum grippers have a number of advantages. On the one hand, these grippers are cheap, lightweight (40 g [15]) and can be completed within a day on a regular 3D-printer. On the other hand, such a gripper poses little risk to the worker as it has no moving or clamping elements. It should be mentioned that if the compressed air fails, the vacuum breaks down and the workpiece can no longer be gripped securely by a vacuum gripper. However, this risk is considered to be low for hairpins for electric traction motors weighing around 50 g. The risk of premature failure of the vacuum gripper due to deformed hairpins or contamination is also considered to be low due to the high requirements for geometric tolerances of the hairpins, as well as cleanliness in stator production in general. One disadvantage is the properties of the suction cups. Very small suction cups are required for small wire cross-sections. However, these lose flexibility with decreasing size, so that slight deviations in position between the hairpin and the suction cups (e.g., an angular offset) can more easily lead to a vacuum leak. For this reason, it is important to ensure that the threaded inserts are inserted at right angles into the 3D-printed base body. In addition, the hairpins must be provided with great precision. In principle, aluminum base bodies could be used, which would better meet the requirements for precision. However, this would result in a higher weight compared to PETG (with an infill of 30% for the 3D-printed part approximately seven times) and increased manufacturing costs, particularly due to the complex installation of the vacuum channels. Grippers with base bodies made of aluminum were therefore not tested. The measures mentioned above ensured secure gripping using an additively manufactured vacuum gripper.

A dependence of the vacuum gripping force on the hairpin insulation, usually PEEK (polyether ether ketone), PI (polyimide) or PAI (polyamide-imide) [16], could not be

determined. This is also consistent with investigations into the coefficient of friction of insulation materials, in which only slight differences were found between PEEK and PAI [17].

Due to their simple design, the vacuum grippers used here can only grip a single hairpin shape. This means that as many grippers are required per stator as there are hairpin shapes in the winding. This is acceptable due to the low costs of a few hundred euros and the short production time. The changeover can be automated using a quick-change system. In case of a new stator design with different wire, the suction cups may also need to be adapted to the wire cross-section. Figure 9b shows one of the vacuum grippers used here.

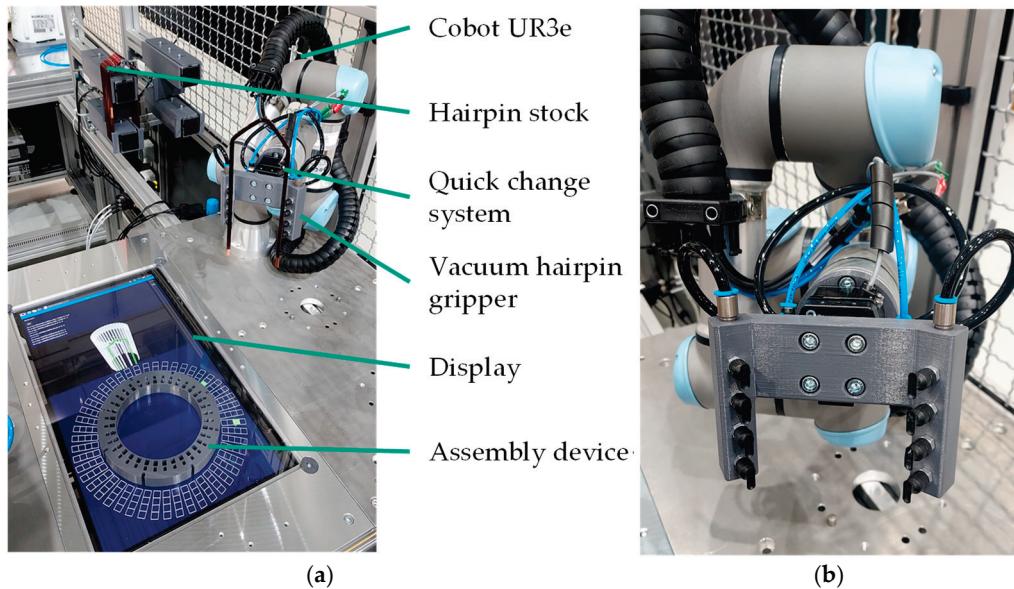


Figure 9. (a) Test setup for collaborative assembly of hairpins; (b) Additively manufactured vacuum gripper.

3.2. Test Setup for Collaborative Hairpin Assembly

Figure 9a shows the entire test setup. A cobot UR3e (Teradyne Robotics (Germany) GmbH, München, Germany) with a quick-change system SWS-007 (SCHUNK SE & Co. KG, Lauffen/Neckar, Germany) is used, on which the vacuum gripper is mounted. The vacuum is generated with an ejector VN-10-H-T3-PQ2-VQ2-RO1 (Festo Vertrieb GmbH & Co., KG, Esslingen, Germany). A screen protected by a plexiglass panel is embedded in the assembly table and provides visual support for the worker. The cobot picks up the hairpins according to the assembly sequence and hands them to the worker for assembly. The assembly device, into which the hairpins are assembled manually, is located directly above the display on the table. The operator can confirm actions via a keyboard. The software for the visual display and for controlling the assembly sequence runs on a ThinkCentre with 32 GB RAM (Lenovo (Deutschland) GmbH, Stuttgart, Germany).

In the current test setup, two different hairpin shapes can be processed to keep complexity low. As is common in industrial applications, they are mounted on rods. In the case of an industrial production line, these rods could be refilled directly from the hairpin bending machine. Future expansion is easily possible within the range of the cobot arm.

3.3. Software for Visual Support

The software developed has two tasks in the new approach. Firstly, it supports the worker during the assembly process and ensures that the correct hairpins are placed in the correct position. Secondly, it can be used during commissioning of the process by

supporting the worker in planning the correct assembly sequence for the hairpins. This is implemented by a collision analysis of the winding, see Section 3.4.

Visual support for the operator is provided by three sections with different illustrations, see Figure 10. The basis of the collaborative assembly is the bottom section (Section 1), which shows the correct slot and position of both legs of the hairpin to be assembled in color. The assembly device is in the centre of the illustration. By pressing the space bar on the connected keyboard, the display is updated to show the correct position for the hairpin to be placed and the vacuum is switched off so that the hairpin can be easily removed from the gripper. During the assembly process by the worker, the cobot fetches the next hairpin for assembly. In section two, there is a 3D-representation of the hairpin basket that has been set up to that point. The hairpin currently to be set is highlighted in color. The 3D-model can be rotated and zoomed in using a mouse if required. The third section contains a list of the last three hairpins set, the current hairpin and the next three hairpins.

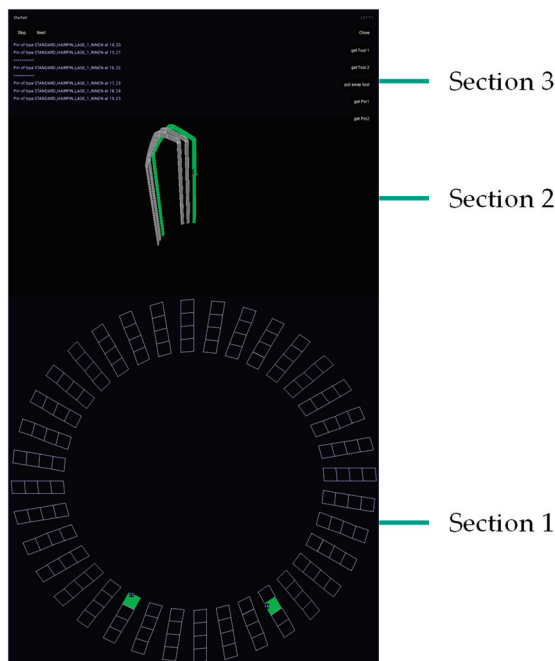


Figure 10. Visual support for the pre-assembly of hairpins.

3.4. Software for Collision Detection

As already described, planning the assembly sequence is a complex process that also requires the planner's experience. For this reason, an approach to automate the planning is being investigated. Based on a 3D-model of the complete hairpin basket, the winding scheme is first analyzed using collision detection. To do this, each hairpin is virtually pulled out of the 3D-model of the finished hairpin basket, and its collisions with other hairpins are detected and recorded. As the subsequent assembly movements by the worker will be either radially inwards or axially downwards, the hairpins are virtually pulled radially outwards and axially upwards. As an example, a section of a winding scheme is assumed in which layers 2 and 3 are occupied by special hairpins (e.g., jumpers, red), referred to as type A. Above these are special hairpins of type B whose legs are in layer 1 and layer 4 (blue). Top and side view of this section can be taken from Figure 11a. The radial collision analysis for the hairpins of type B shows a collision of the second leg in layer 1 with all other hairpins (type A and B) whose legs are in this slot. The axial collision analysis, on the other hand, only results in a collision with its neighboring hairpins of type B. No axial collision with type A is detected, which is a sign that type B can be assembled after type A in an axial way (axial collision analysis for type A results in detected collisions with type B).

Radial assembly, on the other hand, is not possible for type B if type A is already assembled. However, as explained in Section 2.4, purely axial assembly is not possible due to mutual overlap of the type B hairpins. In this case, the rotation around the central axis (Figure 6b) offers a solution for collision-free assembling of the type B hairpins.

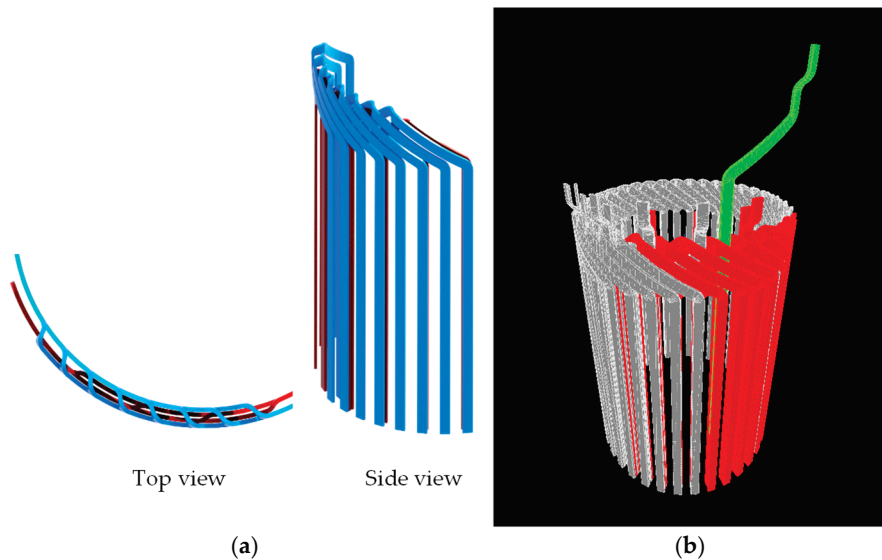


Figure 11. (a) Winding scheme with special hairpins; (b) Screenshot of the collision detection program.

The collision analysis is carried out for each hairpin, resulting in an extensive table containing the collisions between all hairpins. In the current state, manual interventions are still necessary to determine the correct assembly sequence. However, the system can already be used as support for the assembly planer. The collision analysis is only used to determine possible assembly sequences. Collision monitoring of the entire process, including robots and workers, is not carried out.

Figure 11b shows a screenshot of the collision detection program. This illustration shows the collision of an I-pin during axial pullout. Based on the results of the collision analysis, the assembly sequence for collaborative assembly can be defined and recorded in a list. Based on this list, the robot feeds the correct hairpins, the exact position of which is shown on the display.

3.5. Hairpin Basket Gripper

The new hairpin basket gripper design is intended to significantly increase the flexibility of the gripper in terms of stator properties—particularly with regard to the number of slots. In addition, the set-up effort for new stator designs should be significantly reduced. For this reason, the concept presented does not use a large number of adjustable fingers to position the hairpins, as is the case with state-of-the-art grippers, see Section 2.7. Instead, the hairpins are fixed exclusively by radial clamping. As shown in Figure 12, there are two concepts to ensure the necessary precise tangential positioning of the hairpins. In both concepts, radial positioning is performed by the gripper.

For the first concept, an auxiliary device can be designed for hairpin assembly, which allows the hairpins to be tangentially aligned once the hairpin basket has been correctly assembled, see Figure 12a. Three coaxially arranged rings with overlapping slots for mounting the hairpins would be conceivable, see Figure 13a. After assembly, the legs of the hairpins can be precisely aligned tangentially by turning the middle ring, see Figure 13b, before the hairpin basket is gripped, aligned radially and inserted into the lamination stack by the basket gripper. The corresponding hairpin basket gripper would be a mechanically

simpler form of the gripper described below for concept (b) with only one gripping unit consisting of 6 gripper jaws. Since the aim of this work was to use an auxiliary device that was as simple as possible, this concept was not developed further.

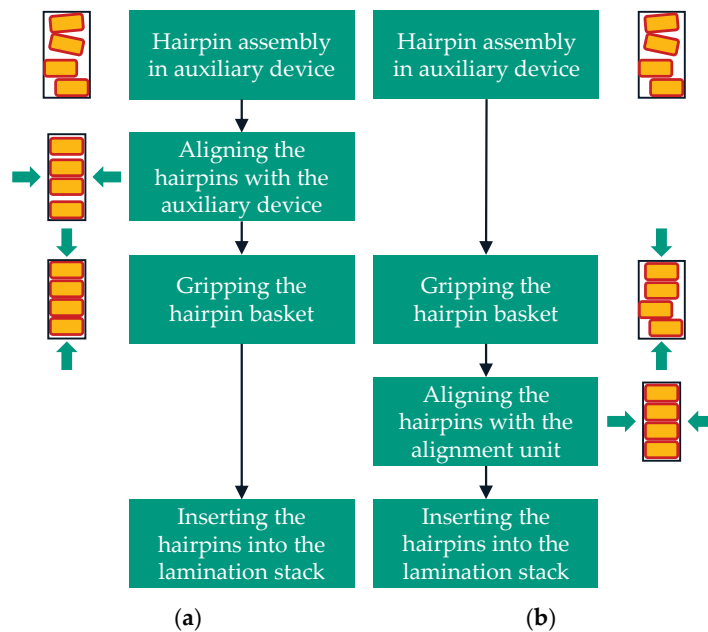


Figure 12. Two concepts for gripping and aligning hairpin baskets with exclusively radial clamping: (a) Aligning the hairpins with the auxiliary device; (b) Aligning the hairpins with an alignment unit.

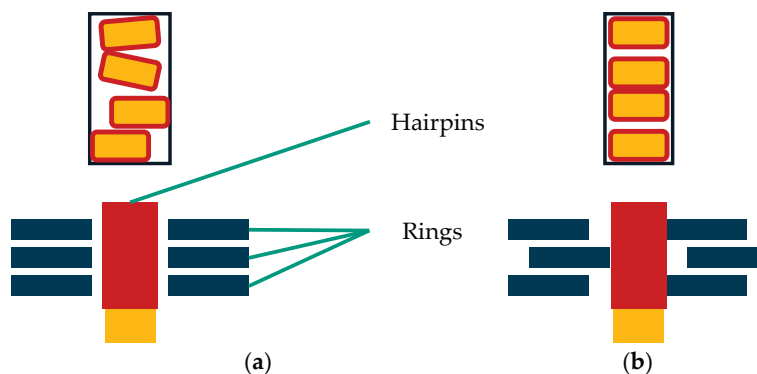


Figure 13. Possible device for tangentially aligning the hairpin basket. (a) Slot before alignment; (b) Slot after alignment.

For the second concept, no special assembly device is required, see Figure 12b. Instead, a separate alignment unit is required in which each slot can be sequentially aligned in tangential direction. The concept is explained in detail in [14]. The hairpin basket gripper for this concept is based on two ring-shaped gripping units that can be rotated against each other. A gripping unit consists of six gripper jaws that can be adjusted radially and clamp the hairpins from the outside against an internal cylinder. This cylinder defines the inner radius of the hairpin basket. While all slots of the hairpin basket can be clamped by the upper gripping unit, one gripper jaw of the lower gripping unit has a recess so that the corresponding slot is not clamped. This particular slot is now guided into an alignment unit so that the hairpins are correctly aligned. All slots including the aligned slot are then clamped again by the upper gripping unit and the aligned slot is moved out of the alignment unit again. The entire hairpin basket gripper is then indexed forward by one slot ($360^\circ/N$) and the lower gripping unit is indexed back accordingly. In this way, the hairpins

of all slots are aligned one after the other in order to be inserted into the lamination stack afterwards. The hairpin basket gripper is attached to a robot that can move the hairpin basket in the alignment unit one slot after the other. The test setup is shown in Figure 14. The alignment unit is a metal 3D-print.

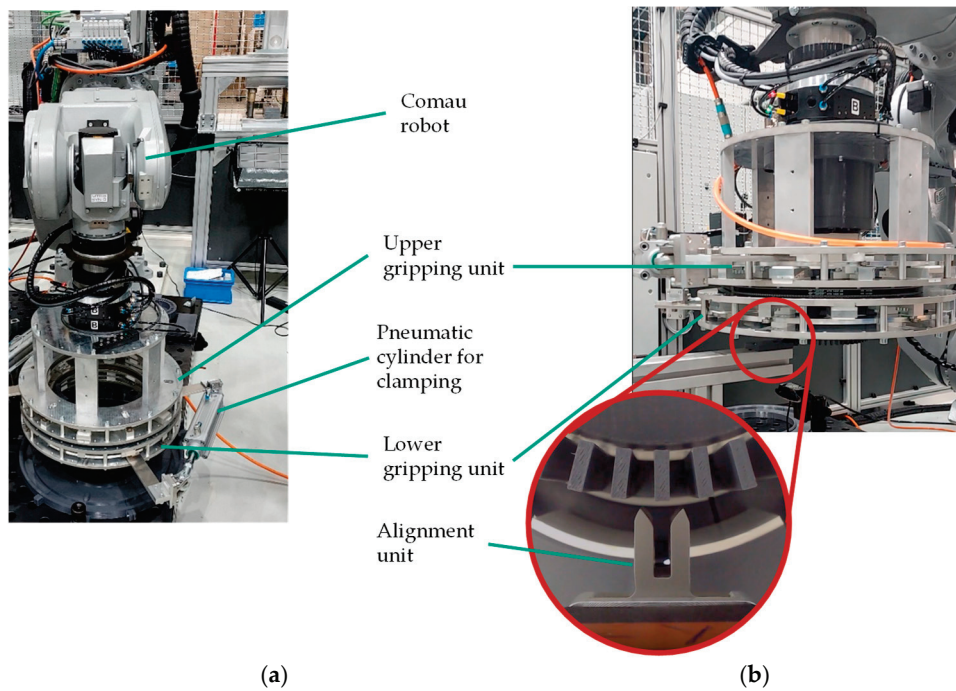


Figure 14. (a) Test setup of the new hairpin basket gripper and sequential alignment; (b) Alignment unit and 3D-printed dummy hairpin basket seen from below.

The entire process chain is summarized again below and illustrated in Figure 15 using a 3D-printed dummy winding. The gripper and the hairpin basket are viewed from below.

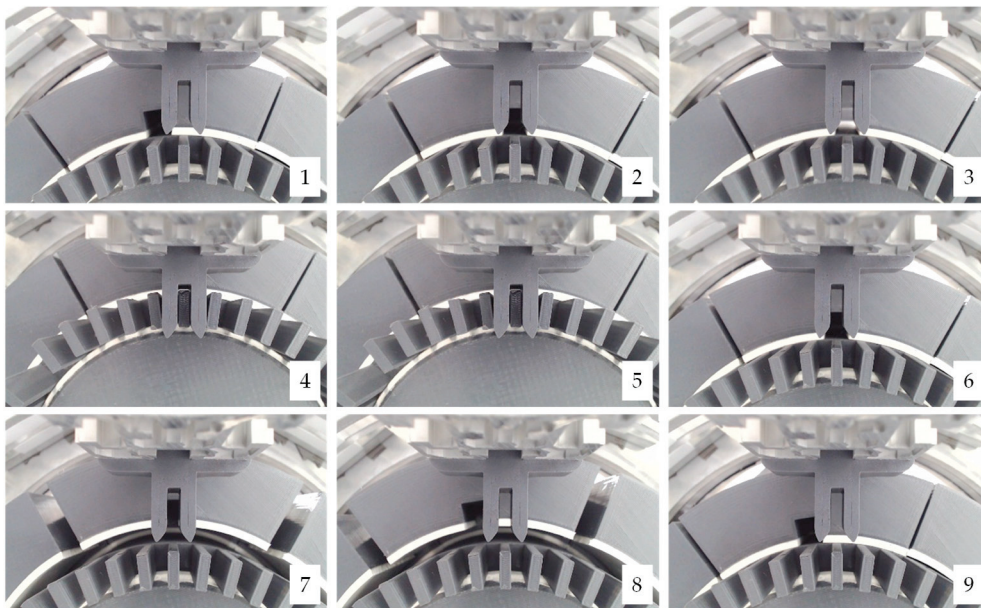


Figure 15. Process chain for gripping and sequential alignment of the hairpin basket. The numbers indicate the corresponding process step.

- Step 1: Upper and lower gripping unit are closed.
- Step 2: The entire gripper is indexed forward by one slot.

- Step 3: The upper gripping unit is opened.
- Step 4: The gripper moves into the alignment unit. One slot is aligned.
- Step 5: The upper gripping unit is closed.
- Step 6: The gripper moves out of the alignment unit.
- Step 7: The lower gripping unit is opened.
- Step 8: The lower gripping unit is indexed backwards by one slot.
- Step 9: The lower gripping unit is closed and the process starts at step 2 again.

4. Results and Discussion

4.1. Collaborative Hairpin Assembly

Initial tests show that the presented concept of a collaborative hairpin assembly works in principle. Storing the hairpins on rods and gripping and handing the hairpins using the cobot and vacuum gripper are also possible. Communication between the Computer and the UR3e controller enables the cobot to respond flexibly to inputs via the keyboard. Figure 16 shows the collaborative hairpin assembly process. First, the cobot picks up the correct hairpin gripper (a). It then picks up a hairpin from the rod (b) and hands it to the worker (c). The worker takes the hairpin and places it in the auxiliary device according to the visual guidance (d).

At the moment the cycle time of the cobot to feed a new hairpin is 17 s, which is slower than the assembly process by the worker, especially at the start of the assembly, as there are only a few hairpins already set that need to be taken into account. The process time for an entire stator scales with the number of its hairpins. For a stator with 48 slots and 6 layers, and therefore at least 144 hairpins, this results in a process time of more than 40 min, which is unacceptable for an industrial use. As there has been no focus on optimising cycle times to date, a series of measures will be implemented in the future to significantly reduce them. Firstly, the speed of the cobot can be increased further, but it is important to ensure that the hairpin can still be gripped securely and that safety aspects relating to the worker are considered. Secondly, the cobot's trajectory can be improved, for example by smoothing the robot path. In addition, the layout can be adjusted to optimize moving distances. However, the greatest potential for savings is seen in speeding up the gripping process itself, since this has accounted for a significant part of the total processing time. To ensure that individual hairpins can be gripped and removed safely from the rod, this process has been very slow up to now. A more efficient way of providing and gripping the hairpins therefore has great potential, but also means a lot of changes and improvements that may also affect the upstream process of hairpin bending in industrial applications. The described changes should cut the cycle time by at least half.

In addition to the current long cycle times, changeover times for the gripper must be taken into account, which are also in the range of approximately 20 s. The number of necessary changes is at least equal to the number of different hairpin shapes in the stator winding and increases if not all hairpins of one shape are assembled one after the other in the assembly sequence. A significant improvement in cycle time would be achieved by using a second robot, which would affect both the feeding of new hairpins and the tool change. In addition to increasing costs for the robot and a second tool set, the increasing complexity and space requirements are the main arguments against this option.

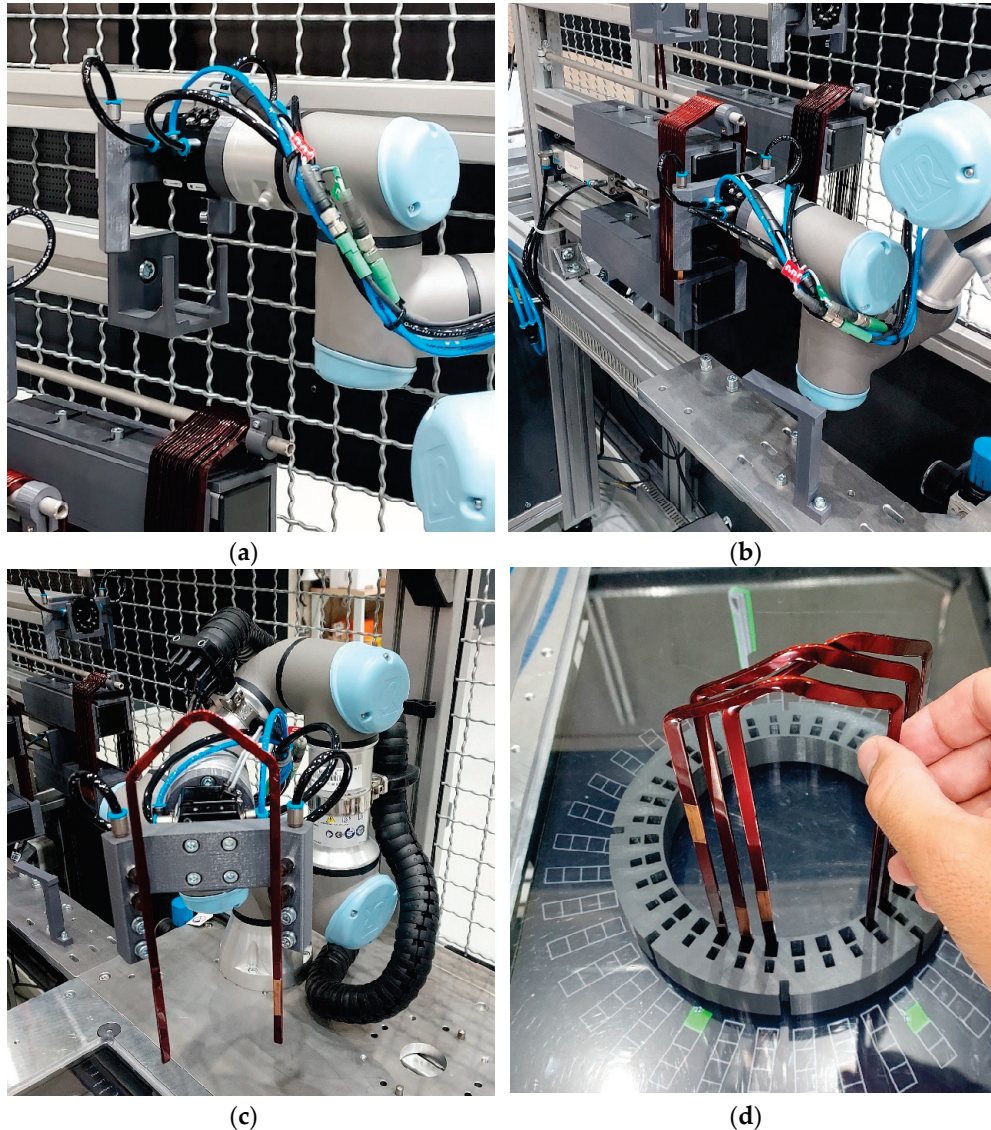


Figure 16. Collaborative hairpin assembly process: (a) Picking up the correct hairpin gripper; (b) Picking up a hairpin; (c) Handing the hairpin to the worker; (d) Visually guided assembly of the hairpin.

Even with the measures described above to reduce the cycle time, it is unlikely that the speed of the worker during the first, easy-to-assemble hairpins will be reached. Nevertheless, there are application scenarios in which collaborative assembly can be useful: The first scenario is the assembly of complex stator designs with many special hairpins. Automated solutions for this are complex, expensive, time-consuming and inflexible. Manual assembly is error-prone. In the second scenario, the standard hairpins of the winding are first assembled in an automated, fast process, as they are easy to assemble. The more complex and time-consuming assembly steps, usually involving the special hairpins, would then be carried out by the collaborative assembly process, completing the winding. Both application scenarios are particularly conceivable for small quantities and a wide variety of stator variants for which an automated solution is not worthwhile and manual assembly is error-prone.

Experimental tests have shown that the operability of the current system is acceptable and intuitive, but mouse and keyboard are impractical for industrial use. Instead of the keyboard, a simple switch is to be used in future to enable the assembly program to be

continued. Using the 3D-model in the middle of the display is particularly useful for better orientation when training new employees or new winding patterns. Active use of the model (in the sense of rotating and zooming) during the ongoing production process is also rather unlikely for time reasons, which is why the mouse can be retained but does not have to be permanently available to the worker. Errors, e.g., if the worker accidentally drops or bends a hairpin during assembly, are not yet taken into account in the system. However, implementing a corresponding response from the system, e.g., supplying the worker with another hairpin of the same type, is considered feasible.

The display supports the worker during the assembly process, as he does not have to determine the assembly sequence and hairpin shape to be assembled himself using lookup-tables. The correct assignment of hairpin shape and position of the two legs is clearly indicated by the software, the cobot and the display. Even if the system does not currently detect incorrect placement of the hairpin, this significantly reduces the number of possible errors.

The collision detection approach shows promising results, which have already been tested for some hairpin topologies and winding schemes. The collision detection algorithm itself works in both the radial and axial directions. The correct assembly sequence can then be derived from the results of the collision analysis for certain, simply structured sections of the hairpin basket. An example is given in Section 3.4. However, it can currently only be used to support the operator in the planning process and not to automatically generate the entire assembly sequence, especially in case of complex winding schemes. For example, the first hairpin to be assembled must be specified by the user, and optimized planning, in which different assembly sequences are tested, has not been implemented. So far there is also no additional information about the correct movement required to assemble the hairpin collision-free (see Figure 6b). This information is particularly lacking for the last hairpins to be set in complex winding schemes, where it would be useful to support the operator.

Table 1 summarizes the final evaluation of the approach in comparison to manual and automated assembly. As described, the new approach can reduce the susceptibility to errors compared to manual assembly, while the cycle time in particular still needs to be improved. Flexibility is slightly reduced compared to manual assembly, as the grippers must be replaced for new stator designs, for example. The costs can only be estimated qualitatively for manual and automated assembly. Provided that the cycle time is reduced in the future, the approach presented is therefore particularly useful for complex winding schemes, small quantities, and a high degree of variant diversity. In these scenarios, the disadvantages in terms of flexibility and cycle time can be offset by a lower susceptibility to errors thanks to visual support for the operator. For highly complex winding patterns, the cycle time can even be improved compared to manual assembly, as there is no need for time-consuming assembly based on lookup tables.

Table 1. Comparison of the new collaborative assembly with the manual and automated process.

Criteria	Manual	Collaborative	Automated
Flexibility	+	0	—
Error susceptibility	0	+	0
Cycle Time	10 s	17 s	1–2 s
Invest	+	0	—

4.2. Hairpin Basket Gripper and Sequential Alignment

The new approach for gripping hairpin baskets and aligning the hairpins in a sequential process was tested using a stator with 48 slots and 6 layers. Even though the concept

works in principle, it still has some issues to deal with. Especially if the hairpin basket has a lot of play in the assembly device, the initial position of the hairpins in the basket gripper is already so poor that sequential alignment is hardly possible, see Figure 17a–c. Nevertheless, the hairpin basket is gripped securely even in this case and the hairpins do not move axially. If the play in the assembly device is reduced, the initial position of the hairpin legs is also significantly better (see Figure 17d) and they can be moved securely into the alignment unit. For this reason, it is conceivable to combine an auxiliary device that can align the hairpins tangentially (Figure 12a) with a gripper consisting of only one gripping unit with 6 gripper jaws. Sequential alignment would not be necessary in this case.

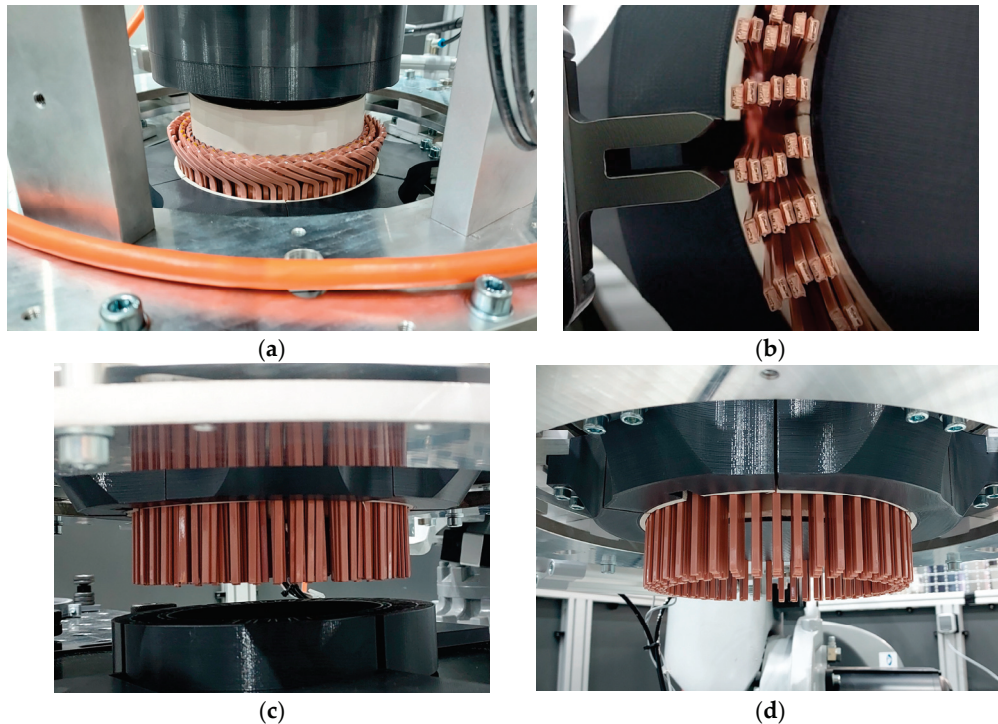


Figure 17. (a) Winding head of a gripped hairpin basket with low positional accuracy; (b) Hairpin legs of a gripped hairpin basket with low positional accuracy (from below); (c) Hairpin legs of a gripped hairpin basket with low positional accuracy (side view); (d) Hairpin legs of a gripped hairpin basket with high positional accuracy (side view).

It was found in the tests that the hairpins partially slip back into their original position before alignment as soon as they leave the alignment unit. The 3D-printed gripper jaws were identified as a possible cause, as they tilt slightly downwards when closing under high pressure, so that instead of surface pressure there is only line load.

Table 2 compares the novel approach with state-of-the-art grippers. Flexibility was increased as desired. The gripper is independent of the number of slots and wire geometry. If the stator diameter changes, only 12 gripper jaws need to be replaced instead of a number of fingers corresponding to the number of slots, e.g., 72. As described above, the approach is still very error-prone, especially if the hairpins in the auxiliary device have a lot of play. Unlike the cycle time for state-of-the-art grippers, it depends directly on the number of slots. With several seconds per slot alignment, this currently results in a cycle time of several minutes to pick up the hairpin basket, align every slot and transport it to the lamination stack. The cost of the novel gripper is approximately €15,000, which is considered to be significantly lower than state-of-the-art grippers, even though exact figures are not available. This does not include the robot currently in use, which is significantly more expensive than the linear axes normally used. Since the robot can also be used for further

steps, such as sequential twisting [18], this is not considered here. Due to the low number of parts that need to be replaced, the setup costs for changing to a new stator design are also significantly lower.

Table 2. Comparison of the new gripper design with state-of-the-art grippers.

Criteria	New Approach	State of the Art
Flexibility	+	—
Error susceptibility	—	0
Cycle Time	—	+
Invest and setup costs	+	—

5. Conclusions

The manual and automated assembly of hairpins into a hairpin basket both have advantages and disadvantages. While manual assembly is flexible due to the use of workers, it is very prone to errors. Automated assembly, on the other hand, can offer short cycle times and a high level of safety, but it is inflexible at the same time. The collaborative assembly presented here is intended to combine the advantages of both approaches and avoid the disadvantages. For this purpose, a cobot is used to hand the worker the correct hairpins. Visual support on a display located under the assembly device shows the worker the correct position of the hairpin. Tests have shown that collaborative assembly is possible and significantly reduces the susceptibility to errors. However, the current cycle time of 17 s is problematic. Creating an assembly sequence can be facilitated by the presented analysis using collision detection. At present, however, this is only a planner's aid; a complete assembly sequence cannot yet be derived from it.

The basic functionality of the hairpin basket gripper with a sequential alignment process was successfully tested. The kinematics and the alignment unit worked as intended. However, there are still challenges to be solved, particularly when it comes to correctly clamping the hairpins so that they keep their aligned position. To solve this problem, the additively manufactured gripper jaws will be replaced with ones made of aluminum. Right now the process can only be used under the condition that the hairpins are already well aligned in the assembly device before gripping. A combination of an auxiliary device that can align the hairpins tangentially with a gripper consisting of only one gripping unit is conceivable; see Section 3.5 concept (a). Due to the solely radial gripping and the low number of moving parts (only six gripper jaws), there would be an even bigger advantage over state-of-the-art grippers with a large number of gripper fingers—particularly in terms of flexibility and set-up time. The disadvantage of this concept is the more complex mechanical auxiliary device for hairpin assembly, which is why it was not examined in detail in this study. Further tests and design adjustments to stiffen the mechanics are planned in order to make the process more robust.

In conclusion, it can be said that both approaches have clear weaknesses in terms of cycle time, but significantly improve error susceptibility (collaborative assembly) and flexibility (basket gripper). For this reason, they are particularly suitable for use in prototype construction or small series production.

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Abbreviations

The following abbreviations are used in this manuscript:

N Number of slots

L Number of layers

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Article

From Jump-Start to Phase-Out—Transitioning Policy Making Towards a Primarily Market Driven Charging Infrastructure Rollout in Germany

Johannes Martin Loehr * and Maik Hanken *

National Centre for Charging Infrastructure c/o NOW GmbH, 10623 Berlin, Germany

* Correspondence: johannes.loehr@now-gmbh.de (J.M.L.); maik.hanken@now-gmbh.de (M.H.)

Abstract: During the early phases of EV market penetration, German policy makers supported the roll-out of a nation-wide charging infrastructure network by extensive state activities, most notably voluminous funding schemes to provide subsidies for publicly owned as well as business-driven charge point operators. An increasing EV adoption rate and therefore an increasing demand has since shifted the focus of policy making towards enabling a privately funded, competitive market. More recently, budgetary constraints have led to abrupt restrictions on policy making and market disruptions. This paper aims to provide insight into policy making during this transitional period, give reason for why a state-funded jump start was necessary for developing the charging infrastructure, and explore how policy makers now intend to foster the development of a functioning market while phasing out detrimental interventionist measures.

Keywords: government policy; charging infrastructure; market development; EV adoption; diffusion of innovation

1. Introduction

Since the early 2010s, the roll-out of EV-Charging Infrastructure in Germany has been guided and supported by extensive public intervention, mostly in the form of public funding schemes to overcome what is often called a ‘chicken-and-egg-problem’ of supply and demand. A rapidly increasing market penetration of EVs in the current decade, however, enables a more market-driven roll-out of charging infrastructure by privately owned and profit driven companies backed by private investments. This development has recently led to a shift in public policies from a main emphasis on subsidies to support the installation of as many public and private charging points as possible towards a focus on creating the framework for a functioning and competitive market design and towards a mid- to long-term phase-out of public interventions.

This article analyses the evolution of public policies towards charging infrastructure in Germany during the initial phases of EV charging infrastructure roll-out and especially the policy measures that were taken to bridge the gap between the demand and supply of a precursory roll-out during this phase.

1.1. Mitigation of External Effects

Road traffic in Germany caused around 145 million tons of carbon dioxide (CO₂) emissions in 2023, which makes up for about 21.5 percent of the country’s total 673 million tons of CO₂ emissions in that year, which in turn accounts for about 1.5 percent of global CO₂ emissions [1]. CO₂ is a greenhouse gas (GHG) and one of the main contributors towards

the increase in global mean temperatures, meaning that Germany—and its road traffic sector—heavily contribute towards the phenomenon of global warming. Economically speaking, GHG emissions are so called external effects, which characterize a form of market failure. Such external effects occur if the production or consumption of a good or service causes costs for the society (or other third parties) that do not get compensated via the price of the good or other market-driven mechanisms. The scale of the external effects of GHG emissions and the potential consequences of global warming have led to an unprecedented amount of international interventionists efforts.

1.2. International and National Emission Reduction Targets

With the 1997 Kyoto Protocol, countries first vowed to reduce their GHG emissions under international law. The protocol included quantified GHG emission reduction targets for every country, classified by their economic state. Through the so called ‘burden sharing’ approach between the then 15 member states of the European Union (EU), Germany agreed to reducing its emissions by 21 percent compared to 1990 [2]. This target was met by 2007, five years prior to the protocol’s obligation and even before the actual commitment period (2008–2012) [3]. The successor of the Kyoto Protocol, the Paris Climate Agreement (2015) does not quantify GHG emission reduction targets but instead pledges to keep the global mean temperature increase to 1.5 percent compared to pre-industrial levels [4]. It is up to the national governments to translate these into climate policies and emission reduction targets. The EU is tackling the resulting obligations with the ‘Fit-For-55’ program [5], and Germany, in turn, implemented the Climate Protection Act (‘Klimaschutzgesetz’, KSG). The KSG does include quantified emission reduction targets by sector, which require the corresponding ministries to set up policy measures and other instruments to meet their sectors target. This multi-level cascade of international, EU and national law manifests not only an economic obligation (mitigation of external effects) but also a legal obligation for interventions and therefore the implementation of climate protection policies.

1.3. Decarbonization of Road Traffic

As previously determined, road traffic is one of the main contributors to Germany’s and most other industrialized country’s total GHG emissions, making it a strong lever for emission reductions. As mobility demand is almost non-elastic in the short and medium term [6], such reductions must, however, be achieved by replacing CO₂-intensive internal combustion engines (ICE) with low emission drive technologies. In the last couple of years, battery-electric vehicles (BEV) have emerged as the most market-ready and best-suited technology available for the decarbonization of most road traffic, especially passenger cars and light duty vehicles. While these cars are not entirely carbon free (vehicle production and power generation still cause GHG emissions), they can already achieve a significant reduction in carbon emissions over their lifetime compared to ICEs as Figure 1 shows.

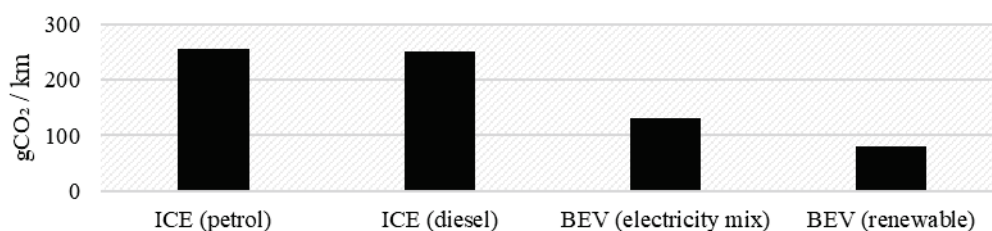


Figure 1. Lifetime CO₂ emissions by drive technology including production process [7].

BEV market penetration, therefore, is a critical parameter when trying to decarbonize road traffic, making an increasing adoption rate of consumers a legitimate policy making goal in order to achieve the relevant emission reduction targets that countries are

both economically and legally obliged to. A necessary prerequisite of a widespread BEV adoption by consumers is the existence of a sufficient electric vehicle charging network. BEV market penetration and charging infrastructure rollout are inextricably linked, which means that the aforementioned emission reduction targets not only constitute the need for interventionist measures to increase BEV adoption rate but also to stimulate the rollout of charging infrastructure, as this paper will demonstrate. The interdependencies between infrastructure rollout and adoption rate require integrated considerations when discussing policy making and its goals, which this paper will provide. According to a 2023 comprehensive literature review, strategies for the roll-out of charging infrastructure have become a major focus in the more recent scientific discussions on EV-Adoption [8] and concurrently a pressing matter of public policy making.

1.4. Methodology

In order to analyze the policy making in regard to electric vehicles and charging infrastructure in the past and present and to derive recommendations for the future, this paper highlights four phases of policy making with unique characteristics as follows:

- Phase 1: Jump starting and ‘Paving the Way’.
- Phase 2: Commitment and Stimulation.
- Phase 3: Scaling and ‘Crossing the Chasm’.
- Phase 4: Moderating and Safeguarding.

It is, however, important to note that these phases can have considerable overlaps and are by no means independent of each other. While the ongoing market penetration of BEVs does not provide a clear distinction between the phases due to its rather continuous nature, notable legislations and other political milestones can determine the beginning of a new phase. Revisions of existing legislations or the passing of a new one often times signal a need for policy adjustments caused by shifts in the market itself. To identify and differentiate between (past) phases, the paper therefore took European and national legislations and especially grants and subsidies into account that could be indicative of observed developments within the market or the political intention to provoke new dynamics. The four phases will be connected with E. Rogers’ model of diffusion of innovations [9] in order to align the intensity of intervention in the different phases with the degree of technology adoption according to Rogers as seen in Figure 2.

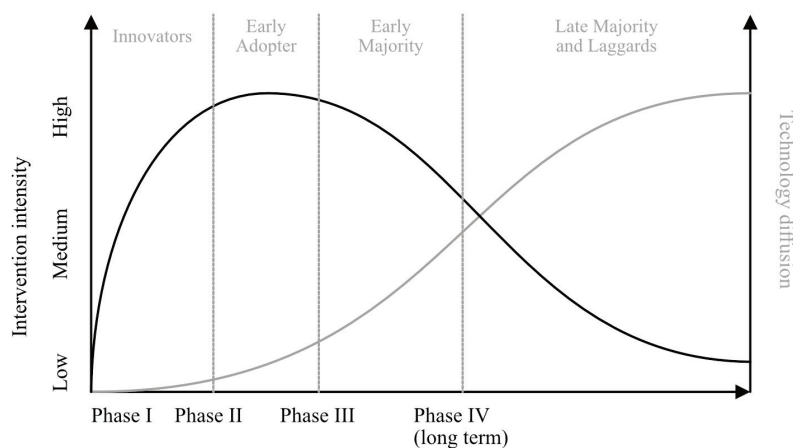


Figure 2. Technology adoption and intensity of public interventions (schematic).

This allows for an analysis of policy making in regard to different consumer groups and therefore the development of such policies throughout the identified phases. It is, however, not within the scope of this paper to evaluate past policy making. Data used

for this paper include data from public sources like the charging infrastructure register of the German Infrastructure Authority ('Bundesnetzagentur'), the German Monopoly Commission as well as data collected from public funding schemes by the National Centre for Charging Infrastructure.

The original impetus for this article was to create a meaningful contribution to the discussions and exchanges at the 37th International Electric Vehicle Symposium and Exhibition in April 2024. Since then, the relevant policy framework for EV-adoption in Germany has significantly changed. Thus, the original article has been revised and updated to take these developments and fresh insights into account [10].

2. Phase I: Jump Starting and 'Paving the Way'

While there have been multiple attempts at electric vehicle technology since the late 19th century, this paper only considers the most recent iteration, starting roughly around the year 2010. Around that time, the first generation of modern BEVs suitable for everyday use came into the market, such as the Tesla Roadster (2008), Nissan Leaf (2010), Tesla Model S (2012), and Renault Zoe (2013). With increased urgency regarding emission reduction regulations, both internationally and nationally, the rollout of electric vehicles became not just a matter for technology enthusiasts but also for the general public, and the adoption of the technology was, generally speaking, embraced by policy makers and governments.

2.1. 'Chicken-And-Egg' Dilemma

The early phases of EV adoption, however, illustrate a common problem with infrastructure-dependent technology diffusion: Consumers' willingness to adopt EVs is highly reliant on the quality and density of the charging infrastructure network [11]. A sufficiently sized charging network on the other hand requires substantial initial investment, which might not be economically viable due to low demand in early diffusion stages [12]. Policy intervention is often considered necessary in these situations in order to be able to foster innovation and avoid lock-in effects [13]. Interventions can include both fiscal as well as regulatory instruments to either incentivize the new technology or disincentivize (or even ban) the use of the old technology, avoiding said lock-in effects. Several studies aim to determine the best policy strategy to overcome the chicken-and-egg dilemma. Studies utilizing game-based model approaches like Ma et al. [14], Brozynski and Leibowicz [13], Yu et al. [15], or Li et al. [16] often found cost efficiency advantages of consumer subsidies for EV adoption while agent-based models such as in Luo et al. [17] find no such significant advantages of either approach but instead come to the conclusion that both infrastructure investments and consumer subsidies are suitable as long as their subsidy level is appropriate.

2.2. Early Funding Schemes and Public Investments

The first attempt at a coherent electric mobility strategy in Germany was the 'Government program Electric Mobility', released in 2011, which included funding schemes as well as other fiscal measures to incentivize EV adoption. The program 'Schaufenster Elektromobilität' provided funding for large scale demonstration and pilot projects and lasted from 2012 to 2016. Simultaneously, the government program introduced tax incentives for EVs, stimulating demand from the consumer group of innovators. These tax incentives included a tax exemption from the vehicle tax as well as tax reductions for company cars and are both still in place as of early 2024. The program 'Modellregionen Elektromobilität' supported the rollout of both EVs as well as charging infrastructure in eight selected metropolitan areas and had a similar demonstration purpose. Most funding schemes of the time had a focus on research and development since the technology was still

in the very early stages of diffusion and market share was vanishingly small. A common denominator of charging infrastructure and electric mobility projects in this phase was the close integration of local municipalities. A unique feature of the German market are the many local grid operators and energy suppliers, which are often controlled by the municipalities. These public entities, often called ‘Stadtwerke’, were responsible for a large share of the charging infrastructure rollout in the early stages in which charging infrastructure investments have not yet been economically viable due to the chicken-and-egg dilemma. In the absence of sufficient private investments, public companies like the grid operators and energy suppliers, supported by public funding schemes, provided a significant share of the necessary investments to jump start a charging infrastructure network.

Despite those efforts, this phase was not designed by policy makers to fully solve the chicken-and-egg dilemma, as subsidy levels had not been sufficient for that just yet. According to the government program electric mobility, the goal was to pave the way and prepare for a market ramp-up which was sighted until 2017.

2.3. Setting up a Regulatory Framework

‘Paving the way’ not only meant funding schemes for demonstrators and other projects but also preparing the regulatory framework to support such a market ramp-up. In those early stages of technology diffusion, European and German policy makers focused on definitions and standardization efforts:

The first major milestone in that regard was the Directive 2014/94/EU on the deployment of alternative fuels infrastructure (AFID), which introduced several new standards into European law including connector types (‘Type 2’ connector for alternating current recharging points and ‘CCS/Combo 2’ connector for direct current recharging points) elevating interoperability across the entire EU. Since directives do not immediately apply to a national level, Germany introduced the Charging Station Ordinance (‘LSV’) to implement the content of the AFID into German law as well as to add additional definitions and regulations regarding public accessibility and reporting obligations. The Electric Mobility Act (‘EmoG’) from 2015 stipulates the granting of privileges for using electric vehicles and consequently includes definitions of vehicles eligible for these privileges. It serves as the de facto standard in German policy making for EV definitions as many other Acts and Ordinances reference the EmoGs definitions of electric vehicles. Many of these regulatory cornerstones are still in place (the AFI Directive is being replaced by the AFI Regulation as per April 2024 but said fundamental definitions are mostly untouched) and therefore span the regulatory framework to this day.

This approach of demonstrating everyday viability, paving the way, and preparing the market for a future ramp-up characterizes the first phase which lasted roughly until the year 2017. Solving the chicken-and-egg dilemma in order to advance to subsequent stages of technology diffusion (early adopters and early majority), however, required a stronger technology commitment and therefore a much higher intervention intensity from policy makers, which was yet to be made.

3. Phase II: Commitment and Stimulation

Generally speaking, subsidies and other interventions are usually set up to influence and change a consumer’s behavior. In order for consumers to act accordingly and adopt a new technology, the policy maker’s goal needs to be credible and dependable to them which requires a certain degree of commitment to the policy strategy. To achieve a credible commitment, policies including subsidies should both have a long-term scope as well as sufficient financial backing. If policy makers suddenly back out of their communicated

strategy (subsidies and other incentives), they might risk consumer's trust in the technology, which can be detrimental to their initial goal of increasing the adoption rate.

3.1. Introducing a Buyer's Premium to Subsidize Consumers

To really foster the market ramp-up, Germany started its first large-scale consumer subsidy, the 'Environmental Bonus', a buyer's premium for BEVs, PHEVs, and FCEVs that was co-financed by OEMs and the federal government from 2016. The premium was ultimately canceled in November 2023 due to a lack of financial backing but had been a continuous policy instrument since its introduction. During a seven-year period from 2016 to 2023 a total of 2.2 million EV passenger vehicles received this premium. A total of around EUR 10 billion was spent on this instrument. In the early phases of the market ramp-up, however, the effectiveness of the buyer's premium was considered low, which was not necessarily due to an inappropriate subsidy level but could be accounted to technology maturity as well as the still present chicken-and-egg dilemma between EV adoption and the charging infrastructure rollout [18].

In return, the lack of EV adoption could not yet facilitate viable business models for private Charge Point Operators (CPO) on its own, which led to additional government measures to not only subsidize consumers but also infrastructure investments, resulting in a mixed policy strategy to ultimately overcome the chicken-and-egg dilemma.

3.2. Charging Infrastructure Master Plan I and Supply-Side Interventions

With the first 'Charging Infrastructure Master Plan', the government for the first time outlined an overall strategy aimed at ensuring a comprehensive, demand-oriented and user-friendly expansion of charging infrastructure. As part of the program, the National Centre for Charging Infrastructure was created as a permanent institution tasked with helping policy makers achieve this goal by supporting and consulting in policy making and implementation. In addition to some adjustments to the legal framework for charging infrastructure, the program particularly contained the intention to comprehensively promote charging infrastructure along its various relevant use cases.

The 'Charging Infrastructure Master Plan' outlined that in contrast to the uniform energy supply of ICEs at uniform fuel stations for all customer groups, EVs can be provided with electricity in different configurations ('use cases') depending on the residential situation, mobility behavior, and settlement structure. The number, location, charging capacity and technical complexity (e.g., authentication and billing capacity) of the charging infrastructure to be established must be tailored to the respective user requirements. The same applies to subsidies and other incentives, which also need to be tailored to meet the specific market they are targeted at as not all funding designs work in all applications. Charging stations located directly in service areas on federal highways offer good accessibility on long-distance journeys. EVs can be charged at such stations while resting on long-distance journeys. However, charging stations away from main highways can also be relevant for long-distance travel. This requires several charging points with a sufficient high charging capacity at the same location and in the immediate vicinity of federal highways. These are very likely to offer a free charging point that enables fast charging. There is also a need to charge EVs quickly and at short notice in local traffic. This is particularly the case when users deviate from their routine journeys, plan a short trip or when unexpected charging needs arise for other reasons. For this use case, there must be fast charging stations in the areas relevant for local transport, which provide a sufficient number of charging points with high power at the same location. If users want to charge their EV during their routine journeys, during shopping, leisure activities or visits to public facilities, there is generally no need for a particularly high charging capacity. If residents do not have private parking

facilities with charging options, they are dependent on publicly accessible charging stations located on the roadside in their residential area or at their workplace as their primary charging option. As the longest standing times are to be expected here, no minimum performance is required. The German Government therefore designed several funding schemes and programs to facilitate the installation of Charging Infrastructure at residential buildings, at carparks for employees' and a companies' fleet vehicles, at car parks at retail stores and fast charging hubs in urban areas, as well as in underserved areas nationwide as listed in Table 1.

Table 1. Government grants for charging infrastructure in Germany.

Years Active	Use-Case	Type of Charge Point	Available Funds (in Million EUR)
2017–2020	Public	AC and DC	300
2019–2021	Non-Public (at Residential Buildings)	AC, 11 kW	800
2021–2022	Public	AC and DC	500
2021	Public (by SME)	AC and DC, up to 50 kW	300
2021–2022	Non-Public (at Employer Car Park and for Fleet Vehicles)	AC, up to 22 kW	350
2023	Non-Public (at Residential Buildings + Solar Energy Production and Storage)	AC, 11 kW	300
2023–2024	Non-Public (for Fleet Vehicles)	DC	400

In general, these funding programs were designed as investment subsidies targeting costs for charging hardware and grid connection. However, since funding programs as a policy instrument are only partially suitable for determining the location and sizing of the installed charging infrastructure, the funding programs led to a sharp increase in the number of charging points but did not result in the complete elimination of the ‘blank spots’ in terms of coverage.

In order to ensure comprehensive and future-proof demand-oriented coverage of the entire country with publicly accessible fast-charging infrastructure, the German government thus designed a public tendering process with the so-called “Deutschlandnetz” (“Germany network”). These tenders were deliberately designed to extend and complement the previous grant-subsidized private-sector expansion of the charging infrastructure. The “Deutschlandnetz” contains approximately 1000 sites for the creation of fast charging hubs. The construction and the at least eight-year operating phase receive up to EUR 1.9 billion in government funding. This program takes into account that consumers’ behavior towards EV adoption is driven in large by range-anxiety. As a result, the visibility and physical presence of charging stations is increasing significantly, which has been deemed highly effective for consumer confidence in EV-technology [19]. Moving from grants to a tender can be considered an early attempt at increasing competitive intensity in the allocation of subsidies for public charging infrastructure.

In recent years, the German government has therefore provided a total of around EUR 5 billion for the various applications of charging infrastructure. These funds were used to kick-start the construction and operation of the public charging infrastructure. Towards the end of 2023, 100,000 publicly accessible and many more non-public charge points were installed in Germany. These measures also achieved important successes in the goal of making the operation of charging infrastructure economically attractive. All subsidy

programs funded the investment costs for the installation of charging hardware and for expenses for grid connections. Concurrently, not only has a nationwide supply of publicly accessible charging facilities been created, but a diversified portfolio of products and services has also emerged to meet individual charging needs. The goal of the infrastructure investment strategy had been to match policy parameters with consumer preferences, lower investment costs by unlocking economies of scale and higher profits for the operating businesses, and also to kick-start business models and the creation of sustainable capacity for further expansion.

3.3. Emerging Markets and Business Cases

During this phase of extensive government supply-side intervention, the number of charge points as well as of operating businesses drastically increased. While data on non-public use-cases is very limited, extensive analyses of public charging infrastructure by the National Centre for Charging Infrastructure clearly show an emerging business landscape around EV charging that developed simultaneously and in response to the aforementioned government programs. As Table 2 shows, the number of public charge points has increased twenty-fold from 2017 to 2024.

Table 2. Public Charging infrastructure in Germany [20].

	Charge Points (CPs)	Percentage of Subsidized CPs	Total Installed Power (MW)
2017	7.862	n. a.	0.17
2018	15.381	31	0.36
2019	25.730	34	0.68
2020	38.345	30	1.03
2021	56.204	26	1.58
2022	83.634	23	2.52
2023	124.590	21	4.37
2024	156.187	19	5.87

As of 1 January 2024, 1,381 companies were registered as operators of publicly accessible charge points in Germany. A total of 102,269 public charge points were in operation on 1 January 2024, of which 22 percent have received public subsidies. While the absolute number of Charge Points that have been installed with the help of government subsidies continuously rises, the relative decline in subsidized Charge Points shows a rise in solely business funded expansion. Data collected in regard to the various funding programs show that charging hardware by more than 300 manufacturers has been installed.

The significance of Public Utility Companies, who had largely driven the initial expansion in Phase I and who still had been responsible for more than 40 percent of newly installed CPs in the year 2017, started to decline in Phase II as shown in Figure 3. In part, this can be explained by newly introduced EU unbundling regulations, strongly separating the operation of electricity grids and charging infrastructure. Instead, investing in Charging Infrastructure has become attractive for a variety of players. The growing activities of OEMs, traditional utility companies, the oil and gas industry, as well as new and solely charging-focused enterprises indicate that EV technology can successfully achieve a broad market ramp-up within various industries and that a diffusion toward the majority of users is expected. This demonstrates that the government supply-side strategy and its thereby communicated commitment towards EV-technology have convinced these market

players to begin large-scale investment strategies. In turn, these observable growing market activities reduced the need for continued government subsidies in the future.

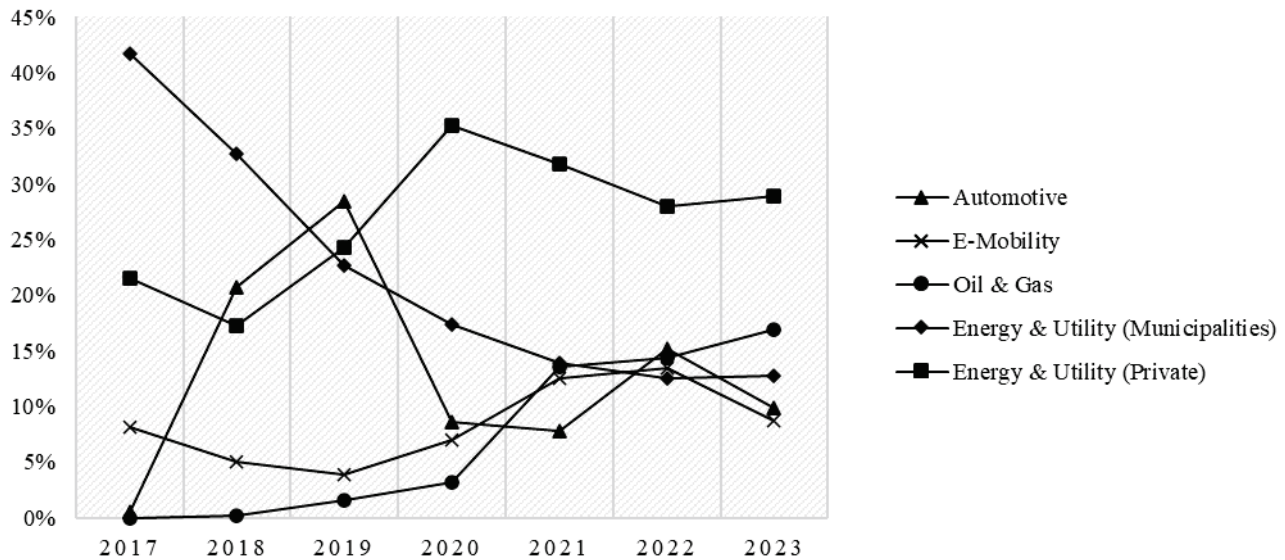


Figure 3. Share of total added charging capacity by selected sectors (2017–2023) [21].

4. Phase III: Scaling and ‘Crossing the Chasm’

During the previous phase, marked by heavy supply-side government intervention in charging infrastructure, the number of registered EVs drastically increased. Between the years 2017 and 2022 the number of registered EVs increased almost twentyfold. By the year 2022 one in four newly registered cars in Germany had been an EV. This increase in EV market share creates a sustainable demand for charging infrastructure, making it more attractive for businesses. For government policy, this increased profitability reduced the need for a continuation of previous supply-side interventions. Instead, the increased pressure by a growing segment of customers has made the existing structural problems ever more apparent. Expanding from innovators and early adopters towards more majority users requires not only the availability of charging infrastructure but also ubiquitously available charging opportunities, which are designed in a user-friendly fashion. Additionally, the future mid-term expansion of the charging network needs to be credible for consumers.

4.1. Streamlining Regulation and Creating a Level Playing Field

For government policy, this meant a shift from direct supply-side interventions, toward creating a regulatory framework, which allows private sector actors to scale. During the phase of initial expansion, the need to create a ubiquitous, nationwide, and consistent charging network collided with the decentralized and multi-layered organizational structure within Germany. Businesses scaling their charging businesses had to face inconsistent and unequal framework conditions within the country. This was mainly caused by the existence of 11,000 municipalities, who are responsible for construction permits, and by the more than 800 electricity distribution network operators. During Phase II, it became more and more apparent that heterogeneous procedures and technical requirements created increased transaction costs for businesses and created barriers for entering local markets, making individual municipalities and grid areas unattractive for CPOs. Against the backdrop of the politically desired market ramp-up of EVs, this had become unacceptable for business and government actors alike. The efficiency of processes at municipalities and distribution network operators therefore emerged as bottlenecks for charging infrastructure expansion and became the focal points of government policy.

4.2. Charging Infrastructure Master Plan II

Leveling these regional disparities and creating a level playing field in which companies, but ultimately consumers too, can find uniform conditions is one of the central goals that the German government has been pursuing with the Charging Infrastructure Master Plan II, which was approved by the Federal Cabinet in October 2022 [22]. The aim of the plan was to reduce the amount of transaction costs, which companies face when providing charging services. Government policy shifted from supply-side interventions towards regulatory streamlining.

Over the course of 2022, the German government carried out a comprehensive review of the expansion of charging infrastructure during Phase II. A total of 68 measures were developed, particularly in the area of electricity grids and municipalities, with the aim of creating a standardized, affordable, and stable long-term framework. The integration of EVs and charging infrastructure into the system of electricity production, distribution and consumption emerged as a further focus of policy making. The policy objective of effective harmonization is being pursued by various measures, among which are the integration and early consideration of charging expansion in the expansion of the electricity grid. To be able to scale charging in the long term, the electricity grid must be prepared. To this end, distribution network operators have been legally mandated to take into account the forecasts on future charging demands based on comprehensive data analyses by the National Centre for Charging Infrastructure.

Additionally, processes and technical requirements in the more than 800 distribution networks are being harmonized to allow for economies of scale. Similarly, the focus in the municipalities is on harmonizing and accelerating permit procedures. Due to the legal and organizational autonomy of the municipalities within Germany, the federal government cannot intervene directly. Instead, the Master Plan contains a series of assistance packages and guidelines. If local authorities follow these, uniformity is created. The third—very decisive—focus of the master plan and a crucial factor on the threshold from early adopters to majority users—to the ‘average consumer’—is user-friendliness. Charging infrastructure that is not user-friendly, e.g., where payment is complicated, which is not easy to find or whose prices are not transparent, weakens the acceptance of EV-technology.

4.3. ‘Crossing the Chasm’ and Continued Government Commitment

The explicit aim of the Charging Infrastructure Master Plan II was to create an advantageous and harmonized framework so that government interventions (especially of a fiscal nature) could be reduced to a minimum as soon as possible. It therefore represents a break with the charging infrastructure policy previously dominated by supply-side interventions. At the same time, the identification and implementation of a total of 68 measures marks the conclusion to the phase of a high degree of government intervention. This peak of government activity towards charging infrastructure coincides with a highly critical stage of EV-technology adoption, which American organizational theorist Geoffrey Moore has termed ‘Crossing the Chasm’ [23]. The ‘Chasm’ describes the difference in needs and expectations between ‘visionary’ Innovators and ‘pragmatic’ Majority Consumers, to which products need to adapt to in order to achieve wider market penetration.

In contrast to the previous years, data on registered EVs in the year 2023 show a plateau in the rate of EV-adoption. A recent survey by the National Academy of Science and Engineering also indicated that the demand by consumers of the Early Adopter variety has been somewhat saturated, while consumers “beyond the Chasm” remain somewhat hesitant [24]. The same survey also examined the population’s attitude towards EVs and has shown a great willingness to embrace change, but also some remaining reservations. Within the group of those who are willing to switch to electromobility, a lack of charging

facilities persists as a main reservation for two thirds. The actual or even perceived lack of charging facilities must therefore be countered by continuous credible political commitment to successfully “cross the Chasm”.

Even if supply-side interventions have mostly been replaced by regulatory measures, continued government involvement signals a commitment to the success of EVs. The preparedness for direct interventions is needed to instill confidence in consumers. This assurance is essential for overcoming reluctance to adopt EVs and fostering a positive perception of the technology among the general public. Of course, not only government policies need to take ‘the Chasm’ into account but it needs to be addressed by OEMs by adjusting their product portfolios, marketing strategies and pricing policies.

4.4. Waiting Beyond the ‘Chasm’: User Experience and Expectations of the ‘Next Segment’

The German market research firm USCALE GmbH operated extensive surveys of electric vehicle (EV) owners’ charging behavior and infrastructure usage in Germany [25]. The aim was to gain insights into charging habits, user segments, and the challenges and needs of EV drivers. The surveys were carried out from March to September 2024 and included a total of 2986 respondents. Various sub-studies were combined to create a comprehensive picture of charging habits and needs. Online surveys using quantitative methods were employed, and participants were recruited through multiple channels to ensure a representative sample of the current user base. To better understand the differences between groups of EV drivers, participants were divided into two main segments:

- **Pioneers:** This group includes “Innovators” and “Early Adopters” based on Everett Rogers’ diffusion model, characterized by high involvement with EV technology and a strong interest in innovation.
- **Next Segment:** Comprising users with lower involvement in EVs, this group typically adopts EVs later and represents a broader societal spectrum, particularly from urban areas, with a different attitude toward charging infrastructure.

For the ‘next segment’ customer groups, their expectations and requirements are specifically the conditions which create the ‘chasm’. Overcoming the ‘chasm’ between ‘pioneers’ and the ‘next segment’ can therefore only be achieved when the differing preconditions are recognized. The surveys found that the user base is becoming more diverse: the “next segment” is younger and more balanced in gender compared to earlier groups, with many from larger cities and higher income brackets. Notably, 59% of all respondents have a household income above EUR 5000 per month. Home charging remains the dominant method, with around 80% of pioneers and next segment users charging at home. Public charging is growing, especially for those unable to install a private charging station. The next segment is increasingly charging at work, public charging stations on the street, and charging hubs at retail car parks. Despite 62% of all users being satisfied with public charging options in general, 50% have encountered issues like blocked or broken stations and payment problems. The next segment feels less secure about charging, which leads to more frequent use and a perception of higher station occupancy. Next segment users demand improvements in charging infrastructure, particularly more public charging points in residential areas and more fast chargers in cities. While pioneers stronger prioritize low charging costs, the next segment values fast and comfortable charging.

The surveys highlight that EV adoption in Germany is entering a new phase. Early adopters were focused on technology and cost, while the next segment is driven by comfort, ease of use, and charging speed. The growing importance of public charging infrastructure presents new challenges for cities and charging operators. Issues such as malfunctioning or occupied charging stations and complex payment methods need to be addressed by market actors and policy makers. The results underscore that the success of EV adoption largely

depends on the user-friendliness of charging infrastructure. Considering these attitudes, it is clear that without continued improvement, the process of EV adoption could stall. The reliability of government programs is needed to further strengthen confidence and technology acceptance.

5. Policy Shifts and Market Reactions: How the Sudden End of the Buyer's Premium Impacted EV Adoption

On 15 November 2023, a ruling by the German Federal Constitutional Court altered the budgetary options available to the German government, which had an immediate and drastic impact on support measures for EV adoption [26]. With very short notice, the “Environmental Bonus”, Germany’s buyer’s premium for BEVs, PHEVs, and FCEVs that had been introduced in 2016, was discontinued. The possibility of receiving investment grants when purchasing a new EV ended abruptly with just five weeks’ notice, leaving consumers and companies without sufficient opportunity to adapt to the change. This politically unplanned and unforeseen decision caused significant damage to public trust, which was reflected in EV registrations, as new registrations in 2024 fell significantly behind the previous year’s figures.

The abrupt policy change led to a sharp increase in very short-term new registrations of battery-electric vehicles (BEVs) in the last weeks of 2023, as many buyers rushed to secure the expiring subsidies. In January 2024, new registrations dropped significantly, due to both a pull-forward effect in 2023 and the increased total cost of ownership for private and commercial customers. At the same time, OEMs attempted to compensate for the lost state subsidies with discounts. After the discontinuation of the Environmental Bonus in December 2023, many OEMs in Germany responded with their own price reductions to maintain a stable pricing of EVs. Volkswagen, for example, offered discounts on its ID models until the end of March 2024, in some cases exceeding the previous subsidy amounts. The price reduction for the ID.4 and ID.5 models amounted to more than EUR 7700 [27]. Other manufacturers, such as Dacia and Tesla, also lowered the prices of their EVs to compensate for the loss of government incentives. Dacia, for instance, granted a discount of EUR 10,000 on its Spring electric SUV, bringing the price down to just under EUR 13,000. Tesla reduced the price of the Model Y by nearly EUR 5000. These measures demonstrate that manufacturers sought to cushion the increased costs for consumers through their own discounts and to sustain EV sales despite the policy shift.

Nevertheless, a significant decline in registrations followed the end of the Environmental Bonus. In 2023, a total of 699,943 EVs were newly registered, accounting for a 24.61% market share. In contrast, EV registrations declined in 2024 after the end of the buyer’s premium. In 2024, EV registrations dropped to 572,514 and a market share of 20.32% (see Table 3). This decline is primarily attributed to the discontinuation of the government purchase premium. This suggests that the downturn in EV registrations in Germany was indeed driven by the loss of consumer confidence caused by the abrupt end of the subsidy rather than merely by price effects. In the time since then, the abrupt removal of subsidies has slowed the market penetration of EVs, particularly in price-sensitive customer segments. While companies and fleet operators continue to benefit from tax advantages such as reduced company car taxation, private buyers, who rely more heavily on purchase incentives, have increasingly postponed their purchasing decisions or turned to the used car market. As a result, the ramp-up of electromobility in Germany is progressing more slowly than initially expected.

Table 3. EV-Adoption (BEV + PHEV; passenger cars only) in Germany [28].

	Newly Registered EVs	Total Registered EVs	EV Share of Newly Registered Cars	EV Share of Total Registered Cars
2017	54,492	98,280	1.58%	0.22%
2018	67,504	150,172	1.96%	0.32%
2019	108,629	238,792	3.01%	0.50%
2020	394,632	588,944	13.53%	1.22%
2021	681,410	1,184,416	25.99%	2.44%
2022	832,652	1,877,721	31.40%	3.85%
2023	699,943	2,330,567	24.61%	4.75%
2024	572,514	2,619,066	20.32%	5.31%

Beyond the economic effects, the abrupt end of the Environmental Bonus has also impacted public acceptance of electromobility. In public discourse, the funding halt was perceived as a breach of trust, particularly by consumers who had expected reliable and long-term political support for the mobility transition. This has led to increased skepticism toward future policy measures in the field of sustainable mobility and has weakened confidence in government incentive systems. This loss of trust occurred precisely at a critical stage of technology adoption, where due to the previously described “chasm”, market dynamics are particularly vulnerable. Crossing the ‘chasm’ dividing early adopters from majority users in the mass market could therefore not be achieved by the end of 2024. This can be attributed to tumultuous political developments. Thus, policy making remains stuck in Phase III for now. After the end of the ‘Environmental Bonus’ Germany’s federal government has repeatedly tried to implement new policy measures to substitute the prematurely stopped buyer’s premium. In July 2024, the government announced the introduction of special depreciation and taxation write-off regulations to incentivize companies to invest in EVs [29]. Due to the premature break-up of the government coalition in November 2024 these plans did not come to fruition.

6. Phase IV: Moderating and Safeguarding

While there is still both economic justification as well as political willingness to continuously support and subsidize the ongoing market ramp-up, there a state of technology diffusion needs to be reached, where most interventions, most notably those detrimental to the development of a functioning market, can be safely phased out without risking any perceived time inconsistencies or a lack of commitment by policy makers. For this point in time, it is worth looking into possible long-term role models between the public and private sector and especially the long-term role of the federal state. Once technology adoption has reached a degree of maturity that allows for it to further run without significant outside stimulation, state activities must shift towards being a moderator rather than an incubator. While the entire market for (public) charging infrastructure might not be a natural monopoly that would require continuous intervention, it is not guaranteed that a sufficient level of competition can be achieved in all of its sub-markets. Figure 4 displays the average market concentration rate CR₁ (which describes the market share of the charge point operator with the highest share) for three selected sub-markets. The sub-markets are classified by technology (AC normal charging, DC fast charging) as well as where the chargers are located (Highway charging) and defined by the amount of time consumers are willing to spend to substitute a charging point with a different one.

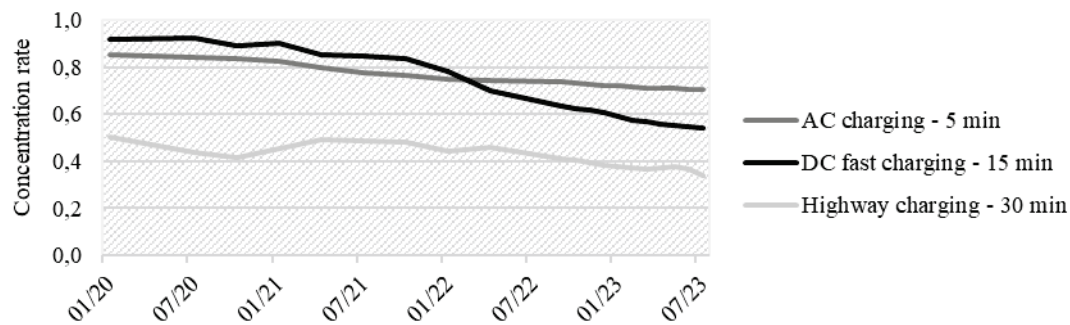


Figure 4. Average market concentration CR1 for selected sub-markets by technology and distance [30].

While the average CR1 value for DC fast charging has been continuously decreasing since early 2020, for AC normal charging it is resting at an extremely high level. Highway charging has a lower concentration rate, mostly due to the longer distances that can be covered in 30 min. German and European competition laws assume a market dominance at a CR1 value of 0.4 or higher, which suggest that a lot of charging infrastructure sub-markets are potentially dominated by one operator. The decreasing tendencies especially in the fast charging sub-markets are a positive signal for an increase in competition intensity, which would allow for a lower level of intervention expenses in the long-term while the ceaseless high level of market dominance in the (mostly urban and rural) AC normal charging market might require ongoing regulatory efforts to protect consumers from the risk of supracompetitive pricing. Regulators and policy makers will have to continuously observe the market and look for signs of market failure in vulnerable sub-markets as well as use all available levers to facilitate an increase in competition intensity on all levels.

First insights into how public agencies intend to approach this moderating role have been provided by the sector investigation of the German federal competition authority (Bundeskartellamt. BKartA) released in 2024 [31]. In this, the BKartA aims to identify structural challenges in competition and ultimately pricing in an early market stage, in order to prevent any negative impacts for consumers, as outlined earlier. The results regarding market concentration match those cited and presented earlier (largely due to being based on the same datasets, see Figure 4); however, the report also outlines instruments and levers available to regulators and policy makers and discusses ways of utilizing antitrust laws in this context. While it focuses on Germany, national antitrust and competition laws are rooted within European competition law. Therefore, the authority's findings are, to a certain degree, applicable to other countries as well. The two main tools of antitrust policies are codified in Articles 101 and 102 of the Treaty of the Functioning of the European Union (TFEU) and prohibit both anticompetitive agreements (ultimately cartels) as well as the abuse of dominance with the latter being identified as the more applicable fact. According to the report, several types of such abuse of dominance can occur within the market for EV charging infrastructure, the so-called 'margin squeeze' of vertically integrated CPOs being the most prevalent. Margin-squeeze can occur if a dominant CPO, which also acts as a distributor of electricity asks prices from end consumers that are lower than what he asks from competing third party EMPs. As a result, third party EMPs are unlikely to be able to realize any margins at those charging stations. Such practices are best addressed by regulations that require non-discriminatory (B2B-) pricing. General antitrust laws already prohibit this for actors with absolute or relative market power (see § 19, 20 of the German Competition Act 'GWB'), additionally, the European AFIR requires non-discriminatory pricing from all market participants, extending such regulations beyond their initial scope. Monitoring and executing these regulations can be a key piece to preventing the undermining of competition and supracompetitive pricing

without dedicated price regulation. In particular, the extension of non-discriminatory pricing requirements can be considered an important instrument to not rely exclusively on antitrust laws which often only provide ex-post levers when problematic market power has already been established organically (practices like merger control can only prevent an increase in market dominance through acquisition or merging).

Even if the charging infrastructure might at one point move frictionless, innovation and technology advancements can, to a degree, constitute a new need for interventions. Electric cars have systemic relevance for the energy system, due to their electricity demand but also their mid- to long-term potential as energy storage and in grid extension. 'Vehicle to Grid' or 'Vehicle to Home' (V2X) technologies connect electric mobility even closer to critical infrastructures and while their advantages also benefit consumers, it will be in a policy maker's best interest to support the rollout of such technologies. The need for adoption and integration of innovations such as V2X technologies has the potential to initiate a new cycle of public interventions, especially if there is a risk of economically disadvantageous lock-in effects.

Both moderating and safeguarding must be the core activities of regulators and policy makers in a long-term mature market due to the systemic relevance of electric mobility and charging infrastructure and the vulnerability of consumers to any market imperfection, especially beyond 2035. In order to reach such a level of market maturity it is furthermore advised to phase out any subsidies and other instruments in a controlled manner to not risk eroding consumers trust in the technology.

7. Conclusions and Outlook

The chicken-and-egg dilemma of supply and demand between EV adoption and charging infrastructure has required extensive public intervention, most notably subsidies and other incentives for consumers and infrastructure investments. The market ramp-up starting in 2017 indicates that these efforts at overcoming the dilemma have been successful for now. The observed plateau in EV adoption lately, however, suggests that there is a real risk of a 'chasm' in the technology adoption. Crossing that chasm most likely requires continuous policy efforts to incentivize and support the ramp-up of both EV adoption and infrastructure investments for now. Additionally, phasing out subsidies too quickly can cause not only economic shocks but also erode consumer's trust in the credibility of policy makers, as seen by the sudden end of the buyer's premium [32]. Correspondingly, policy makers should communicate at a fairly early stage a predictable and gradual phase-out process of continually reduced government measures.

Further comparative studies examining EV market adoption in other comparable countries could help to further identify effective and ineffective approaches to guide EV technology adoption in order to provide policy makers with further guidance. Since extensive case-studies of these comparative countries would be required beforehand, this article is limited in making such comparisons. In any case, the trade-off between ramp-up pace and market maturity needs to be considered for future policy instruments, especially in the transition from Phase II to Phase III. Enabling competition should be a cornerstone of the policy strategy in order to prepare for a long-term phasing out of subsidies and other interventions. Once a certain degree of market maturity is achieved, the role of the state and its regulators and policy makers needs to shift towards moderating and safeguarding. The interconnection with the highly regulated energy systems will continue to impose a baseline regulatory demand and technological innovations could start a new cycle of interventions if there is a risk of disadvantageous lock-in effects once again.

Additionally, the transition of the light- and heavy-duty sector towards electric mobility is on the horizon and regulations are being put in place already. This poses both

a challenge due to even higher technological demands of said vehicles (for example so called ‘megawatt charging’ with a power output of up to 1 megawatt) but also a chance to apply the learnings from the EV and infrastructure rollout thus far. As infrastructures will most likely not be fully interoperable, the sector will face an entirely new chicken-and-egg dilemma and a fresh technology adoption cycle. While there have been various funding schemes in the past that subsidized both vehicles and infrastructure, German policy makers intend to stimulate the rollout by an extensive investment into the infrastructure with a tender to install and operate 350 charging stations across motorways (Tender 553148-2024 ‘Germany—Vehicle refuelling services—Planung, Errichtung und Betrieb von Schnellladeinfrastruktur für E-Lkw’). This, once again, follows the approach from passenger cars where a sufficient charging network is seen as a prerequisite for vehicle adoption, prioritizing infrastructure investments to overcome the dilemma. The tender design, most notably regulations regarding third party access to charging stations, contains elements of the ‘essential facilities doctrine’ of competition policies, indicating increased attention towards a competitive market design early on in the technology adoption cycle.

This paper tries to shed light on policy making in regard to the rollout of charging infrastructure in Germany and especially the transition of the state’s role and policy strategies towards a more mature market. For a more comprehensive understanding, the same considerations can be made for other countries as well. Future research should also focus on evaluating past and present policy instruments and strategies that have been utilized for overcoming the ‘chicken-and-egg’ dilemma. A potential future phase-out of all or most subsidies should also be monitored closely to avoid falling victim to the chasm of technology adoption.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
AFID	Alternative Fuels and Infrastructure Directive
AFIR	Alternative Fuels and Infrastructure Regulation
BEV	Battery-electric Vehicle
BKartA	Bundeskartellamt

CPO	Charge Point Operator
CO ₂	Carbon Dioxide
DC	Direct Current
EMP	Electric Mobility Provider
EU	European Union
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
GHG	Greenhouse Gas
GWB	Gesetz gegen Wettbewerbsbeschränkungen (Competition Act)
ICE	Internal Combustion Engine
KW	Kilowatts
KSG	Klimaschutzgesetz (Climate Protection Act)
LSV	Ladesäulenverordnung (Charging Station Ordinance)
MW	Megawatts
OEM	Original Equipment Manufacturer
PHEV	Plug-In Hybrid Vehicle
TFEU	Treaty on the Functioning of the European Union
V2X	Vehicle-to-X

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Article

Longitudinal Exploration of Regularity and Variability in Electric Car Charging Patterns

Chansung Kim * and Jiyoung Park

Korea Transport Institute, Sejong-si 30147, Republic of Korea; parkjy@koti.re.kr

* Correspondence: cskim@koti.re.kr

Abstract: As the number of electric vehicles increases, effective charging infrastructure planning and grid load management strategies become more important. This requires a better understanding of charging behaviors and accurate forecasting of charging demand. This study aimed to analyze the charging patterns of electric cars using the panel data of one year from 2023. Using this longitudinal data, we explored the spatiotemporal characteristics of charging patterns in Korea, examined the regularities of charging patterns, and quantified the variability in charging and travel behaviors. According to the results, the proportion of drivers with regular charging patterns was 75%, and the proportion of drivers with irregular charging patterns was 25%. We applied a method to quantify the variability in EV travel and charging patterns and explored factors affecting the variability. The variability in charging frequencies and trips showed similar patterns, which implies that EV trips and charging behaviors are highly correlated, and travel characteristics are an important factor in explaining charging behaviors.

Keywords: electric car; Korea; longitudinal data; charging pattern; charging interval; Gaussian Mixture Model (GMM); regularity; variability

1. Introduction

The expansion of electric vehicles (EVs) is being driven by policies to reduce exhaust emissions, such as greenhouse gases and pollutant materials, from internal combustion engine vehicles. Global electric car sales are expected to grow to 17 million by 2024, with the market share of electric cars reaching 45% in China, 25% in Europe, and 11% in the United States [1]. To accelerate the adoption of EVs, sufficient charging infrastructure is critical to alleviate driving range anxiety and provide stable charging opportunities. However, the increase in EVs and the expansion of charging infrastructure can lead to an increase in electricity demand and have a negative impact on the power system. Therefore, as the number of EVs increases, power grid load management strategies have been introduced to mitigate the significant impact of the charging demand on the power grid.

For EV infrastructure planning and regulations and power grid load management, understanding the charging behaviors of EV drivers is most important. In the early days, when observations of electric vehicles were insufficient, research modeling EV charging behaviors was limited to theoretical hypotheses [2–4]. However, as the number of EVs increases, various charging pattern analysis studies are being conducted using observed data. Studies on EV charging patterns include charging behavior analyses for public charging infrastructure planning [5–9], studies analyzing the impact and potential of EV charging demand on the power grid [10–12], and charging load analyses to predict future EV charging demand [13,14]. Among recent studies, refs. [12,13,15] analyzed the

spatiotemporal distribution of charging patterns based on longitudinal charging session data collected over a long period of time. Ref. [12] estimated synthetic charging load profiles by analyzing charging patterns in residential areas and workplaces based on charging session data collected for one year in Sweden. In [15], the authors analyzed travel and charging patterns by collecting data on 76,000 electric vehicles operating in Beijing, China for one month, and presented policy implications for introducing Time-of-Use tariffs and infrastructure planning. Ref. [13] analyzed 3.99 million sessions collected for 11 months in California, USA, and derived various charging segments, and the results were used to predict future charging demand profiles.

Charging pattern analyses using longitudinal data can contribute to improving charging infrastructure planning by understanding the variability in charging patterns and predicting realistic charging demand. Traditionally, transportation demand analysis methods have involved the hypothesis that there are regularities in human activity and movement, and the efforts to prove this hypothesis [16,17]. Understanding the regularities and diversity of activity and movement behaviors enables advanced predictions to improve infrastructure planning and operational efficiency. Previous studies that analyzed the regularity and variability in traffic patterns include [16–19]. Ref. [17] discussed a method of quantifying the variability found in travel behaviors by dividing it into interpersonal variability and intrapersonal variability. It has been also suggested that the effect of day-to-day variability in individuals' travel behavior is an important factor in predicting travel demand. Among studies related to charging behaviors, Refs. [6,20,21] discussed the regularity and variability in charging behaviors. In [6], the authors defined charging regularity as heterogeneity in terms of charging intervals and analyzed public charging session data collected in the Netherlands and found that only 10% of users showed regular patterns. On the other hand, Ref. [20] analyzed charging transaction data in the Netherlands and found that only 15% showed irregular and non-repetitive charging patterns. In [21], the authors analyzed large-scale charging data divided into weekdays, weekends, and holidays and found that there was regularity in charging behaviors, similar to the results of [20]. Therefore, previous studies have not yet fully elucidated the regularities and variability in charging patterns, and continued exploration is needed as available data increases.

Factors affecting charging behaviors include internal factors, such as individual characteristics and preferences, as well as external factors, such as advances in battery technology and expansion of charging infrastructure. As argued by [22], charging behavior on the supply side is mostly analyzed based on simple assumptions, while EV drivers' charging behavior varies with evolving battery technology and driving range. Changes in charging infrastructure, such as the expansion of public charging opportunities, will also bring about behavioral changes. In terms of the charging infrastructure environment, Korea is evaluated as having an excellent public charger scale with a ratio of less than two cars to chargers, and the law mandates the installation of a minimum number of chargers in all facility parking lots [1]. Therefore, analyzing the charging patterns of Korean electric vehicle drivers can be a good opportunity to examine what decisions drivers make in an environment where various charging opportunities are provided. Ref. [23] classified the charging patterns of Korean EV drivers into four types based on the choice of charging location and charger type through a latent class analysis using EV driver survey data. The first type is drivers who charge mainly with slow chargers at various locations, such as at home, public charging stations, and workplaces, with a probability of 69.3%. The second type is drivers who charge mainly with slow chargers at home, with a probability of 16.5%. The third type is drivers who charge mainly at public charging stations regardless of charger type, with a probability of 8.2%. The fourth type is drivers who charge mainly with slow chargers at work, with a probability of 6.1%. However, this study had limitations in

analyzing the variability in charging patterns due to limited data, and there are few studies on charging patterns targeting Korean drivers other than this study.

In summary, previous studies have not sufficiently explored the regularities and variability in charging behaviors, and further research is needed to capture expected changes in charging behavior due to advanced battery technologies, driving ranges, and expanding charging infrastructure. This study aims to analyze EV charging patterns in Korea by utilizing EV travel and charging data collected through onboard devices (OBDs) in individual EVs over a period of one year. The data used in this study are the latest data collected from March 2023 to February 2024 and are suitable for analyzing charging patterns that reflect battery technology advancements and the expansion of public charging opportunities. In the charging pattern analysis, the variability in EV travel and charging is also discussed based on longitudinal data.

This paper is structured as follows: Section 2 presents the data and methods used in this study. Section 3 describes the results of the charging pattern analysis. Section 4 discusses the implications derived from the results. Section 5 summarizes the application of the analysis results and gives suggestions for future studies.

2. Materials and Methods

2.1. Data

This study utilized EV travel and charging data collected by Korea Electric Power Corporation. Korea Electric Power Corporation (KEPCO), the exclusive utility operator in Korea, has started a project to collect travel and charging data from EV drivers as of 2022 for the purpose of analyzing the long-term impact of the increase in EVs on the power grid. Data collection was carried out by attaching an OBD to individual vehicles, collecting information through intra-vehicle communication, and transmitting it to a server via a telecommunication network. Information related to travel and charging activity is mainly collected from the global position system (GPS) and battery management system (BMS) and is transmitted to the server every 5 s. Figure 1 shows the information provided to vehicle drivers by processing the OBD data and the OBD attached to the vehicle.



Figure 1. OBD device and information application.

Participant recruitment was based on the area of residence, age, and the electric vehicle model. The regional allocation was composed of 35% in the metropolitan area, 35% in other metropolitan areas, 20% in other areas, and 10% in Jeju Island, considering the number of registered electric vehicles. The allocation by electric vehicle model included various

models and reflected the number of registered vehicles for each model. Due to limited statistical data on the EV driver population, the age distribution was allocated based on the overall population proportion.

As a result, this study utilized data collected from 351 electric cars from 1 March 2023 to 29 February 2024. The data collection period differed because the participation period for each vehicle was different, but the analysis was limited to vehicles for which data was collected for at least one month. For vehicles where long-term data transmission failures were found during the collection period, data continuity was ensured by checking for errors through driver contact and vehicle diagnosis.

The electric car models are 100 Hyundai IONIQs, 77 Chevrolet Bolts, 64 Kia EV6s, 53 Kia Niro, and 57 others. All vehicles are the latest models from the 2020 model year or later, and the battery capacity ranges from a minimum of 58 kWh to a maximum of 77 kWh. Information on the main driver of the electric car was collected through an entry survey before data collection began, including information on family members, occupation, income, residential area, and workplace. In order to secure statistical significance, the main driver of the survey vehicle was selected by sampling allocation considering region and age, but the gender distribution was more than 90% male. Table 1 summarizes the key characteristics of electric cars and drivers.

Table 1. Characteristics of corresponding electric cars and drivers.

Characteristics	Ratio (%)	
Gender	Male driver	90.9
	Female driver	9.1
Age	Under 40	30.5
	40 to 60	63.5
	Above 60	6.0
EV model	IONIQ	28.2
	BOLT	22.2
	EV6	19.4
	KONA	14.2
	Others	16.0
Battery capacity	Under 70 kwh	52.1
	Above 70 kwh	47.9
Description of family	Single family	14.5
	Dual family	36.7
	Multi family	48.7
Occupation	Office worker	40.7
	Others	59.3
Average monthly income	Low income	19.1
	Middle income	63.0
	High income	17.9
Region	Metropolitan area	32.2
	Others	67.8
Home charging availability	Available	70.1
	Unavailable	29.9

2.2. Method

This study processed the collected vehicle information into individual vehicle travel and charging data as follows. First, travel was processed into a trip by integrating a set of observations in movement using GPS trajectories and ignition on and off information.

The engine off-time criterion was set to 5 min, and the trip was considered to have ended when the vehicle was stopped for more than 5 min. Next, charging was processed into charging session units using data collected from the BMS and GPS, and each session data includes information, such as charging point, charger type, plug-in time, plug-out time, and charging capacity. Among the charging data collected from BMS data, cases where there was no change in State of Charge (SOC) or the duration was very short were excluded. Charging points were analyzed by matching them with the home and workplace addresses of respondents and classified into home, workplaces, and other public charging stations.

The analysis conducted in this study can be divided into two parts: spatiotemporal charging patterns and charging interval analyses and quantified analyses of variability in travel and charging patterns. The analysis methods for each part are as follows.

2.2.1. Spatiotemporal Charging Patterns and Charging Interval Distributions

Variables that characterize the charging pattern include charging points, charging time (start and end time, charging duration), charging frequencies, and charging interval (inter-charging time). We defined the charging interval as the difference between the start time of the previous charging session and the start time of the latter charging session in two consecutive charging sessions, and the formula is as follows:

$$\lambda_{ij} = t_{ij+1} - t_{ij}, \quad (1)$$

where λ_{ij} is j th charging interval of individual i , and t_{ij} is the start time of charging session j .

The charging interval was analyzed according to charging points, and the time-of-day distribution of plug-in start time for each charging point was also analyzed.

During the analysis period, the total number of charging sessions and the charging interval between each charging session varied for each vehicle. Therefore, this study analyzed the regularity of the charging pattern based on the distribution of charging intervals for individual vehicles, as in [6]. The Gaussian Mixture Model (GMM) was utilized to statistically classify the distribution of charging intervals. GMM is a modeling method that finds complex distributions of data by mixing several Gaussian distributions and is very effective for clustering. Clustering is the task of classifying data with similar characteristics, and GMM performs clustering by calculating the probability that each data point belongs to a cluster. In this study, the distribution of charging intervals of individual vehicles was estimated using Stata analysis software [24].

2.2.2. Quantified Analysis of Variability in Travel and Charging Patterns

Based on the regularity analysis of the charging pattern, this part quantified the variability in the charging patterns and analyzed the factors affecting the variability. The method of quantifying the variability utilized the variability formula of travel presented by [17,25]. Ref. [17] quantified the total variability in individuals' travel behavior by distinguishing it into two factors: interpersonal variability and intrapersonal variability, as shown in the figure. In his study, WPSS (Within Person Sum of Squares) is the result of estimating intrapersonal variability. A large value means large variability between individuals, and a small value means small variability within individuals. WPSS is decomposed into BDSS (Between-Day Sum of Squares) and WDSS (With-in Day Sum of Squares) and it was assumed that BDSS is decomposed into day-of-the-week variability and unexplained probability part. Next, BPSS (Between Person Sum of Squares) is the result of estimating interpersonal variability. A large value means large variability between individuals, and a

small value means small variability between individuals. These variables can be calculated using the following formulas.

$$WPSS_i = \sum_{k=1}^{K_i} (t_{ik} - \bar{t}_i)^2, \quad (2)$$

$$WPSS = \sum_{i=1}^I \sum_{k=1}^{K_i} (t_{ik} - \bar{t}_i)^2, \quad (3)$$

$$BDSS = \sum_{k=1}^{K_i} I(\bar{t}_k - \bar{t})^2, \quad (4)$$

$$BPSS = \sum_{i=1}^I K_i (\bar{t}_i - \bar{t})^2, \quad (5)$$

where $WPSS_i$ is the within-person sum of squares of individual i , K_i is the number of observation days for individual i , t_{ik} is the number of stops made by person i on day k , $\bar{t}_i$ is the mean number of stops made by person i , $BDSS$ is the Between-Day Sum of Squares, $\bar{t}_k$ is the mean number of stops made on day k , $\bar{t}$ is the mean number of stops made by all persons in the sample, and $BPSS$ is the Between-Person Sum of Squares.

In Formulas (2)–(5), if the variables related to travel behavior are replaced with variables associated with charging behavior, the variability in charging patterns can also be quantified. This study analyzed both the variability in travel behaviors and the variability in charging behaviors. Finally, a linear regression model with intrapersonal variability as a dependent variable was analyzed to derive factors affecting intrapersonal variability in charging patterns. The logarithmic value of variability was used to secure the normality of the dependent variable, and the model analysis was performed using Stata analysis software (Version 17).

Figure 2 illustrates the data collection and processing, and analysis methods used in this study.

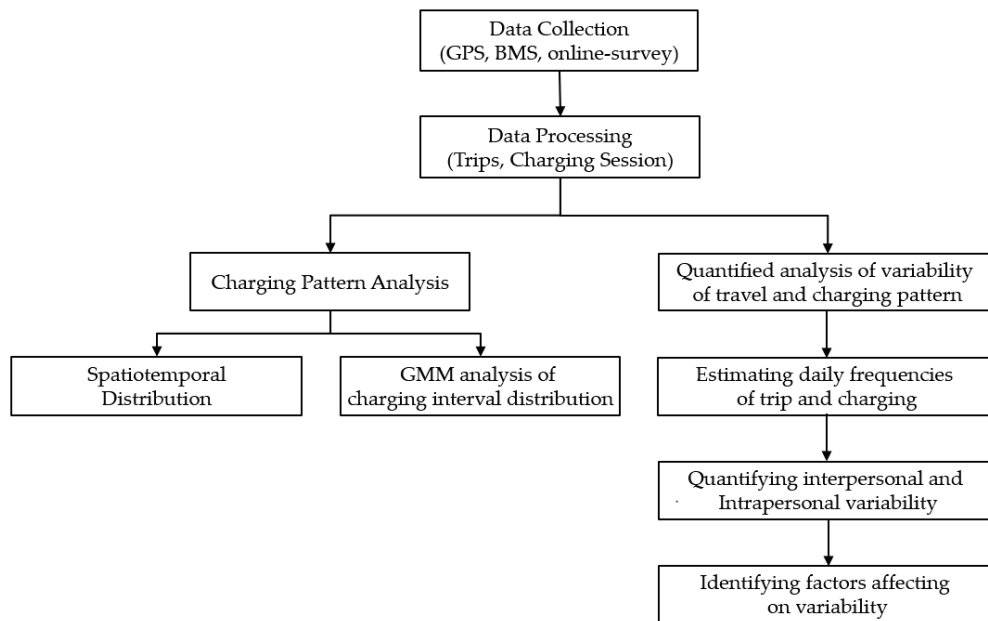


Figure 2. Analysis procedure and methods.

3. Results

3.1. Charging Pattern Analysis

3.1.1. Spatiotemporal Patterns of Charging Behaviors

The spatiotemporal distribution of charging intervals was analyzed using 17,206 charging session data from 351 electric vehicles collected over 115 days from 9 June 2023 to

1 October 2023 [26]. The number of observations by charging point was 6138 (35.7%) at home, 2324 (13.5%) at workplaces, and 8743 (50.8%) at public charging stations.

The aggregated average value of the charging interval was estimated by aggregating all charging intervals derived from the entire charging session data. The average was 2.25 days calculated using Equation (6). Next, to calculate the disaggregated average, the average charging interval of individual vehicles was estimated, and the average of the values was calculated. The disaggregated average was 3.64 days calculated using Equation (7). The difference between the aggregated value and the disaggregated value was relatively large, which means that there is considerable heterogeneity among individuals.

$$\text{Aggregated average of charging interval} = \sum_{i=1}^I \sum_{j=1}^{\eta_i} \lambda_{ij} / \sum_{i=1}^I \eta_{ij}, \quad (6)$$

$$\text{Disaggregated average of charging interval} = \sum_{i=1}^I \left(\sum_{j=1}^{\eta_i} \lambda_{ij} / \eta_{ij} \right) / I, \quad (7)$$

where λ_{ij} is j th charging interval of individual i , η_{ij} is the number of observations of the charging interval of individual i .

We extracted users who only charge at a single location to analyze the charging interval by charging point. As a result, 103 out of 351 vehicles (29.4%) used only one charging point, consisting of 6% charging at home, 1% charging at workplaces, and 22.8% charging at public charging stations. The average charging interval was 2.86 days at home, 1.58 days at workplaces, and 2.53 days at public charging stations. Home charging had the longest charging interval and the largest standard deviation. Table 2 summarizes the charging interval estimation results presented above.

Table 2. Charging interval statistics.

Classification	Average of Charging Interval (Day)	Standard Deviation of Charging Interval (Day)
Aggregated average	2.25	2.88
Disaggregated average	3.65	3.30
Home charging only	2.86	3.56
Workplace charging only	1.58	1.08
Public charging only	2.53	2.88
Mixed charging *	2.14	2.83

Note: * is mixed with (home and public) or (work and public) or (home and work) charging.

Figure 3 shows the time-of-day (TOD) distribution of charging start times by charging point. Home charging has a high charging frequency after work hours, and the peak time is 22:00–23:00. Work charging has a peak time from 8:00–9:00 before work hours start, and charging mainly occurs during the day. Public charging has a peak time from 22:00–23:00, the same as home charging. As shown in Figure 3, the temporal distribution of charging demand varies depending on the charging point.

3.1.2. Distributions of Charging Interval: Aggregated Versus Individual

As analyzed in the previous session, a large difference between the aggregated average and the disaggregated average of the charging interval means that there is heterogeneity between individuals. We examined the heterogeneity of the charging interval through GMM analysis. The GMM was used to analyze the distribution and number of components in the charging interval, and the distribution form was examined for both normal and log-normal distributions, and the log-normal distribution was found to be more suitable.

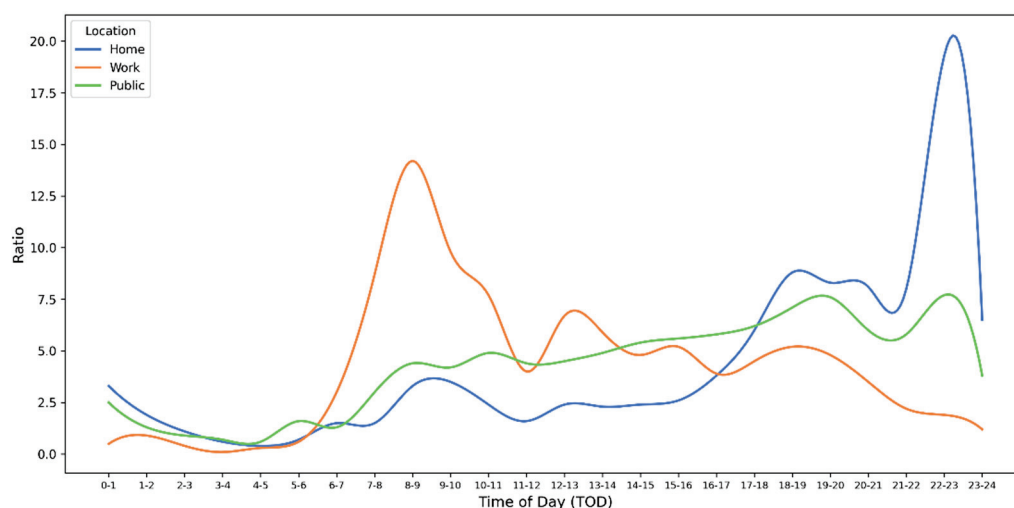


Figure 3. TOD distribution of charging start time by location.

First, we derived the charging interval value and frequency distribution using aggregated charging interval observations. Then, we analyzed the number of distribution components in the GMM from two to seven to derive the optimal model. Depending on the number of components, the log-likelihood value, AIC (Akaike Information Criterion) value, BIC (Bayesian Information Criterion) value, and component weight were estimated. We selected the two-component log-normal distribution with the smallest AIC and BIC values as the optimal model. Table 3 shows the results of the model analysis, and Figure 4 compares the density distribution of the model with that of charging interval observation.

Table 3. Effect of components of log-normal distribution on charging interval.

Component Type	Ratio (%)	Average (Day)	Variance (Day Square)	Information Index
Component 1	13.3	−2.30	−0.18	Log-likelihood = −29,341.8, AIC * = 58,693.6, BIC ** = 58,732.1
Component 2	86.7	0.52	−0.09	

Note: * Akaike's information criterion and ** Bayesian information criterion.

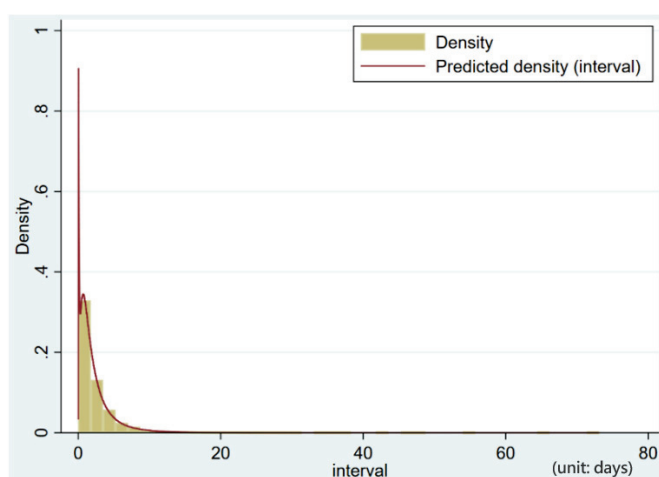


Figure 4. Density distribution of aggregated charging intervals.

Second, we analyzed the distribution of charging intervals for each vehicle using a GMM analysis. The Shapiro–Wilk test was used to verify the normality of distribution for all vehicles, and four vehicles were excluded from the analysis as they were not suitable due to insufficient observations.

The analysis of the charging interval distribution of 347 EVs revealed that 75% of the vehicles followed a log-normal distribution similar to the aggregate distribution. Figure 5a shows the density distribution of vehicle ID 1241172640 as one of the results. It shows that the vehicle has a regular charging pattern, typically charging every four or five days. On the other hand, the remaining 25% of vehicles show different patterns, such as a normal distribution or uniform distribution. Figure 5b shows one example for vehicle ID 1241225136, which follows a normal distribution. The vehicle has scattered charging intervals and has relatively low regularity in its charging pattern.

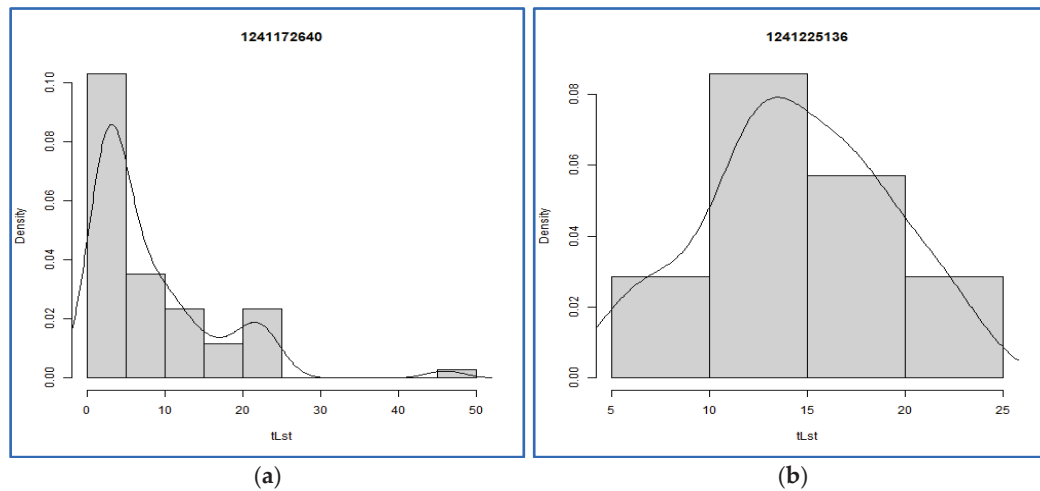


Figure 5. Examples of EV charging interval distributions; (a) log-normal distribution for vehicle ID 1241172840; (b) normal distribution for vehicle ID 1241225136.

The results show that our observation sample also contains a mix of drivers with regularity and drivers with irregularity in their EV charging patterns. Therefore, infrastructure planning based on a single static charging pattern, such as the aggregated results, will have difficulty capturing the actual EV charging demand.

3.2. Analysis of Variability in Charging Patterns

As shown in the results of the previous section, individual charging patterns show variability in charging points, charging times, and charging intervals. We analyzed the variability in travel and charging patterns of electric cars through the equations that quantify the variability in the travel patterns presented in [17,25]. To sufficiently include variability due to weather and season, the analysis was based on data collected from 351 electric cars for one year from March 2023 to February 2024.

3.2.1. Trips and Charging Frequencies per Day

We selected trips and charging frequencies as variables with daily values to estimate the day-to-day variations in travel and charging patterns. The individual averages are calculated by dividing the total number of trips and charging frequencies performed by an individual during the analysis period by the number of observation days, as shown in Figure 6. On the other hand, the daily averages are calculated by dividing the total number of trips and charging frequencies on that day by the number of observed vehicles, as shown in Figure 7.

The mean and standard deviation for both the individual average and the daily average are shown in Table 4. When comparing the mean of the individual average and the mean of the daily average for trips, the two values are similar, but the values of standard deviations have a relatively large difference. Similarly, the mean values of the

individual average and the daily average for charging frequencies are similar, but the standard deviations have a relatively large difference.

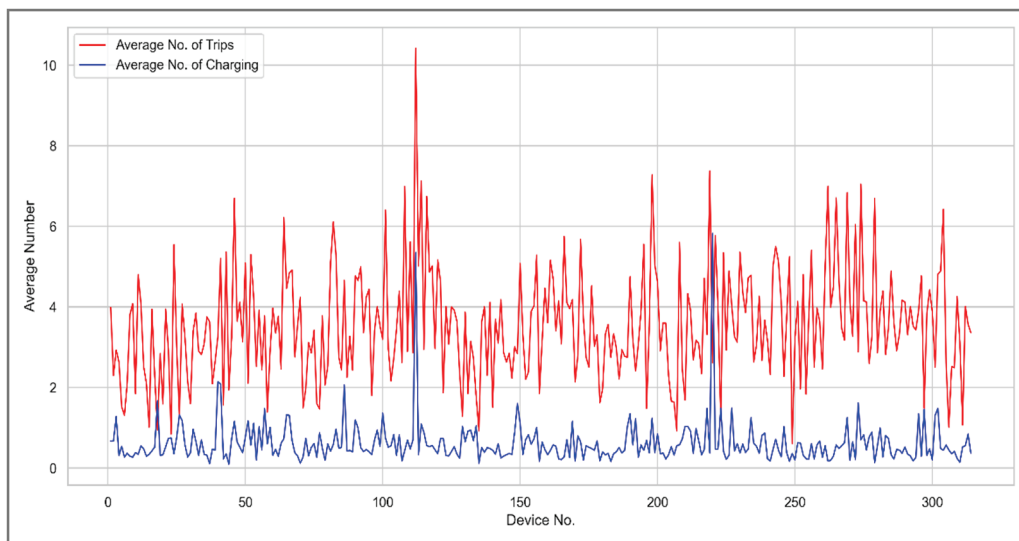


Figure 6. Individual averages of trips and charging frequencies of 351 electric cars.

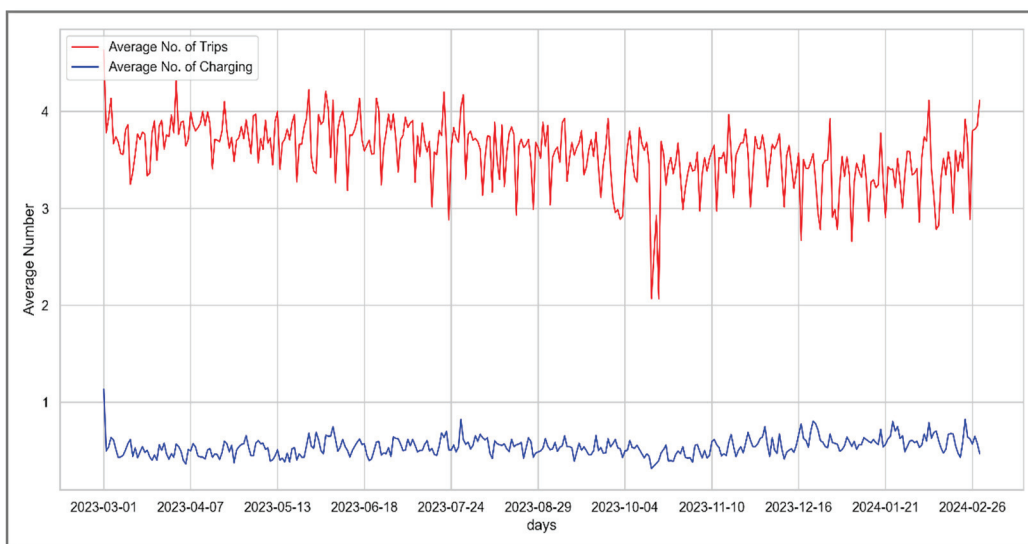


Figure 7. Daily averages of trips and charging frequencies from 1 March 2023 to 29 February 2024.

Table 4. Comparison of means and standard deviations between individual averages and daily averages.

Classification		Mean	Standard Deviation
Individual averages	Trips	3.55	1.39
	Charging frequency	0.62	0.54
Daily averages	Trips	3.56	0.38
	Charging frequency	0.54	0.10

Note: average unit is frequency/day.

3.2.2. Quantified Variability in Trips and Charging Frequencies

In the previous Section 2.2.2, the Equations (2)–(5) were applied to calculate the variability indices of travel frequency and charging frequency. The results of calculating the WPSS, BDSS, BPSS, WDSS, and TSS, respectively, are summarized in Table 5.

Table 5. Interpersonal and interpersonal variability analysis for trips and charging patterns.

Variability		Trips	Charging Frequency
Total variability	TSS	794,552	115,203
Interpersonal variability	BPSS	203,410	26,665
	WPSS (C = A + B)	591,142	88,538
Intrapersonal variability	BDSS (A)	15,154	946
	WDSS (B)	575,988	87,592
	Ratio of (A) to (B)	2.56%	1.07%
Ratio of BPSS to TSS		25.6%	23.15%

The results of decomposing the intrapersonal and interpersonal variability in trips and charging frequencies are summarized as follows. The proportions of interpersonal variability in the total variability in trips and charging frequencies are 25.6% and 23.2%, respectively, showing similar proportions. Both trips and charging patterns show that intrapersonal variability accounts for a larger proportion of the total variability than interpersonal variability. The proportion of daily variability in intrapersonal variability is 2.56% for trips and 1.07% for charging frequency. The results show that, similar to the [17,25] study, daily variability has a low impact on within-person variability. The variability decomposition of trips and charging frequencies confirms that charging frequency shows an overall trend that is similar to the variability patterns of trips.

3.2.3. Factors Affecting Intrapersonal Variability in Charging Patterns

The intrapersonal variability decomposition results show that the proportion of daily variability is very low. Therefore, this study applied a regression model to explore factors affecting the intrapersonal variability in charging patterns other than daily variations. The dependent variable was the WPSS_i of the individual, and the log value was used to secure normality. The explanatory variables are composed of the vehicle and driver characteristic variables and the driving and charging frequencies of individual vehicles, as shown in Table 6. To avoid the multicollinearity problem, we analyzed the model by controlling for only variables with a VIF (variation inflation factor) of less than 10. The estimated model has a sufficiently large F value to secure the significance of the model itself, and R² was 0.53. The results of the model analysis are shown in Table 7.

The statistically significant explanatory variables include five variables (BOLT, Others, high income, average number of trips, and average number of charges) at the 95% significance level and one variable (battery capacity) at the 90% significance level. First, vehicle-related variables were significant in factors impacting intrapersonal variability, and the BOLT and other model vehicles tended to have relatively lower variability. Battery capacity also showed a negative coefficient value, which means that the larger the capacity, the lower the variability. In addition, it was found that the higher the income level, the lower the variability. Both trips and charging frequencies have positive coefficient values, which means that the variability increases as trips and charging increase.

Although this study applied only limited variables due to data limitations, trip pattern is considered an important factor in interpreting the variability in charging patterns, and various trip characteristics, such as the trip purpose, trip time and duration, location, and dwell time, should be reviewed to explain the variability. In this study, we included the average number of trips and region as variables related to the trip pattern. The number of trips was statistically significant with the variability in the charging pattern, and the more

trips there were, the higher the variability in the charging pattern. However, the region, which can reflect the driving environment, was not statistically significant.

Table 6. Explanatory variables of regression model.

Key Variables	Specific Variables	Definition
Gender	Male	If (gender = male), 1, otherwise 0
Age	Age30	If (age < 30), age30 = 1, otherwise age30 = 0
	Age4050	If (age >= 30 and age < 50), age4050 = 1, otherwise age4050 = 0
	Age60	If (age >= 60), age60 = 1, otherwise age60 = 0
EV model	IONIQ	If (EV model = IONIQ), 1, otherwise 0
	BOLT	If (EV model = BOLT), 1, otherwise 0
	EV6	If (EV model = EV6), 1, otherwise 0
	KONA	If (EV model = KONA), 1, otherwise 0
	Others	If (EV model is not above type), 1, otherwise 0
Battery capacity	Battery capacity	Battery capacity of EV
Number of family	Single family	If (number of family = 1), 1, otherwise 0
	Dual family	If (number of family = 2), 1, otherwise 0
	Multi family	If (number of family = 3), 1, otherwise 0
Occupation	Office worker	If (occupation = office worker), 1, otherwise 0
Average monthly income	Low income	If (average monthly income of the respondent's household (KRW 10,000) < 300), 1, otherwise 0
	Middle income	If (average monthly income of the respondent's household (KRW 10,000) > 300 & income < 1000), 1, otherwise 0
	High income	If (average monthly income of the respondent's household (KRW 10,000) >= 1000), 1, otherwise 0
Region	Region	If (Region of residence is metropolitan area), 1, otherwise 0
Home charging	Home charging availability	If (Home charging is available) 1, otherwise 0
Trip	Average number of trips	Average number of trips per day
Charging	Average number of charging	Average number of charging frequencies per day

Table 7. Regression model of intrapersonal variability.

Variables	Coefficient	Standard Error	z	P > z
Male	−0.022	0.138	−0.16	0.871
Age60	−0.227	0.167	−1.36	0.174
IONIQ base				
BOLT	−0.615 (***)	0.211	−2.92	0.004
EV6	−0.061	0.112	−0.55	0.586
KONA	−0.093	0.245	−0.38	0.704
Others	−0.487 (**)	0.237	−2.06	0.040
Battery capacity	−0.027 (*)	0.016	−1.74	0.083
Multi family	0.083	0.076	1.10	0.274
Office worker	0.004	0.110	0.04	0.967
High income	−0.375 (**)	0.162	−2.31	0.022
Region	0.080	0.080	1.01	0.312
Home charging availability	0.031	0.132	0.24	0.814
Average number of trips	0.061 (**)	0.029	2.08	0.038
Average number of charges	1.047 (***)	0.077	13.66	0.000
Constant	6.329	0.2154	0.79	0.431

Number of observations = 314, F (14,299) = 23.85, Prob > F = 0.0000, R-squared = 0.5276, Adj R-squared 0.5055.
 Note: *** 99% significant level, ** 95% significant level, * 90% significant level.

Although not addressed in the above model, seasonal characteristics also have a significant impact on charging patterns. We estimated the intrapersonal variability in charging frequency by season. As a result, as shown in Figure 8, the variability in the charging frequency was the greatest in winter, and the average variability was similar in

other seasons. This trend is believed to be due to the lower temperature in the winter, which lowers the charging speed and fuel efficiency.

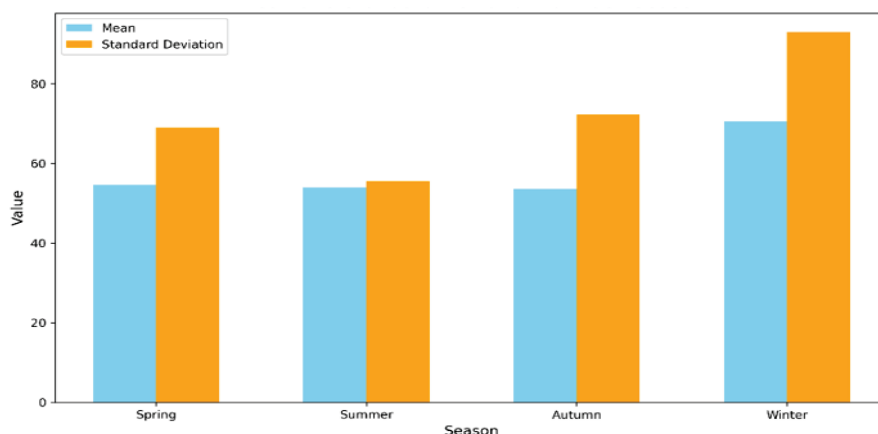


Figure 8. Intrapersonal variability in charging frequencies by season.

4. Discussion

We analyzed electric cars' charging patterns in Korea using panel data collected over a year via OBDs installed in cars. As a result, we summarize the following key implications regarding the regularity and variability in charging patterns.

The average charging interval was 2.25 days for the aggregated average and 3.65 days for the disaggregated average. We found that charging decisions were made more frequently than the required charging needs, considering that the average daily driving distance of Korean passenger cars is 39 km per day and the average range of electric cars is over 400 km per charge. It also means that charging opportunities are increasing due to the expansion of public charging infrastructure in Korea. When we analyzed the entire charging session data by dividing the charging points into home, workplaces, and public charging stations, the public charging frequency was the highest. The reason why public charging is so frequent in Korea is believed to be due to the residential nature of many multi-unit dwellings and the high accessibility of public charging. This characteristic is even more pronounced when compared to other countries. In the California study, 53% of drivers only charge at home, and home charging is the primary charging method for all drivers [27]. The German study also assumes that home charging has the highest frequency [28]. The distribution of charging start times by charging points showed similar distributions for home charging and public charging, and the peak hours were also the same, at 22:00–23:00. However, the charging ratio at night was higher for home charging, and the charging ratio during the day was higher for public charging.

The distribution of charging intervals was estimated by applying the GMM to explore the regularity of charging behaviors. As a result, 75% of the individuals have a regular log-normal pattern of charging intervals, while 25% show an irregular pattern. This result means that the charging demand derived from a simple assumption about charging behaviors at the aggregated level in infrastructure planning or power demand forecasting may differ from the actual charging demand. Therefore, as the number of electric vehicles increases, research on charging behaviors and the variability in charging patterns and factors affecting them becomes more important.

Finally, we applied a method to quantify the variability in charging patterns and decomposed it into intrapersonal variability and interpersonal variability. As a result, the intrapersonal variability was more than three times higher than the interpersonal variability, and the proportion explained by daily variation within the intrapersonal variability was low, at about 1%. The variability in charging frequencies and trips showed similar patterns,

and the variability in electric car trips was also similar to the results of the variability in conventional car trips analyzed by [17]. It implies that EV trips and charging behaviors are highly correlated, and travel characteristics are an important factor in explaining charging behaviors. Therefore, future research is needed to analyze charging patterns combined with travel characteristics (time and place, duration, and travel purpose).

5. Conclusions

As the number of EVs increases, effective charging infrastructure planning and grid load management strategies become more important. This study aimed to analyze the charging patterns of electric cars using panel data from 351 vehicles for one year from 2023. Using this longitudinal data, we explored the spatiotemporal characteristics of charging patterns in Korea, examined the regularities of charging patterns, and quantified the variability in charging and travel behaviors.

This study is one of the few studies on EV charging in Korea using longitudinal panel data. Nevertheless, future research is suggested for the regularity and variability in charging patterns. First, considering the characteristics of EV charging, seasonal and monthly variability analyses can be discussed. Second, regularity and variability can be explored, centered on charging and activity locations. In addition to the variability indices applied in this study, alternative indices, such as the Herfindahl–Hirschman Index, are suggested to be reviewed [29–31]. The previous studies have shown that travel characteristics, such as the location and transport mode, have repetitiveness, and this approach is also valid for charging pattern analyses. Future research will be needed to clarify the regularity through the combined analysis of travel and charging activities. It can also provide an in-depth look at the impact of travel patterns, such as the travel distance, travel time, location, and activity period, on charging patterns.

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Article

The Overlooked Role of Battery Cell Relaxation: How Reversible Effects Manipulate Accelerated Aging Characterization [†]

Markus Schreiber *, Theresa Steiner, Jonas Kayl, Benedikt Schönberger, Cristina Grosu
and Markus Lienkamp

Institute of Automotive Technology, Department of Mobility Systems Engineering, School of Engineering & Design, Technical University of Munich (TUM), 85748 Garching, Germany

* Correspondence: markus.schreiber@tum.de

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Abstract: Aging experiments are pivotal for car manufacturers to ensure the reliability of their battery cells. However, realistic aging methods are time-consuming and resource-intensive, necessitating accelerated aging techniques. While these techniques reduce testing time, they can also lead to distorted results due to the partially reversible nature of cell behavior, which stems from the inhomogenization and rehomogenization of conducting salt and lithium distribution in the electrode. To accurately capture these phenomena, cell relaxation must be incorporated into the test design. This work investigates the impact of the test procedure and several stress factors, namely depth of discharge and C-rate, on the formation and rehomogenization of cell inhomogeneities. The experimental results reveal increasing cell inhomogenization, leading to growing reversible capacity losses, particularly under conditions with shorter cycling interruptions (check ups and rest phases). These reversible capacity losses are associated with a significant reduction in cycle life performance of up to 400% under identical cycling conditions but shorter cycling interruptions. Similar trends are observed for increasing cycle depths and C-rates. Optimized recovery cycles effectively mitigate cell inhomogenization, doubling cycle stability without requiring considerable additional testing time. Furthermore, a clear correlation is found between increasing inhomogenization and cell failure, with lithium stripping confirming the occurrence of lithium plating shortly before failure. These findings emphasize the critical importance of considering cell relaxation in cycle aging studies to ensure reliable and accurate lifetime predictions. Under realistic conditions, substantially enhanced cycle stability is expected.

Keywords: lithium-ion battery; aging characterization; accelerated aging; cell inhomogeneity; reversible degradation; capacity recovery

1. Introduction

Lithium-ion battery (LIB) cells for automotive applications require high cycle stability and long calendar lifetimes to compete with conventional internal combustion engines. Due to limited time scales of several months during battery and vehicle development [1,2], aging tests need to be accelerated compared to real-world applications. One common approach for this is the omission of intermediate rest phases [3,4], as they account for up to 96.8% of the vehicles' lifetime [5,6].

The lack of regularly repeated rest phases during accelerated laboratory tests impedes the compensation of reversible effects [7,8]. In the long term, the aging behavior is permanently manipulated, and premature cell failure can be triggered. Morales Torricos et al. [9] state that continuous cycling potentially promotes lithium plating due to the persistent inhomogenization of the lithium distribution within the negative electrode and thus can ultimately lead to cell failure. Therefore, lifetime predictions based on accelerated aging tests might be inaccurate or even falsified, underestimating the realistic lifetime.

During operation, irreversible degradation effects occur, called calendar and cycle aging. These effects cause an inevitable decrease in capacity due to the loss of active material and lithium, as well as growth of resistance resulting from contact loss between particles and the current collector and from thickening cover layers on the electrodes [10,11]. This cell deterioration is commonly measured via regularly repeated check ups (CUs) throughout the aging study. From diverse measurements, the current cell conditions can be captured, and by comparing these to the pristine state, the changes in the cell condition are quantifiable. Usually, these changes are directly interpreted as irreversible degradation. However, several studies have recently shown pronounced cell recovery during cycle aging tests [9,12–14]. The authors have attributed these recovery phenomena to diverse reversible mechanisms during cycle aging tests. These include the impact of the negative electrode's overhang, the inhomogeneity of conducting salt induced by electrolyte motion, and the inhomogeneous lithium distribution within the active material.

1.1. Fundamental Electrochemical and Physical Processes Impacting Cycle Life

These reversible mechanisms cause temporary capacity loss in the short term, which is partially recovered during idle periods or CUs when the cell is unstressed or only slightly loaded, and thus, equalization processes can take place [15,16]. However, if cycling continues, the effects of these mechanisms become irreversible in the long term and ultimately cause rapid cell failure. This is especially noticeable when cycle aging tests are performed in an accelerated manner, meaning at elevated stress levels and omitted rest phases.

Passive electrode effect or overhang of the negative electrode: The overhang denotes the geometric oversizing of the negative electrode [17], designed to prevent lithium plating at the electrode edges [4]. Consequently, this part has no positive counter-electrode and therefore takes part in de-/intercalation processes only by means of in-plane solid-state diffusion. Depending on its state of charge (SOC) in relation to the SOC of the active part of the electrode, the overhang acts as a source or sink for lithium and can cause reversible capacity gains or losses [18]. This is commonly observed in the initial stage of an aging test until a dynamic equilibrium between storage or cycling conditions and the intermediate CUs is established. The measurable impact varies between hours and several days [4]. Due to its dependency on the operating conditions, ultimate equalization of the overhang is not possible. Changes in the acting stresses or unintended rest phases impact the state of the overhang and can manipulate the measurement data through steps in the capacity progression.

Electrolyte motion-induced salt inhomogeneity: The electrolyte motion induced salt inhomogeneity (EMSI) effect describes the inhomogenization of the conducting salt distribution within the jelly roll caused by the motion of the electrolyte [19]. This motion is induced by volume changes in the negative electrode due to de-/intercalation processes and therefore enhances with increasing depth of discharge (DOD). As a result, the active material acts as a pump, displacing the electrolyte from the jelly roll during charging and drawing it back in while discharging. The polarization due to the applied electrical load superimposes this electrolyte movement and leads to the formation of through-plane

conducting salt gradients between the electrodes. During charging, lithium is transported from the positive to the negative electrode, leading to the enrichment of conducting salt in the positive electrode and the depletion in the negative. The simultaneous pump effect causes a movement of inhomogeneously distributed conducting salt and therefore evokes in-plane gradients. These mechanisms are illustrated in the literature [14,19]. This effect is more pronounced for silicon–graphite composites, as the volume change of silicon is three times higher than that of pure graphite [20]. Through-plane concentration gradients in the range of a few hundred micrometers typically equalize within minutes to hours, while in-plane gradients require weeks to months of relaxation time [19].

Inhomogeneous lithium distribution: Apart from conducting salt gradients in the electrolyte, lithiation gradients of the active material have also been reported in the literature [7,9,16,17,21–23]. Like the conducting salt gradients, these lithiation gradients form across the electrode thickness as the active material are de-/lithiated from the surface towards the current collector [24,25]. Moreover, in-plane gradients have been observed and identified as a result of the EMSI effect described above [19]. However, Berhaut et al. [26] found very similar lithiation distributions during the first and second cycles, concluding that cell manufacturing could lead to preferential lithiation pathways due to non-uniform electrode morphology, varying diffusion paths, local electronic and ionic conductivities, and path lengths. Since through-plane conducting salt gradients require at least one complete charge–discharge cycle to form, the EMSI effect does not explain the inhomogeneous lithiation observed in the first cycle. For this reason, we assume that electrode-related characteristics, such as the aforementioned morphology, together with cell-related properties like local pressure distribution and winding radii, constitute another cause of inhomogeneous electrode lithiation, as they influence local tortuosity and porosity. The EMSI effect further exacerbates this inhomogeneity.

Lithiation inhomogeneities cause inhomogeneous and incomplete utilization of the active material of the negative electrode and lead to the earlier reaching of the cut-off potentials [16]. Due to local lithiation variations within the negative electrode, the local electrode potential fluctuates. During charging and discharging, the areas of maximum and minimum potential terminate the de-/lithiation process of the entire cell. This is amplified by increasing DODs and C-rates [9]. As inhomogeneous lithiation aggravates, these potential fluctuations also increase, leading to the earlier reaching of the cut-off voltage. Consequently, the extractable capacity declines, which appears as cell degradation. This effect increases with progressive cycling [7,14].

Equalization of lithiation inhomogeneities: The equalization of inhomogeneous lithiation can be categorized into three mechanisms [27,28]: (i) inter-particle equalization, occurring within a particle between the surface and bulk on the μm scale and below (dominant in the first few minutes); (ii) through-plane equalization, taking place between the current collector and separator on the μm scale, where transport in the liquid phase is assumed to be dominant; and (iii) in-plane equalization, occurring across the electrode sheet on the cm scale. The latter is particularly relevant for wound cylindrical cells with small tab dimensions, as it leads to inhomogeneities over very long distances. Again, the transport across these regions is assumed to be dominant in the liquid phase [27]. Simulations indicate that even small inhomogeneities, with local deviations of approximately 0.5% from the average concentration, remain unbalanced even after 6 h [27]. This highlights the sensitivity of the negative electrode to inhomogeneities and their long-term impact on cell behavior if not accounted for.

Two cell-internal factors impact the relaxation behavior. Firstly, gradients in the local electrode potential drive the equalization of adjacent, inhomogeneous areas [7,16,29]. These gradients are particularly high in the low full-cell SOC range as well as around the inter-

calation steps of the graphite at 15–25% and 55–60% full-cell SOC. Elevated temperature accelerates these compensation effects by increasing conductivity, diffusivity, and reaction rates [7,30]. Secondly, mechanical pressure gradients within the cell promote the formation of inhomogeneities during cycling and presumably impede their potential-driven compensation [8,15]. This is due to the higher volume expansion of areas with a higher lithiation state and vice versa. Thus, equalizing such areas would counteract the mechanical volume changes and, therefore, cannot take place on its own.

A distinct effect has been reported for silicon–graphite composites, where the de-/lithiation of the different materials is assumed to occur in a staggered manner [24,31]. This behavior results from the differing open-circuit potentials of the materials, which drive the de-/lithiation reactions. Since silicon exhibits a higher open-circuit potential up to approximately 50% SOC, the lithiation of the graphite fraction is delayed during charging, while it is primarily delithiated first during discharging [24,31]. This non-uniform lithiation is further amplified at higher C-rates and temperatures, as kinetic and transport limitations in silicon promote the preferential lithiation of graphite [32,33]. In addition to the equalization of lithiation gradients between graphite particles explained above, lithium redistribution from graphite to silicon occurs during relaxation [24,26,32]. This so-called buffer effect has been particularly observed after charging pulses and intensifies with increasing C-rates, as the two materials exhibit increasingly different lithiation levels, which enhances the driving force for redistribution. The first 4 h are the most dominant phase of this effect [24,28].

1.2. Contributions and Layout

Summarizing the presented fundamentals reveals a substantial impact of reversible phenomena on the long-term operating and degradation behavior of LIBs. Moreover, it highlights the required diligence for the interpretation of measurement data, particularly for data obtained from accelerated aging tests, since both the magnitude of these effects, as well as their equalization, strongly depend on the acting operating conditions. However, recapitulating the state of the art indicates that such effects are largely overlooked, leading to incorrect conclusions in certain applications. This particularly applies to applications with frequent and extended rest phases, such as many automotive use cases.

This work studies the influence of the test procedure and several stress factors on the homogeneity of lithium distribution and the relaxation behavior to better understand the impacts on lifetime predictions and the battery performance during operation. Section 2 describes the methodology and experimental setup. In Section 3, the results are presented and discussed with a particular focus on reversible and irreversible aging. The first part illustrates the formation of inhomogeneities and their impact on aging characterization (Section 3.1) and provides a brief discussion of the statistical significance and robustness of the measurement data (Section 3.2). Based on these findings, Section 3.3 focuses on the effects of the test procedure, followed by the impact of the DOD and C-rates in Section 3.4. Subsequently, Section 3.5 assesses methods to promote the intermediate equalization of inhomogeneities. Sections 3.6 and 3.7 discuss the implications of cell behavior on cycle life, as well as its relevance for accelerated aging characterization and BEV applications. Finally, Section 4 summarizes the key findings and provides a brief outlook. The main contributions are as follows:

(1) Understanding the impact of the test procedure on cell inhomogeneity:

We address how the test procedure induces cell inhomogeneity, how it manifests, and how it affects both short- and long-term cell behavior as well as cycle stability. For this purpose, cell conditions before and after regular rest phases in the cycle

aging tests are captured, and capacity differences, indicating equalization processes, are analyzed.

(2) Investigating the impact of various stress factors on cell inhomogeneity:

The impact of DOD and C-rate during cycling is assessed. We investigate the correlation between stress levels, the degree of inhomogenization and equalization, and the occurrence of lithium plating.

(3) Supporting cell relaxation and rehomogenization during cycling:

Based on these findings, we focus on rehomogenization behavior. We investigate static and dynamic methods to actively promote the equalization of inhomogeneities during accelerated cycle aging tests, aiming to minimize their impact on cell performance and degradation.

2. Materials and Methods

The subsequent sections provide a detailed description of the investigated battery cell and measurement equipment, the methodology and experimental framework, as well as the analytical methods utilized in this work, based on our earlier publication [34].

2.1. Cell Specifications

This study was conducted with the INR21700-50G (Samsung SDI, Yongin-si, South Korea), an automotive-grade 21700 cylindrical cell from the mass-production vehicle Lucid Air (Lucid Motors, Newark, CA, USA). Silicon-graphite was used for the negative electrode, and nickel cobalt aluminium oxide (NCA) was used for the positive electrode. The cells were extracted from a benchmarking vehicle during a teardown process in an almost new condition. The start of production (SOP) of the respective vehicle model was in September 2021. Based on the cell code, the production date of the tested cells can be traced back to the beginning of May 2021. Before our aging tests, the cells underwent about two years of storage after sporadic cyclic loading in the vehicle. An initial characterization yielded mean capacity and internal resistance values of 4.83 Ah and 26 m Ω , with standard deviations of 18.5 mAh and 0.4 m Ω , demonstrating a strong agreement with the data sheet specifications and the values reported by Kim et al. [35], as well as negligible cell-to-cell variation. Table 1 summarizes the relevant cell specifications.

Table 1. Specifications of the investigated battery, taken from the datasheet [36] and Kim et al. [35].

Parameter	Value
Manufacturer	Samsung SDI
Cell type	INR21700-50G
Cell format	21700 cylindrical
Positive electrode material	NCA (LiNi _x Co _y Al _z O ₂ , stoichiometry unknown)
Negative electrode material	Silicon-graphite (stoichiometry unknown)
Nominal capacity ¹	4.9 Ah
Nominal voltage	3.63 V
Minimum voltage	2.5 V
Maximum voltage	4.2 V

¹ Measured at C/5 and 25 °C.

2.2. Measurement Equipment

The cell tests were performed using a CTS and XCTS battery test system (BaSyTec GmbH, Asselfingen, Germany). Test cases involving currents higher than 5 A were performed with the XCTS test system, whereas all other test cases, as well as all CUs, were carried out using the CTS test system, due to its higher measurement precision. The cells were electrically connected with Arbin single-cell battery holders (Arbin Instruments,

College Station, TX, USA) with 4-wire sensing in a horizontal orientation inside an IPP110eco climate chamber (Mettmert GmbH + Co.KG, Schwabach, Germany) and a BINDER KB115 E4 climate chamber (BINDER GmbH, Tuttlingen, Germany) at a constant ambient temperature of 25 °C without additional active temperature control. The cells' surface temperatures were measured throughout the entire experiment using a negative temperature coefficient thermistor. These temperature progressions are provided in Appendix B. Small temperature fluctuations between the cells due to the location inside the climate chamber cannot be precluded. However, the surface temperature data show only small deviations.

2.3. Test Design and Measurement Procedures

A specific test design was created to examine the impact of cell relaxation, with one cell tested per condition. Typical cycle aging studies consist of alternating patterns of CUs and cycling sequences without prolonged rest phases. In this way, cycle aging tests can be performed in a time-efficient manner. However, this concept does not account for intermediate rest phases, which are a key characteristic of vehicle applications and make up the majority of the lifetime. For this reason, we propose a test design incorporating an additional dedicated rest phase after every cycle interval.

A shortened pre-rest CU is performed right after the last cycle to directly assess the cell behavior after cycling. The influences of the idle period and the associated relaxation processes after cycling are captured by the post-rest CU. Figure 1 visualizes the general testing scheme and organizes the four experimental substudies presented in this work.

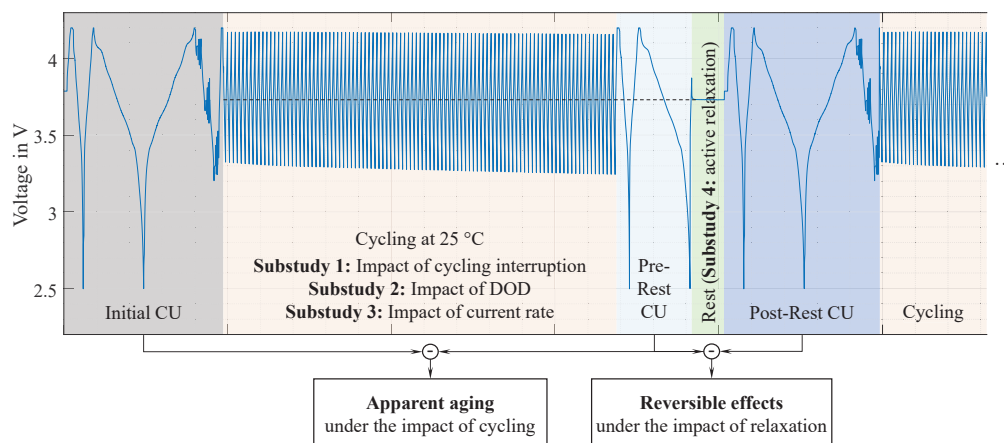


Figure 1. General testing scheme of the aging study. The pre-rest and post-rest CU procedures are identical for all test cases. The cycling interruption, DODs, and C-rates during cycling are varied in the respective substudies 1–3. During the rest phase, the storage SOC is set to the average SOC of the preceding cycling sequence to minimize the impact of the negative electrode's overhang, except for substudy 4, where optimized relaxation methods are investigated. This figure has been adapted from our earlier publication [34].

2.3.1. Check-Up Procedures

To continuously assess the cells' condition alongside the inhomogenization and relaxation behavior throughout the aging study, CUs are performed on a regular basis every 100 cycles directly after cycling (pre-rest) and after the subsequent ten-hour rest (post-rest). This rest phase represents common periods of vehicle standstill during the day or night. The CU procedure contains three primary sequences: first, the C/3 discharge capacity is measured, followed by a low current discharge and charge at C/15. Finally, the direct current (DC) resistance is determined using a hybrid pulse power characterization (HPPC) with several C-rates at various SOC levels. The pre-rest CU is a shortened version of the

general CU, including only the C/3 discharge capacity and the C/15 discharge pseudo open circuit voltage (pOCV) measurement. This minimizes incipient relaxation effects, which are prone to occur during the CU due to the low electric load. Hence, those effects would impact the measurement after cycling and thus distort the assessment of the dedicated rest phase.

2.3.2. Cycle Aging Test Procedures

The cycle aging tests performed in this work include four consecutive substudies investigating the inhomogenization behavior during cycling and the rehomogenization behavior during relaxation.

Substudy 1: Impact of cycling interruption due to CUs and rest on cell inhomogenization.

Substudy 1 focuses on the inhomogenization behavior due to continuous cycling impacted by intermediate cycling interruptions due to CUs and rest phases. For this purpose, the reference test procedure is reduced stepwise by individual measurement and/or resting sequences, as illustrated in Figure 2. The reference case follows the general testing scheme depicted in Figure 1, including cycling, pre-rest CU, rest, and post-rest CU. Cycling is performed at 1C/1C in the 20 to 100% SOC range.

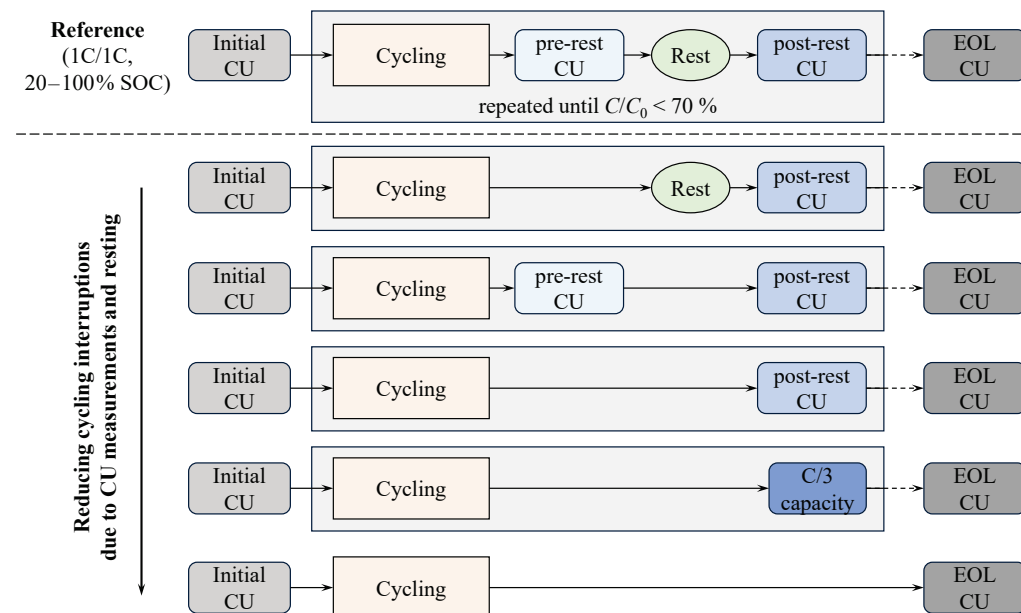


Figure 2. Test design of Substudy 1: The initial and EOL CU are identical across all test cases, and cycling is uniformly performed at 1C/1C within the 20 to 100% SOC range.

Substudy 2: Impact of the DOD on cell inhomogenization.

In this substudy, cycling is performed in various SOC ranges. These are depicted in Figure 3 in relation to the cell's differential voltage (DV), as this parameter is, in addition to the internal pressure, a substantial characteristic linked to the SOC and affects the lithium intercalation into the silicon and graphite particles. Thus, the in- and rehomogenization are influenced differently in diverse SOC ranges. To minimize the impact of the negative electrode's overhang during the rest phase, the cells are stored at the average SOC of the preceding cycling sequence. C-rates are kept uniform at 1C/1C for all test cases to eliminate the impacts of this stress factor.

Substudy 3: Impact of the current rate on cell inhomogenization.

Like Substudy 2, in this substudy, the impact of the current rate during charging and discharging is assessed. For this purpose, cycling is performed between 0 and 100% SOC at varying charge and discharge rates, as summarized in Figure 3.

Substudy 4: Relaxation methods promoting cell rehomogenization.

Based on the findings regarding cell inhomogenization during cycling, Substudy 4 investigates relaxation methods to actively promote cell rehomogenization. The test procedure is built upon the reference case for comparability, including cycling, pre-rest CU, relaxation, and post-rest CU. Cycling is performed at 1C/1C in the 0 to 100% SOC range. In contrast to the reference case, cell relaxation is carried out in diverse static and dynamic manners. In the static cases, the cells idle in the open-circuit condition like in the reference case, but at differing SOC levels. As depicted in Figure 3, three rest SOC levels in the area of characteristic stage transitions of the negative electrode have been chosen. The corresponding voltages were approached by constant current constant voltage (CCCV) charging until the cut-off current of C/20 was reached. For dynamic relaxation, the resting phase was substituted by a low current charge with a C-rate of C/15.

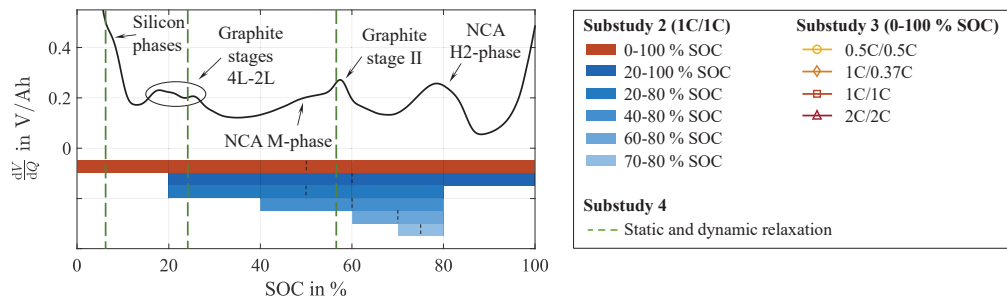


Figure 3. Test design of Substudies 2, 3, and 4 in relation to the cell DV and the characteristic lithiation stages of the positive and negative electrodes: In Substudy 2, the SOC range is varied, and the current rates remain fixed at 1C/1C, while in Substudy 3, the SOC range is kept constant at 0 to 100%, and the current rates are modulated. Substudy 4 comprises three static relaxation test cases with idle phases at the SOC levels indicated by the green dashed lines, as well as one dynamic test case that includes a low-current charge cycle from 0 to 100% SOC. This figure has been adapted from our earlier publication [34].

2.4. Analysis Methods

Several analysis methods are performed based on the gathered data in the pre-rest and post-rest CU. The cell capacity is extracted from the C/3 constant current (CC) discharge measurement. R_{DC} is calculated from the 20 s 1C current pulses in the charge direction at 50% SOC. The capacity difference analysis (CDA) introduced by Lewerenz et al. [21] is used as a measure for the lithiation inhomogeneity. We further denote this parameter as CD_{C-rate} because it is defined as the difference between a low and high current discharge; in our case, C/15 and C/3:

$$CD_{C-rate} = C_{C/15} - C_{C/3} \quad (1)$$

Due to different discharging durations, inhomogeneities have varying periods to equalize, resulting in a higher extractable capacity at lower C-rates. We emphasize that overpotentials due to increased cell resistance have a negligible impact on this capacity difference, as the voltage curves are very steep towards the end of discharge. In analogy to this parameter, we define the capacity difference $CD_{resting}$, which quantifies the deviation between the C/3 discharge capacities during post-rest and pre-rest CU:

$$CD_{resting} = C_{C/3, post-rest} - C_{C/3, pre-rest} \quad (2)$$

This characteristic is an indicator of cell relaxation during rest and gives insights into capacity recovery. Low constant values indicate a minor extent of relaxation effects and thus a dynamic equilibrium state, while high increasing values imply pronounced and growing relaxation as a consequence of aggravating inhomogeneity.

In addition, the cell inhomogenization behavior during cycling is evaluated either based on end of discharge (EODC) voltage U_{EODC} or the extractable amount of charge $Q_{\text{extractable}}$ in each cycle. Both values provide information about the homogeneity of the negative electrode's lithiation degree, as higher inhomogeneity leads to widening of the traversed voltage window, thus reaching the cut-off voltage earlier [16]. The U_{EODC} is utilized in the case of partial cycles if cycling is terminated above 2.5 V after a fixed amount of charge has been extracted. For this purpose, the last voltage value of every cycle is captured. It has to be noted that this is also impacted by decreasing capacity due to cell aging. The presented values should, therefore, rather be understood as trends instead of a precise quantification of the respective effect. $Q_{\text{extractable}}$, in contrast, is assessed when cycling is performed across the entire voltage range from 4.2 to 2.5 V, ensuring that U_{EODC} remains unchanged. The relaxation behavior is analyzed based on these two parameters. Therefore, we quantify the alterations ΔU_{relax} and ΔQ_{relax} during CUs and rest between every 100th cycle and the first cycle of the subsequent cycle interval.

Finally, the stripping behavior serves as an indicator of preceding lithium plating, as it reveals the dissolution of previously deposited metallic lithium. This metallic lithium returns to its ionized state and re-participates in the de-/intercalation reactions [28,32]. To analyze this effect, the differential voltage during the resting phase immediately after a CC charge is examined.

3. Results and Discussion

In the following, we evaluate and discuss the results of the conducted cycle aging studies. First, the formation of cell inhomogeneities during cycling is outlined, followed by the impact of the test procedure and cycling interruptions due to CUs and rest phases. Based on these findings, the influence of DOD and current rate on in- and rehomogenization behavior is presented. Finally, methods to actively support intermediate cell rehomogenization are analyzed.

3.1. Formation of Cell Inhomogeneities During Cycling

Several studies have reported inhomogeneous cell conditions in terms of negative electrode lithiation [9,12,15] and conducting salt distribution [37]. These inhomogeneities result from cell cycling, which triggers the formation of concentration gradients. Electrolyte motion due to volume changes of the jelly roll further enhances these gradients [19]. As a result, the kinetic overpotentials increase, leading to the earlier reaching of the cut-off voltage and consequently reducing the extractable capacity [21]. These effects are reversible as long as a critical cell condition has not been exceeded. However, they lead to an increasingly uneven distribution of the locally acting stresses, promoting localized degradation spots, e.g., due to lithium plating.

To show these effects and the underlying cell behavior, the 20 to 100% SOC test case is considered exemplary because it shows the most pronounced effects and allows for the analysis of U_{EODC} , in contrast to the full DOD test case. For the latter, discharging is always terminated at 2.5 V; therefore, no U_{EODC} alterations occur. The reversibility mentioned above becomes evident in Figure 4a, illustrating the relative capacity during the cycle aging study. The dashed line represents the capacity measured in the pre-rest CU directly after cycling, while the solid line depicts the capacity extracted from the post-rest CU after the subsequent ten-hour rest. Both measurements follow the same procedure, though they

reveal a clear discrepancy in the extractable capacity, as shown by the red curve in Figure 4b. In addition, the capacity differences CD_{C-rate} between low ($C/15$) and high current ($C/3$) discharge, obtained from the pre-rest (blue curve) and the post-rest CU (black curve), are depicted, also revealing a discrepancy, as presented in our earlier publication [34].

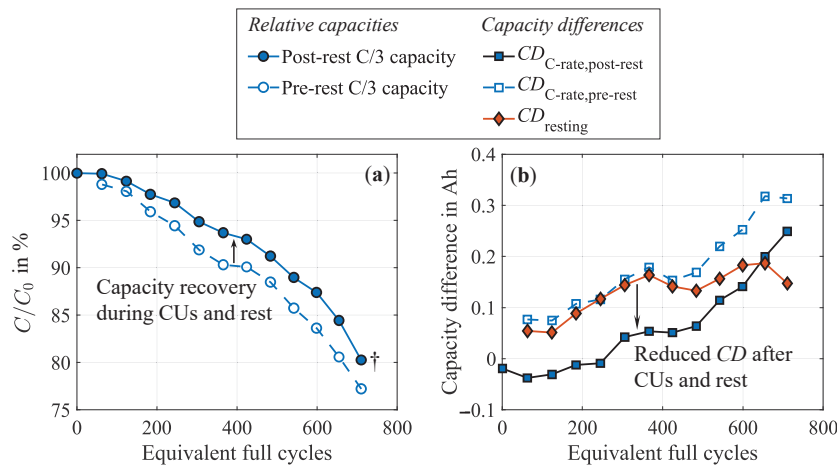


Figure 4. Formation of reversible capacity losses during cycling: relative capacity measured before and after the ten-hour rest (a), capacity differences regained during CUs and rest (b). The cell failed only a few cycles after the last CU point presented, indicated by the † symbol. This figure has been adapted from our earlier publication [34].

Since measurement impacts can be precluded, these differences must result from effects occurring during the rest phase and the CUs. After cycling, the cell exhibits inhomogeneities in terms of lithiation and conducting salt distribution mentioned above to a certain degree. As a consequence, shares of the active lithium are inaccessible. During the rest phase and the CUs, which are characterized by predominantly low current charge and discharge sequences as well as several additional rest phases, these inhomogeneities can partly equalize, leading to a redistribution of lithium within the negative electrode and increasing the lithium accessibility. Therefore, the capacity increases. An inverse correlation with the CD_{C-rate} ($C_{C/15} - C_{C/3}$) is evident, revealing a reduced capacity difference after relaxation. Moreover, both capacity differences, $CD_{resting}$ and $CD_{C-rate, pre-rest}$, exhibit a high similarity, supporting the explanation given by Lewerenz et al. [21]. They emphasize that the capacity difference mainly results from inhomogeneous lithium distribution, which strongly limits the extractable capacity. Due to the different time scales during discharging at low and high current rates, these inhomogeneities equalize to varying degrees, explaining the capacity difference. While increased overpotentials due to increased internal resistance also reduce the extractable capacity as the cut-off voltage is reached earlier depending on the C-rate, this impact is minor since the voltage curves are very steep at the end of discharge. The impacts of the negative electrode's overhang during the rest phase are assumed to be negligible since the rest SOC matches the average SOC during cycling. Hence, no considerable lithiation differences should occur between the active and passive areas of the negative electrode, which is in agreement with findings from the literature [15,17,38].

It becomes evident that the capacity differences grow with progressing cycling. This suggests that as the cell is stressed, it becomes increasingly inhomogeneous, leading to growing capacity recovery during CU and rest. Starting at around 500 equivalent full cycles (EFCs), the previously observed high similarity ceases, and the capacity differences begin to diverge. One EFC represents a complete charge and discharge cycle, normalized to the nominal cell capacity. While CD_{C-rate} further increases, $CD_{resting}$ reaches a maximum and subsequently drops significantly. This could either indicate the establishment of a dynamic equilibrium between inhomogenization and rehomogenization or the progres-

sively increasing incompleteness of the rehomogenization process. Moreover, this further implies changes in degradation behavior and the dominant mechanism, which will be further discussed in Section 3.6.

The U_{EODC} further supports this interpretation with its characteristic sawtooth pattern, as can be seen in Figure 5a. Herein, one continuous cycle interval corresponds to one sawtooth, presented for an early aging state during the first 100 cycles in Figure 5c and for an advanced aging state in the cycle interval between 901 and 1000 in Figure 5d. These observations give further insights into the ongoing phenomena, revealing two interlinked effects: Firstly, U_{EODC} descends towards lower values within one cycle interval as cycling progresses. This results from increasing inhomogeneities in conducting salt distribution and lithiation degree within the negative electrode, leading to local SOC variations in the active material. Consequently, areas with decreased SOC are discharged to a lower voltage when extracting the same amount of charge, shifting U_{EODC} to lower values. In addition, increasing cell polarization due to growing conducting salt gradients causes the overpotentials to increase, specifically the concentration overpotential. During cycling, concentration gradients form within the cell, which aggravate with progressive, continuous cycling. Electrolyte motion due to volume changes leads to local conducting salt enrichment in the center of the jelly roll, while salt depletes at the edges [19,37]. It needs to be considered that such characteristic behavior can also result from a drift of the SOC window caused by small deviations between the discharged and recharged amount of charge. In our tests, however, this can be excluded because both charging and discharging were terminated charge-based; therefore, this impact is negligible.

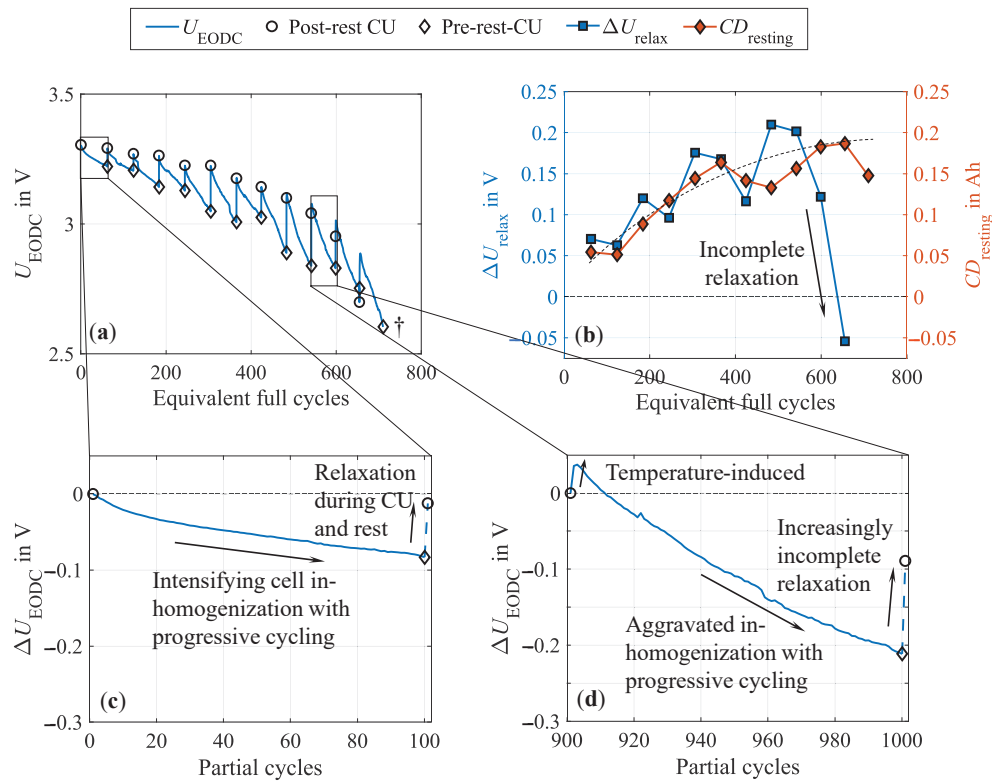


Figure 5. Alterations in the end of discharge voltage throughout the cycle aging test: Shift in U_{EODC} during cycling, CU, and rest; the $\dagger$ symbol indicates failure of this cell, which occurred a few cycles after the last CU point shown (a). ΔU_{EODC} during two specific cycle intervals, normalized to the respective initial value of each interval, at an early aging state from cycle 1 to 100 (c) and an advanced aging state from cycle 901 to 1000 (d). Correlation between end of discharge voltage relaxation ΔU_{relax} and capacity recovery during CU and rest (b). This figure has been adapted from our earlier publication [34].

Secondly, the spike after the 100th cycle reveals cell relaxation during resting and CU. During rest, the lithium distribution in the negative electrode rehomogenizes and the concentration gradients of the conducting salt equalize, leading to more uniform lithiation. This manifests itself in the observable reset of the U_{EODC} , as illustrated in Figure 5b.

Comparing the cell behavior in the two highlighted cycle intervals provides insights into the long-term behavior. The intensity of both the inhomogenization during cycling and the rehomogenization during rest amplifies with progressing cycling. This is evident from the increasingly steep decline of U_{EODC} during cycling and the subsequently more pronounced voltage spike. However, the inhomogenization effects grow disproportionately compared to the rehomogenization. Despite intensified relaxation effects over the course of the experiment, Figure 5d reveals significantly more incomplete and prolonged cell relaxation compared to the early aging state. This effect, indicated by the peak during the first cycles, is temperature-induced, as the cell cools down during CU and rest and heats up during the first cycles. The rising temperature supports equalization processes [27] and reduces overpotentials, ultimately leading to increased U_{EODC} . The correlation between the end of discharge voltage and the temperature progression is exemplarily depicted for the cycle interval between 900 and 1000 cycles in Appendix A. The increasingly incomplete relaxation aligns with our previous findings regarding the growing capacity difference and the declining capacity recovery rate. In addition, Figure 5b illustrates the progressions of CD_{resting} , representing the regained capacity during relaxation, and the voltage relaxations ΔU_{relax} during CU and rest, proving a strong correlation of both. The values of the voltage relaxation represent the difference of U_{EODC} between every 100th cycle (indicated by the diamond marker) and every first cycle of the subsequent cycle sequence (indicated by the circle marker). Consequently, ΔU_{relax} serves as a measure for the voltage relaxation, such as $CD_{\text{C-rate}}$ represents the charge regain. This behavior seems plausible, as the redistribution of lithium during rest leads to a more homogeneous SOC distribution throughout the negative electrode, and the polarization declines due to the equalization of concentration gradients. Therefore, the voltage window tightens.

It has to be noted that the reversible capacity losses are inherently superimposed by irreversible ones due to unavoidable degradation mechanisms, including, e.g., solid electrolyte interphase (SEI) growth consuming active lithium or loss of active electrode material, e.g., due to particle cracking as a result of volume changes [10]. This irreversible capacity loss also causes a widening of the traversed voltage window. However, sole irreversible degradation would not exhibit the observed voltage reset during rest. Moreover, precisely quantifying the difference between reversible and irreversible capacity loss is extremely difficult, if not impossible, due to the asymptotic nature of rehomogenization and capacity regain. As a result, identifying the exact point at which the cell has fully equalized, which is essential for determining the distinction between reversible and irreversible capacity loss, is highly challenging. Therefore, our focus was on revealing the trends and intensities of these phenomena as influenced by the cycling conditions applied earlier.

3.2. Statistical Significance and Robustness

In our study, only one cell was investigated per test case, with the exception of the 1C/1C test at 100% DOD. The initial characterization, however, revealed minimal cell-to-cell variation, thereby enhancing the comparability between different cells. In addition, the 1C/1C test condition showed only minor deviations among the three tested cells throughout the entire experiment—both in pre-rest and post-rest behavior—as illustrated in Figure 6. It should be noted that the presented data are subject to a certain degree of uncertainty due to the limited statistical validation. Despite this limitation, we are confident that the results are sufficient to qualitatively demonstrate the discussed effects. As emphasized

throughout this work, the goal is not precise quantification but rather the identification and qualitative assessment of the observed phenomena and their implications for cell behavior and aging characterization.

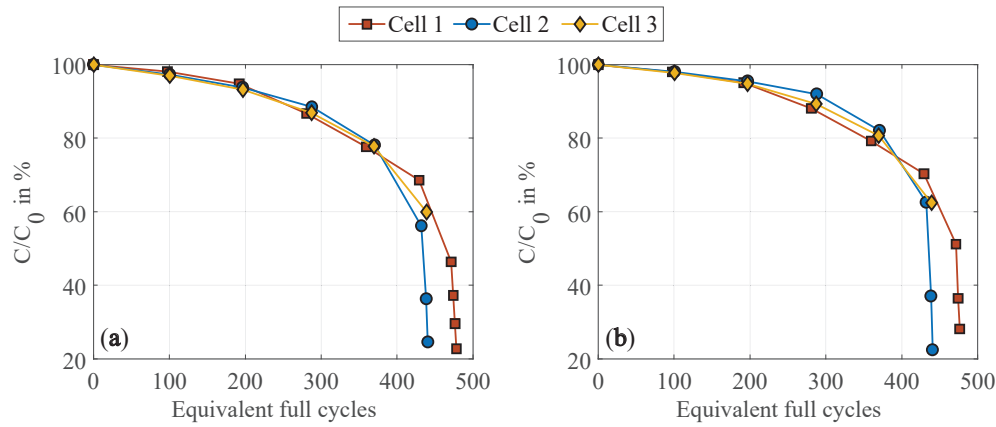


Figure 6. Deviations in aging progression among three cell specimens during 1C/1C cycling at 100% DOD: Pre-rest CU (a) and post-rest CU (b) both demonstrate a high degree of consistency across the three cells.

3.3. Impact of the Test Procedure on Cell Inhomogeneities

The observed behavior during cycling and the subsequent CUs and rest phase emphasizes considerable reversible effects triggered by continuous cycling. To further investigate how these effects are influenced by the test design and how they manipulate long-term cell behavior, we now focus on the impact of cycling interruptions through CU procedures and rest phases. For this purpose, we reduced the cycling interruption stepwise and sequentially removed specific CU elements and the rest phase. The associated degradation behavior is visualized in Figure 7. While the reference case (dark blue curve) as one edge case contains the entire pre-rest CU, the ten-hour rest, and the complete post-rest CU every 100 cycles, in the opposite edge case (dark red curve), the cell is continuously cycled and CUs are performed only at beginning of life (BOL) and end of life (EOL). The cycling procedure and the associated stress factors, however, are identical in all cases.

The relative capacities of the cells show a clear trend: shorter cycling interruptions trigger significantly higher degradation rates, as shown in Figure 7a. The best-performing cell completes four times as many cycles as the worst-performing cell before reaching 80% of the initial capacity. Unexpectedly, the BOL-EOL cell (dark red curve) exhibited a longer cycle life than the cell with intermediate capacity measurements every 100 cycles (orange curve). We assume that these capacity measurements, which were performed in the entire voltage range between 2.5 V and 4.2 V, caused additional cell inhomogenization and degradation in contrast to the sole cycling between 20 and 100% SOC. Particularly in the low SOC range, where silicon particles are primarily de-/lithiated [31] and pronounced volume changes occur in the graphite, mechanical stresses were induced in the jelly roll. These stresses promote electrode degradation and electrolyte motion. Despite noticeable cell relaxation during these capacity measurements, which are evident in the peaks of the U_{EODC} in Figure 7b, the damaging impact is expected to dominate. However, it should also be noted that already, the first cycle interval of this particular cell (orange curve) deviated from the others, as U_{EODC} declined significantly during the first 100 cycles. This is suspicious since cell preparation, BOL, CU, and cycling were identical in all test cases and therefore do not explain this behavior. We cannot preclude outlier behavior of this specific cell.

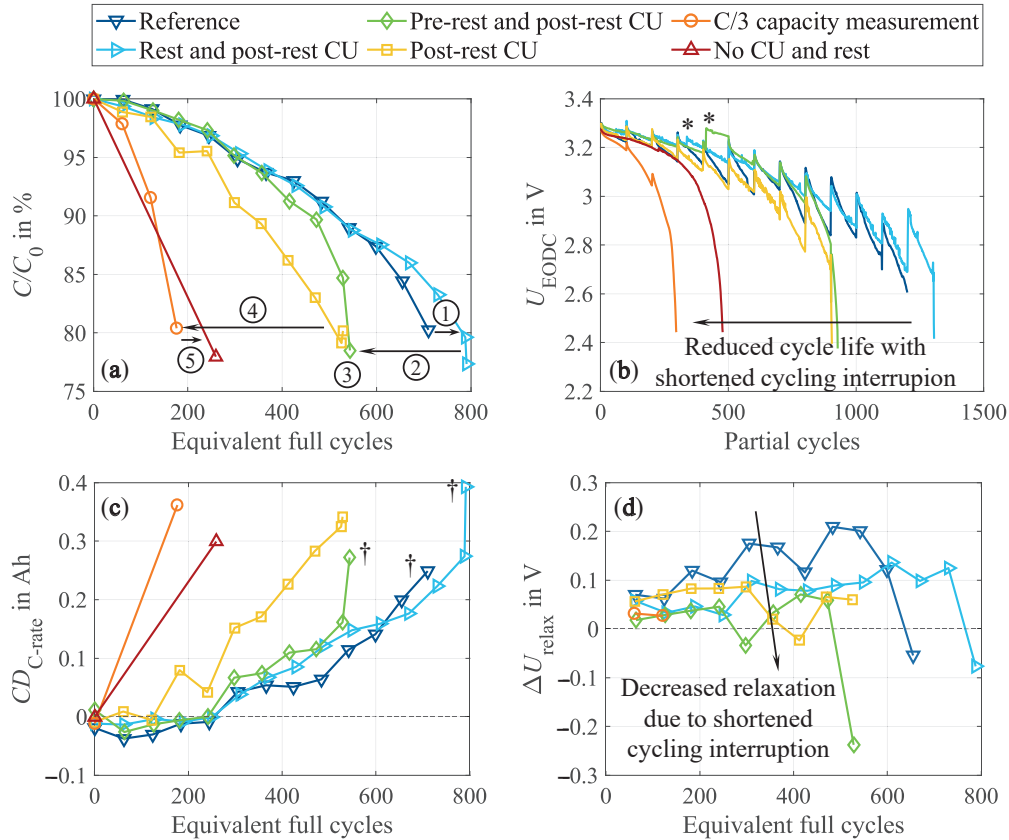


Figure 7. Impact of reduced cycling interruption through CUs and rest on the cycle life performance and inhomogenization behavior: ① omission of the pre-rest CU, ② omission of the rest phase, ③ omission of the pre-rest CU and rest phase, ④ omission of all CU elements and rest phases except for the C/3 discharge measurement, ⑤ omission of all intermediate cycling interruptions, depicted based on the relative capacity (a). Progression of U_{EODC} over cycles; the asterisk markers indicate voltage relaxation due to unintended rest phases caused by a power outage (b). CD_{C-rate} as an indicator for cell inhomogenization; the † symbol demonstrates cell failure, which occurred a few cycles after the last presented CU point (c). Voltage relaxation during CUs and rest (d).

In good agreement with the relative capacity, U_{EODC} shows a faster decline for test cases with shorter cycling interruptions. The ten-hour rest seems to be especially beneficial for the degradation behavior, as highlighted by the comparison between the blue and green curves. Moreover, the voltage relaxation in the test case with only capacity measurements is significantly lower compared to the test cases with extended CUs and rest. This is caused by the considerably shorter relaxation time. Consequently, equalization processes can only take place to a minor extent. Unintended intermediate voltage relaxation is observable for the test case without pre-rest CU (light blue curve) at 336 cycles and the test case without rest (green curve) at 411 cycles, denoted by asterisk markers. In both cases, a power outage led to a test interruption followed by an unintended resting period of several hours. The relaxation was particularly pronounced for the latter because restarting the test caused several further interruptions shortly after the restart. We assume that the combination of this resting phase and current pulses promoted cell relaxation, explaining this significant voltage setback.

The capacity difference CD_{C-rate} depicted in Figure 7c shows the inverse behavior of the capacity loss while revealing a high correlation. With decreasing cycling interruptions, the capacity differences increase faster, indicating faster inhomogenization of the conducting salt and lithium distribution. This coincides with less pronounced voltage relaxation for shorter cycling interruption, as illustrated in Figure 7d. Due to these shorter interruptions,

less time is available during which inhomogeneities can equalize. In addition, three of the cells show a prominent drop in ΔU_{relax} directly before reaching EOL.

3.4. Impact of Stress Factors During Cycling

After demonstrating how the test procedure, especially the resting phase, impacts the cell behavior by partially reversing capacity fade during CUs and rest phases, we now focus on the influences of different stress factors during cycling. For this purpose, we investigate the cell behavior during cycling and relaxation during rest phases. In contrast to the results presented above, the cells of the subsequent two substudies were all subjected to the identical pre- and post-rest CU procedure, as well as the intermediate ten-hour rest. Instead of 1C/1C cycling in the 20 to 100% SOC window, in the first substudy, the DOD and SOC range was varied, while the current rates remained fixed at 1C/1C. In the second substudy, the DOD was set to 100%, and the current rates were modulated.

3.4.1. Depth of Discharge

At first glance, the cells exhibit typical degradation behavior, revealing well-established dependencies on the DOD as a stress factor, as plotted in Figure 8. These dependencies are reported as increasing degradation rates with higher DOD [39,40] and average cell SOC [40,41]. Stronger degradation at higher DODs is commonly attributed to intensified volumetric changes and thus increased mechanical stress, notably in the negative electrode [42]. This is further aggravated for silicon-containing cells when cycling in low SOC areas due to even higher volumetric changes because of the de-/intercalation of the silicon particles [39]. The influence of increasing average SOC on higher capacity fade is often linked to the enhanced dissolution of nickel-rich materials [40–43], caused by elevated cell voltage, with subsequent deposition of the oxidation products in cover layers on the negative electrode [42–45]. In this regard, it should be considered that the CUs are carried out after an equal number of 100 partial cycles across all test cases. As a result, for decreasing DOD, the CU frequency increases with respect to testing time and charge throughput. This leads to higher cell exposure due to the full cycles performed in the CU. For this reason, we expect a superimposing impact, falsifying the observable SOC dependency. Moreover, it has to be noted that these results represent the cell behavior directly after cycling, thus not incorporating any relaxation effects.

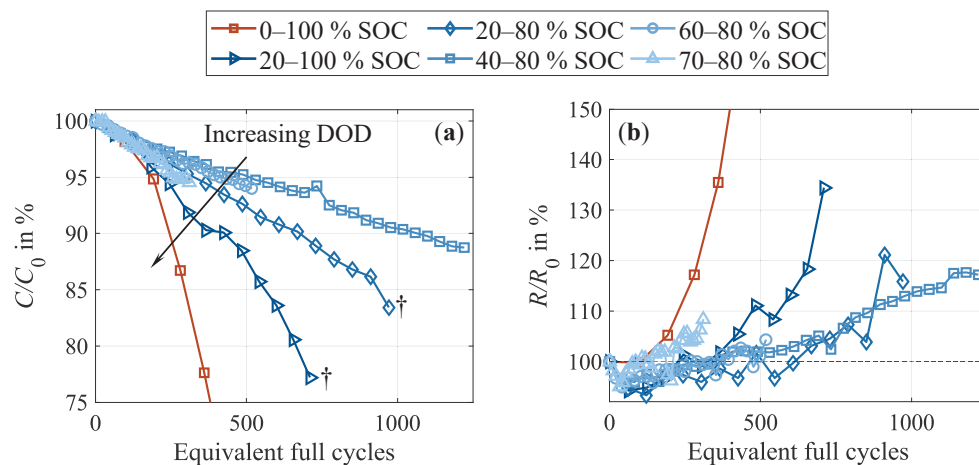


Figure 8. Measurable cell deterioration depending on the applied DOD in terms of capacity loss; the † symbol indicates cell failure, which occurred a few cycles after the last presented CU point (a) and resistance increase (b). This figure has been adapted from our earlier publication [34].

However, what is commonly not considered is the occurrence of reversible capacity loss [34]. Hence, a different picture emerges when looking deeper into the cell behavior

during cycling. The capacity difference under various DODs enables the assessment of the DOD's impact on reversible capacity loss. Corresponding to Figure 9a, the cells follow a logarithmic increase. A trend consistent with the one observed for shortened cycling interruptions is evident, with higher DODs causing more severe capacity differences and a faster growth rate in the early cycles. This suggests that inhomogenization effects are more pronounced at higher cycle depths, which is in alignment with findings from the literature [9,15] and explained by the more pronounced EMSI effect due to stronger volume changes [19]. As the electrolyte motion is intensified, this leads to more severe conducting salt gradients and aggravates cell inhomogenization. These enhanced gradients could explain the higher capacity differences and the higher observable capacity loss when cycling at higher cycle depths.

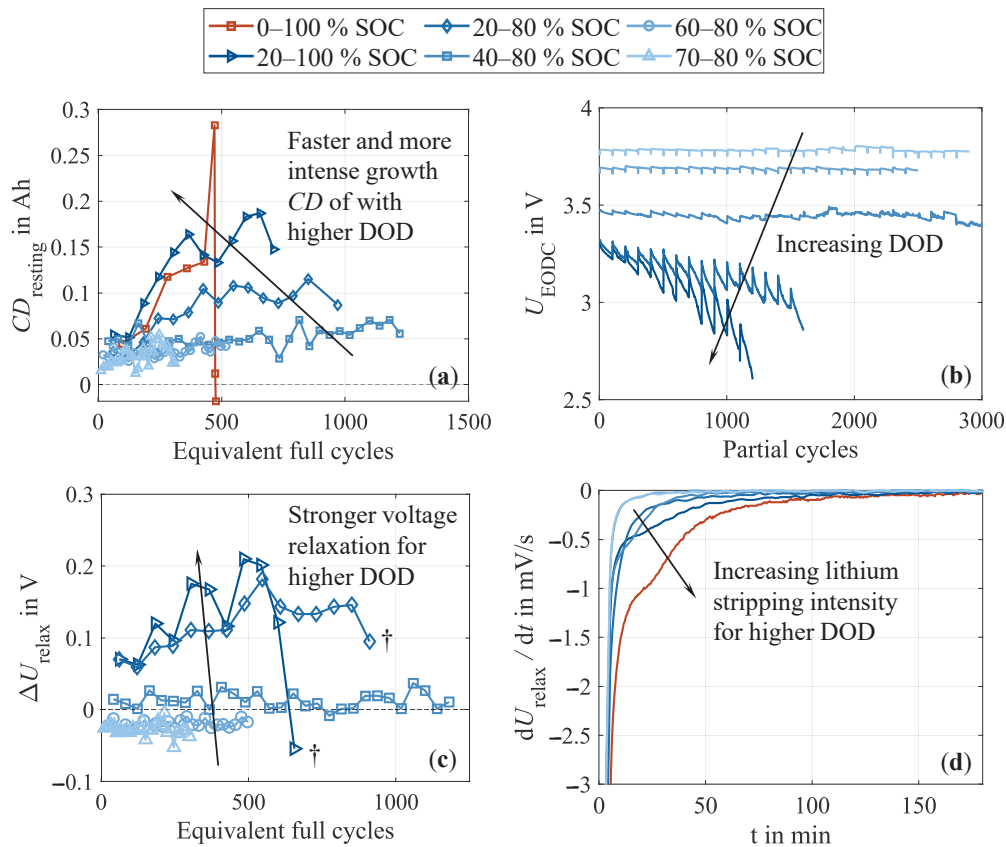


Figure 9. Underlying cell behavior under the impact of the DOD: $CD_{resting}$ representing the capacity recovery (a), end of discharge voltage during cycling indicating cell inhomogenization (b), ΔU_{relax} as a measure for cell relaxation and equalization of inhomogeneities; the † symbol indicates cell failure, which occurred a few cycles after the last presented CU point (c), lithium stripping analysis proving the occurrence of lithium plating at the end of the experiment (d). This figure has been adapted from our earlier publication [34].

This can be traced back to the non-linear volume expansion across the SOC. Heugel et al. [46] demonstrate the change in jelly roll thickness as a function of cell SOC, revealing a flat plateau between 40 and 60% SOC, while significant volume changes occur in both high and low SOC ranges. These findings are consistent with those of Morales Torricos et al. [9]. Due to the relatively small volume change observed between 40 and 60% SOC, the test case with 40% DOD, ranging from 40 to 80% SOC, likely exhibits only slightly more pronounced volume changes during cycling compared to test cases with 20 and 10% DOD, which range between 60 to 80% and 70 to 70% SOC, respectively. In contrast, higher DODs, which correspond to lower SOC, result in more pronounced volume changes due to the

primary lithiation of silicon in the low SOC range [24]. This explains the similar behavior observed in the 40% DOD test cases compared to those with lower DODs and the contrast with the higher DOD test cases. It is important to note that in this context, the dominant parameter is not the DOD itself but rather the SOC window traversed during cycling.

As a result, cells cycled at DODs of 40% and less showed identical increases in capacity difference. In contrast, 60%, 80%, and 100% DOD led to a pronounced drop in the capacity difference shortly before transitioning into an accelerated capacity loss and subsequent cell failure, commonly denoted as the knee point. Consequently, the measurable capacity loss is superimposed by growing shares of reversible capacity losses.

In good agreement with these results, the impact on U_{EODC} is enhanced by increasing DODs, revealing the same trend and consequently indicating stronger cell inhomogenization when applying larger cycle depths [34]. This becomes evident in Figure 9b,c, showing the progressions of the end of discharge voltages as well as the voltage relaxations during CU and rest. As observed earlier, the intensity of inhomogenization, as well as incomplete relaxation during rest, amplifies with progressive cycling, suggesting a self-reinforcing behavior [14]. In this regard, it should be recapitulated that the number of cycle repetitions between two subsequent CUs is the same for all test cases. Thus, cells with a larger DOD experience higher charge throughput during cycling between two subsequent CUs than cells with a lower DOD. This higher charge throughput causes even stronger inhomogenization during cycling, supporting the self-reinforcing behavior. In addition, a lower CU frequency related to the charge throughput allows for less frequent cell relaxation and thus rehomogenization, limiting the comparability of the observed magnitudes of inhomogenization between the different DOD test cases.

A specific behavior is observable in Figure 9c for cells with a DOD of 40 % or less. For these cells, ΔU_{relax} ranges around or below 0 V, indicating a decrease in U_{EODC} during CU and rest, while it increases during the first cycles of each cycling sequence. This is traced back to temperature influences. During CU and rest, the cells experience thermal relaxation because of the low cyclic stresses and the extended rest phases, enabling the cells to approach the ambient climate chamber temperature. As cycling restarts, the cells heat up again due to internal resistive effects. This cell heating follows a logarithmic progression and takes several cycles to fully establish and approach its dynamic equilibrium point. Self-heating of the cells, as well as external heating, generally promotes equalization processes, since elevated temperatures improve conductivity, diffusivity, and reaction kinetics, which follow the Arrhenius relation [7,30]. This correlation has also been reported in the literature at advanced stages of aging experiments [14]. Increases in temperature due to rising internal resistance reduce the impact of inhomogenization effects during cycling and are therefore associated with the asymptotic slowdown of capacity recovery and voltage relaxation during rest. However, local temperature gradients within the cell may, in turn, promote further inhomogenization by affecting local current densities.

Moreover, all three cells that failed during the aging experiment, namely 60% DOD, 80%, and 100%, showed a pronounced drop in capacity difference before the last CU. This coincides with a significant rise in resistance, as well as a plateau in the stripping potential, depicted in Figure 9d. Again, a clear dependency on the DOD can be seen, with higher capacity differences, higher internal resistance growth, more pronounced lithium stripping, and earlier occurrence of cell failure linked to higher DODs. These symptoms of accelerated capacity loss accompanied by increased resistance growth, as well as the occurrence of lithium stripping, are often associated with lithium plating [28,32,42]. This interpretation aligns with the expected degradation behavior of severely inhomogenized battery cells [9,14,47] and seems plausible, considering the underlying mechanisms. Due to the metallic deposition of lithium on the surface of the negative electrode caused by the

plating reaction, active lithium is consumed, which explains the capacity loss. Moreover, due to the cover layers formed by plated lithium, the active surface of the negative electrode decreases, resulting in a significant resistance increase [42]. Finally, the initially localized plating spots rapidly spread across the entire negative electrode surface, explaining the degradation dynamics manifesting in the capacity knee point and the sudden exponential resistance increase.

Consequently, once a critical point is surpassed, the reversible behavior becomes irreversible, causing rapid cell degradation, ultimately leading to cell failure. Therefore, according to our results, sufficiently long and repeated rest periods should be provided, especially for large DODs.

3.4.2. Current Rate

The same trend becomes evident for the current rate, with increasing currents causing more severe apparent capacity loss and resistance growth, as depicted in Figure 10. Such measurement data represent common observations presented in the literature and are often explained by increased negative electrode degradation as a consequence of high currents or electrode surface passivation and lithium loss due to lithium plating [42,48].

However, increasing the current rates not only aggravates the observable capacity loss but also intensifies cell inhomogenization. This coincides with increasingly declining charge throughput during cycling and more pronounced resets during CUs and rest. Like for the DOD, the capacity differences prove an intensifying and faster-growing lateral lithium-ion flow with increasing current rates and progressive cycling, which is shown in Figure 11a,b. Overall, these findings agree with the results presented in the literature [9,19].

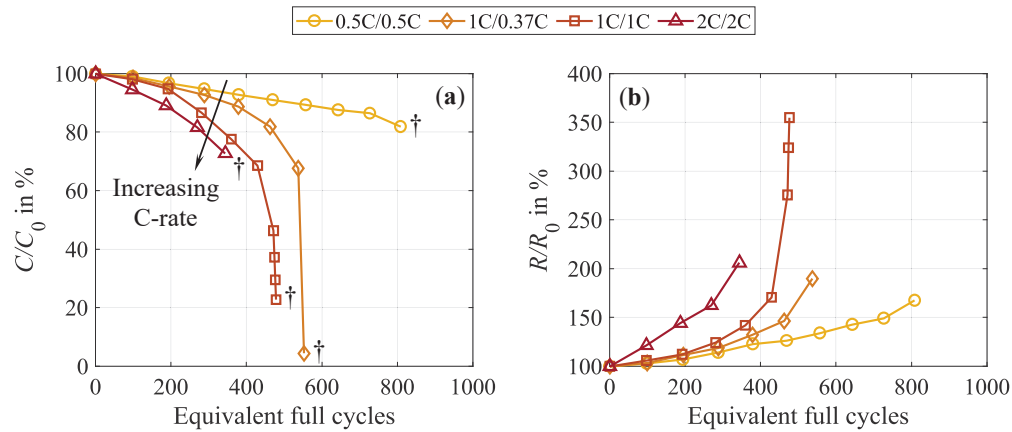


Figure 10. Measurable cell deterioration, depending on the applied C-rates in terms of capacity loss (a) and resistance increase (b). The † symbol indicates cell failure, which occurred a few cycles after the last presented CU point

As evident from Figure 11b, cycling at $C/2$, which is the lowest C-rate investigated in this study, exhibits an almost constant capacity difference until approximately 900 cycles. Afterwards, the knee point is reached, and the cell fails shortly thereafter. At the same time, an approximately linear progression of the extractable charge during cycling occurs with no peaks around the CU and rest phases, as shown in Figure 11a. Since the cells are cycled in the entire SOC range in this substudy, the discharging is terminated uniformly at 2.5 V. Consequently, no alterations in U_{EODC} can be used to indicate cell inhomogeneity. However, as the DOD remains identical, changes in the extractable charge in each cycle give insight into cell homogeneity. This suggests that no considerable rehomogenization and therefore no capacity recovery occurs in this test case, which is visualized in Figure 11c. As an equivalent indicator to ΔU_{relax} , ΔQ_{relax} is analyzed in this case. It represents the amount of regained capacity during CUs and rest and is calculated as the difference between the

discharge capacity of the first cycle in a cycle interval directly after a CU and the last cycle of the preceding cycle interval before a CU. This parameter is not equivalent to the capacity difference between pre-rest and post-rest CU mentioned earlier. Unlike the capacity difference, ΔQ_{relax} is derived from cycling data rather than CU measurements. Nevertheless, it reflects the same cell behavior.

In contrast, for the 2C/2C test case, marking the other edge case in this substudy, significant capacity recovery during CUs and rest is found. However, this effect sets in at 300 cycles, while until 200 cycles, no signs of recovery are observable. This coincides with the initial linear decline in discharge capacity during the first 200 cycles and the missing indicators for cell relaxation during rest and CU. Temperature effects can partly explain the behavior before this point. Due to the significantly higher C-rates during cycling than in the other test cases, the cell heats up considerably more. This is assumed to reduce cell inhomogenization during the initial phase of cycling. As this self-heating takes a few cycles and the cell cools down during CU and rest, the extractable capacity during the first cycles of every sequence is lower. Consequently, recovery and temperature effects are superimposed and conceal each other. In addition, the self-heating impacts the pre-rest CU, which is performed directly after cycling, while the cell cools down during the pre-rest CU and rest phase. As a result, the extractable capacities in the pre-rest CU are higher due to the supporting effect of the elevated temperature, which manipulates the capacity difference calculation with the post-rest CU.

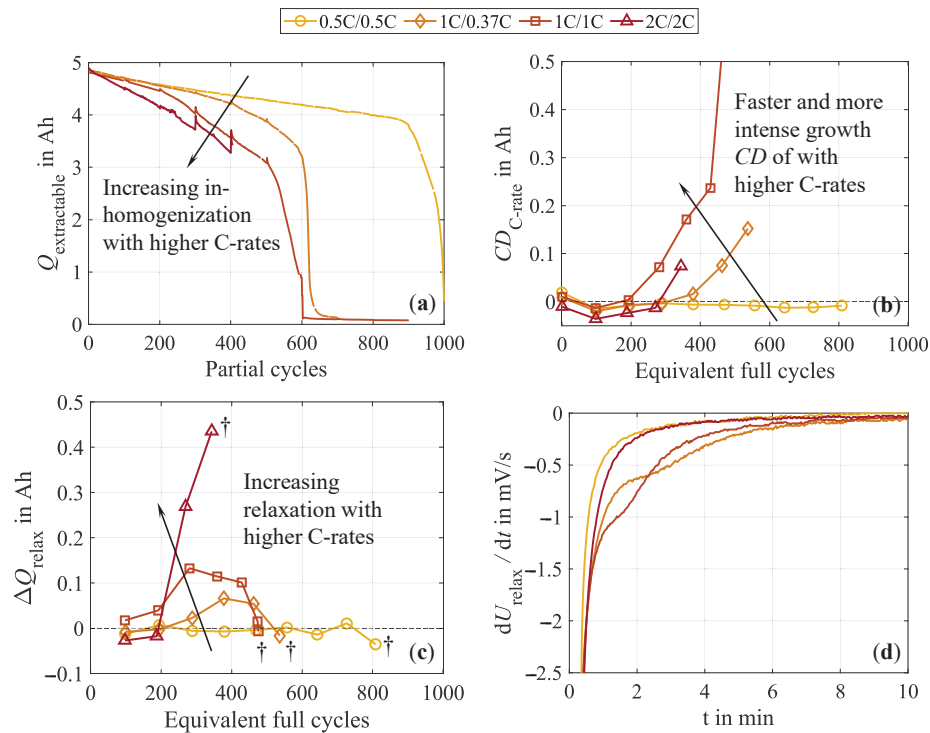


Figure 11. Underlying cell behavior under the impact of the C-rate: extractable charge during cycling (a), $CD_{\text{C-rate}}$ indicating cell inhomogenization (b), ΔQ_{relax} as a measure for cell relaxation and equalization of inhomogeneities; the † symbol indicates cell failure, which occurred a few cycles after the last presented CU point (c), lithium stripping analysis proving the occurrence of lithium plating at the end of the experiment (d).

The capacity regained during CU and rest, depicted in Figure 11c, indicates the approaching EOL, as already observed in the first substudy. The 0.5C/0.5C, 1C/0.37C, and 1C/1C test cases demonstrate a prominent decline shortly before reaching EOL, implying that the earlier reversible behavior turns irreversible. This is expected to result from severe

lithium plating triggered by the highly inhomogeneous cell condition, causing pronounced, rapid, irreversible lithium loss. The stripping behavior of these cells, provided in Figure 11d, supports this theory, as distinct plateaus are evident for the 1C/0.37C and 1C/1C test cases shortly before reaching the knee point. Thus, this proves the earlier occurrence of lithium plating [28]. Such plateaus are not observable for the 2C/2C test case. However, this does not prove the absence of lithium plating; it only shows the missing recovery of earlier plated lithium.

3.5. Supporting Cell Recovery During Cycling

In this section, we focus on methods to actively support cell relaxation during cycling in order to compensate for the triggered inhomogenization effects. For this purpose, we investigate two approaches based on the above findings, further denoted as static and dynamic relaxation. As shown in Figure 12, both methods (green curves) positively impact cell behavior in terms of capacity loss and resistance increase, significantly enhancing the cycle life performance. This becomes particularly clear when comparing them to the 1C/1C case from substudy 2 (red curve), with more than double the completed equivalent full cycles in the best-performing case until a relative capacity of 70 %. All test cases exhibit identical cycling procedures and only differ in the relaxation conditions. While the relaxation in the 1C/1C test case was performed at 50% SOC representing the average SOC during cycling, the rest conditions in the recovery cycles were explicitly designed to support cell relaxation.

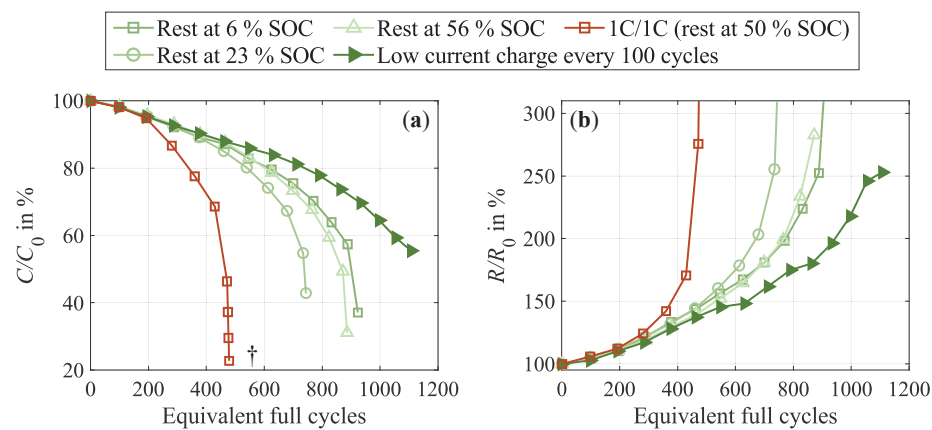


Figure 12. Impact of recovery cycles on capacity loss (a) and resistance increase (b). The † symbol indicates cell failure, which occurred a few cycles after the last presented CU point

The first approach focuses on optimizing static relaxation, which has been shown to positively impact cell homogenization and degradation, as presented in Section 3.3. In contrast to the 1C/1C test case, the rest SOC levels are located in ranges of high potential gradients in the negative electrode to trigger equalization processes in the case of local lithiation differences. As evident in Figure 12, the rest SOC levels at 6 % and 56 % have a higher beneficial impact on cell behavior than the rest SOC at 23 %. This is consistent across all analysis techniques applied in this work. This behavior could result from local potential gradients that occur within the negative electrode in the case of local lithiation inhomogeneities. It could be that in the 23 % SOC test case, the storage SOC was not exactly located around the stage transition, leading to a reduced driving force for equalization processes [16,29,49]. However, the electro-chemical reason for this behavior remains unclear from the data presented and requires further analysis. Also, outlier behavior cannot be precluded in this case.

The second approach, denoted as dynamic relaxation, is based on a low-current charging sequence instead of resting at a specific SOC, which seems to obtain better results.

The idea behind the dynamic relaxation cycle is to pass through different potential regions of the negative electrode in order to provide states with sufficient potential gradients, which trigger lithium redistribution processes in the case of local SOC inhomogeneities. In contrast to the static approach, this is not as sensitive to the precise storage SOC level, which might shift throughout the cycle aging test due to reversible and irreversible capacity loss.

The capacity difference CD_{C-rate} between low and high current discharge, shown in Figure 13b, accurately reflects the observed aging behavior. More severely degraded cells exhibit earlier and faster-growing capacity differences. This is in agreement with the extractable charge during cycling, depicted in Figure 13a. For test cases with optimized relaxation, it remains considerably higher throughout the entire test, while it significantly declines in the 1C/1C case without optimized relaxation. This observation suggests that the relaxation cycles effectively suppress the earlier-discussed cell inhomogenization, which reduces the lateral lithium flow and better preserves the extractable amount of charge. The behavior of the cell with dynamic relaxation is particularly noteworthy, as it exhibits a negligible capacity difference until approximately 800 EFC and almost no signs of recovered charge during CU and rest up to this test progress, indicating a highly beneficial impact of this method.

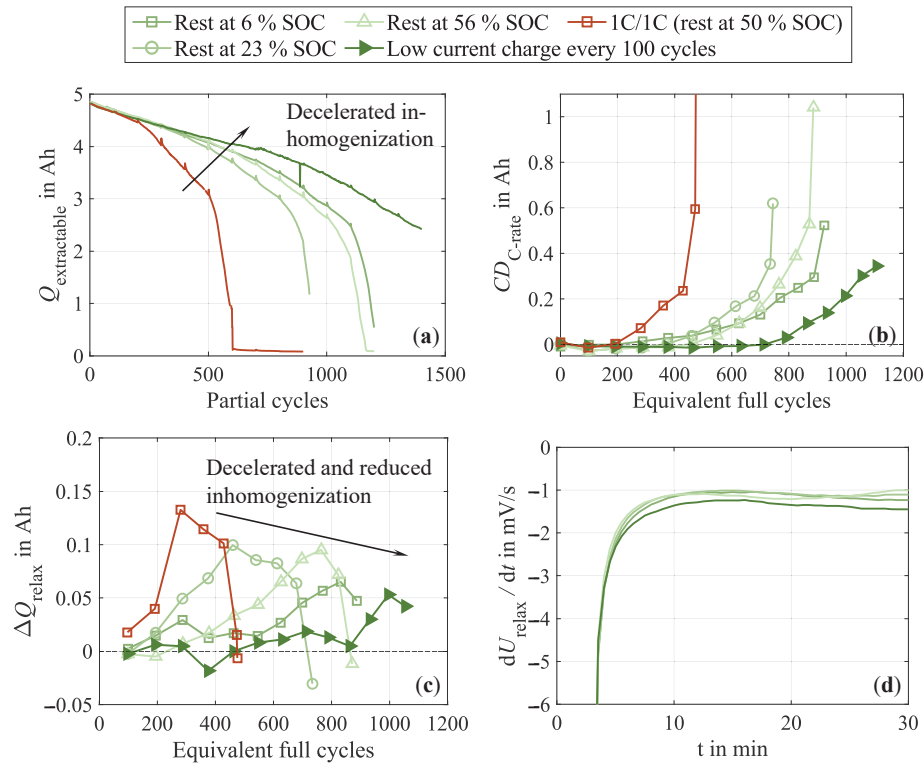


Figure 13. Impact of recovery cycles on cell behavior: extractable charge during cycling (a), CD_{C-rate} (b), ΔQ_{relax} (c), lithium stripping analysis (d). The stripping behavior of the 1C/1C test case is not visualized due to differing measurement durations among these substudies.

As shown in Figure 13c, the recovered amounts of charge confirm the previously observed trend. The faster the capacity fades, the faster and more pronounced the recovered charge increases. Once a critical cell condition is reached, the recovered capacity surpasses its peak and rapidly drops. This behavior coincides with the occurrence of the knee point, thus suggesting that reversible effects intensify with progressive cycling, and rehomogenization during cycling becomes increasingly incomplete. At this tipping point, the reversible behavior seems to become irreversible and causes subsequent rapid cell failure. The stripping potential analysis, visualized in Figure 13d, reveals characteristic plateaus at the end of the cycle aging test, indicating the occurrence of lithium plating

in all test cases, which is in alignment with the other substudies. Overall, the analysis demonstrates that the applied recovery cycles effectively reduce the inhomogenization rate and delay the critical tipping point.

3.6. Implications of Cell Inhomogenization and Relaxation on Cycle Life

Summarizing and connecting the findings from the four substudies under the diverse impacting factors presented above reveals characteristic cell behavior and suggests a common specific mechanism influencing cycle life performance. Figure 14 visualizes the correlation of capacity fade, capacity difference, and the amount of recovered capacity during CU and rest. This behavior is evident in nearly all test cases, with variations only in the timing of characteristic events.

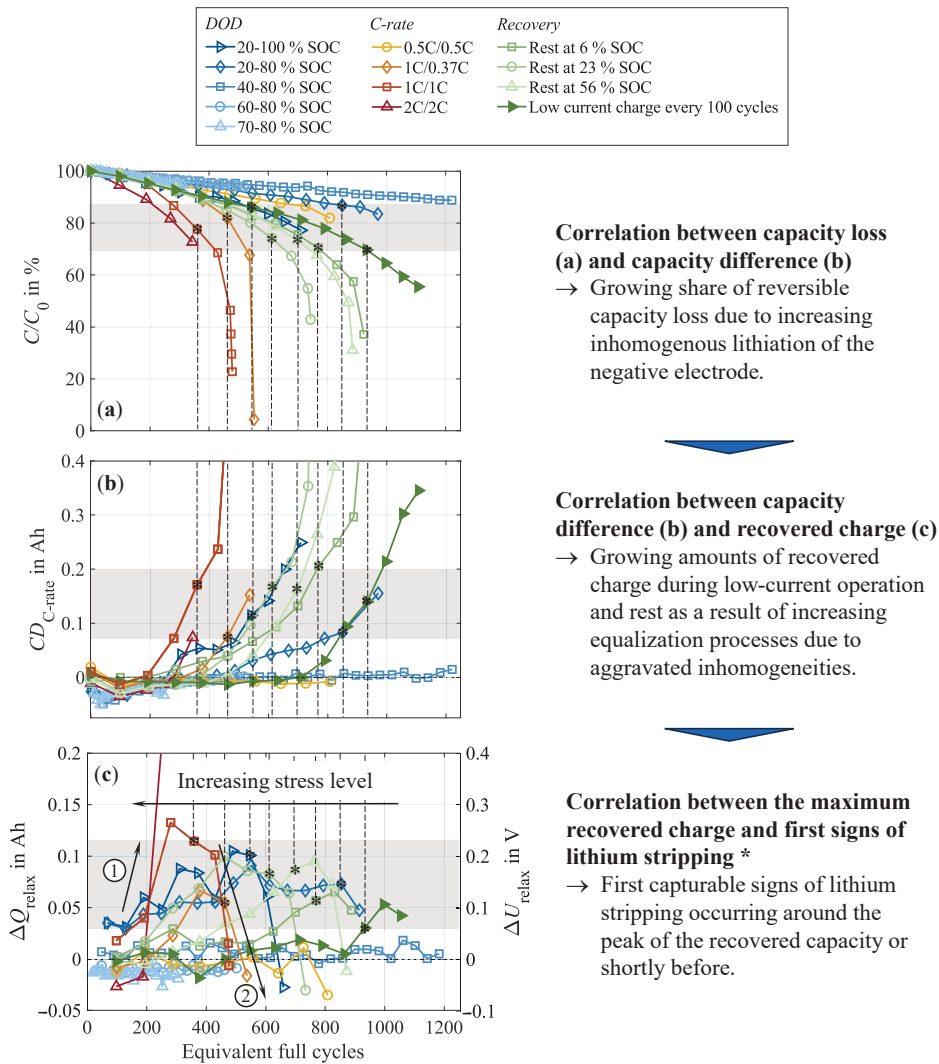


Figure 14. Correlation between capacity loss (a), increase in capacity difference (b), and growth of recovered charge (c). Note that ΔQ_{relax} represents the results of the C-rate and recovery substudy, while ΔU_{relax} corresponds to the results of the DOD substudy. The latter shows a distinct behavior, initially growing ① and significantly declining from its maximum shortly before cell failure ②. The asterisk markers indicate the first detectable signs of lithium stripping for the individual test cases, while the gray shaded areas highlight the ranges in which these initial lithium stripping observations occur.

Firstly, a high correlation between the capacity loss and the increasing capacity difference is evident from Figure 14a,b. The capacity difference results from inhomogeneous electrode lithiation and represents a reversible loss of lithium. Consequently, this correlation

indicates the strong superimposition of reversible losses and the measured capacity fade. A growing share of reversible losses becomes evident, especially towards the end of the tests, where the capacity difference significantly increases. This implies aggravating inhomogenization of the negative electrode and is in line with the literature, where increasing inhomogeneity with progressive cycling has been reported [9,21].

Secondly, the capacity differences coincide with the progression of the recovered charge and the relaxed end of discharge voltage during CUs and rest. The aggravated inhomogeneities mentioned above lead to increasing equalization intensities of concentration gradients and the redistribution of lithium within the negative electrode during CUs and rest. This manifests in growing amounts of recovered charge during low-current operation and rest. As a comparison of Figure 14b,c shows, the significant increase in the capacity difference occurs around the peak values of this recovered charge, indicating a change in the underlying cell behavior.

Finally, the first capturable signs of lithium stripping occur two or three CUs before the last data point. This coincides with the peak in the recovered capacity or shortly before, suggesting lithium plating is triggered once a critical degree of inhomogeneity is surpassed. However, based on the data, only the earliest occurrence of lithium stripping can be identified, proving that lithium plating must have occurred beforehand. The onset of lithium plating, in contrast, cannot be determined.

The 2C/2C test case differs from this characteristic behavior, not showing a drop in ΔQ_{relax} or any signs of lithium stripping. Nevertheless, severe lithium plating is assumed in this cell, which would explain the early cell failure after approximately 350 EFC causing the activation of the current interrupt device (CID), which is in alignment with the high currents applied. Moreover, the DOD test cases of 40 % and below do not evince significant capacity differences, ΔU_{relax} , or indicators of lithium stripping. This supports the previously outlined theory, as it demonstrates that inhomogeneous cell conditions correlate with and precede lithium stripping. However, in these test cases, the cyclic stresses appear to be mild enough to prevent significant inhomogenization, which aligns with earlier findings in the literature [9,16].

This leads to the question of which stress factor influences cell inhomogenization the most. From the data presented in this study, C-rates appear to have the highest impact. However, the data suggest that a certain minimum DOD is required to trigger the observed mechanism. This is plausible, as one key process is the EMSI effect, which results from volume changes in the negative electrode and therefore is enhanced by increasing cycle depths. However, the data presented are obtained from only a few test cases, which allows for derivation of only generic high-level trends. Revealing detailed stress factor impacts and analyzing respective trends, in contrast, requires a comprehensive parameter study, particularly considering various C-rate and DOD combinations. Moreover, further stress factors need to be considered.

3.7. Implications for Accelerated Aging Characterization and BEV Applications

The presented findings raise important questions regarding their implications for conventional aging characterization strategies as well as battery electric vehicle (BEV) applications.

To what extent does the proposed methodology differ from conventional aging characterization approaches?

Standard aging prediction methods typically neglect the effects of intermediate cell relaxation, approximating capacity fade corresponding to our pre-rest measurements (see Figure 4a). This leads to a notable discrepancy of up to 10 % in relative capacity under high-rate (2C/2C) cycling conditions (Figure 11c), which significantly affects lifetime predictions,

especially in light of commonly applied EOL criteria of 70 or 80% relative capacity. In addition, long-term tests (Figure 7) demonstrate that neglecting relaxation can lead to increasing underestimation of cycle stability over time. A comparison between cells undergoing 10 h relaxation phases (blue) and conventional tests (green) reveals a lifetime deviation of approximately 33 % at 80% relative capacity. This increasing divergence is attributed to the progressive buildup of internal cell inhomogeneities. As discussed in Section 3.6, these effects are only partially reversible and may reach a critical threshold beyond which recovery is no longer possible. Retrofitting conventional degradation frameworks to explicitly model such recovery effects is highly complex. Consequently, we propose that test protocols themselves be adapted to better capture the influence of relaxation behavior rather than attempting to post-process such effects.

How can the presented findings be leveraged to optimize conventional accelerated aging protocols, and what implications would this have for test design?

Accelerating degradation testing while accounting for reversible capacity losses requires a careful balance between test duration and representativeness. To capture reversible phenomena, test protocols should allow for periodic equilibration, either through passive storage phases or actively induced relaxation cycles. Although these approaches may increase total test time, they enhance the transferability of results to real-world scenarios. Evaluating the investigated recovery methods emphasizes an overall positive impact on cycle life performance and cell homogeneity, particularly with the dynamic strategy. An additional advantage of this procedure is that intermediate low-current charge cycles can easily be integrated into the cycle aging test and provide valuable measurement data, which gives further insights into the cell behavior, e.g., through DVA. Otherwise, resting in the very low SOC range or around the graphite stage II phase transition proves effective. Analogous to the influence of stress factors, it needs to be considered that the data presented are not the result of a parameter study or optimization. The static method could yield better outcomes under optimized conditions, e.g., rest SOC, duration, and temperature. As diffusion effects and reaction rates follow the Arrhenius correlation, better and faster results could be obtained at elevated temperatures, as previously discussed in the literature [7,14,22,30]. Consequently, relaxation cycles could be carried out at higher temperatures. Moreover, intermediate charging pulses have been reported to positively impact equalization processes [14,50] and therefore could offer further potential for intermediate cell rehomogenization. While further research is required to determine ideal relaxation conditions, our results indicate that periodic relaxation, e.g., a few additional hours every 50 to 100 EFCs, can significantly improve lifetime prediction accuracy. This approach enables more realistic yet still time-efficient aging protocols.

What is the potential impact of optimized relaxation cycles on the long-term durability of LIBs under real-world vehicle operation?

In typical private BEV usage, battery systems spend substantial time at rest, naturally allowing for intermediate relaxation. Therefore, the practical impact of active relaxation strategies on lifetime extension may be limited in these scenarios. However, the omission of relaxation in accelerated aging tests can result in systematic underestimation of battery longevity under realistic use conditions; a discrepancy supported by recent field data and aging studies [47,51]. In contrast, applications with higher utilization rates, such as commercial fleets or stationary energy storage systems, present a greater risk of inhomogenization due to reduced idle time. In such contexts, the deliberate integration of optimized relaxation phases offers a promising route to mitigating irreversible degradation and extending service life. These findings highlight the importance of tailoring degradation protocols and system operation to the specific application profile.

How can the presented findings be translated into adaptive battery management system (BMS) strategies?

BMS strategies can utilize indicators of internal cell homogeneity to assess the need for relaxation in real time. Based on this information, the BMS could adaptively trigger measures to promote equilibration, such as suggesting optimal parking SOC levels, initiating low-current charging routines, or scheduling periodic rest phases while temporarily adjusting the battery temperature. Such adaptive strategies would enable the system to mitigate inhomogenization effects proactively, thereby preventing irreversible degradation and extending battery lifespan. Crucially, the BMS could tailor these actions based on dynamic inputs, including usage intensity, environmental conditions, and observed degradation patterns. The integration of relaxation-aware BMS functionality could thus become a key enabler for improving durability, particularly in high-demand applications.

4. Summary and Conclusions

In this study, we assessed the aging characteristics of LIBs, particularly focusing on the inhomogenization of the cell during cycling as well as relaxation during CUs and rest. Several cycle aging studies have been conducted, investigating the impact of the test procedure, diverse stress factors, and dedicated recovery cycles. The following key takeaways can be summarized:

(1) Impact of the test procedure and stress factors on cell inhomogeneities.

Continuous cycling leads to the inhomogenization of the lithium distribution within the negative electrode. During CUs, which are commonly performed at low current rates, as well as rest phases, these inhomogeneities partly equalize. Consequently, shortening these cycling interruptions by reducing the CU procedures or eliminating the rest period accelerates cell inhomogenization. This is furthermore influenced by the stress factors applied during cycling, with increasing stress levels supporting cell inhomogenization. High current rates have been found to be particularly detrimental. No dependency on the cycle depth was observed below 40 % DOD when cycling between 40 and 80% SOC. While initially reversible, this inhomogenization progressively promotes permanent degradation in the form of lithium plating. A correlation between increasing cell inhomogeneity, reduced equalization intensity, and lithium plating has been proven shortly before the knee point, followed by immediate cell failure.

(2) Implications for aging characterization in vehicle applications.

A distinctive feature of vehicle applications is the prevalence of frequent and extended intermediate rest phases, combined with relatively short sequences of continuous cycling compared to laboratory tests. This characteristic, on the one hand, leads to marginal cell inhomogenization during operation, as well as to frequent relaxation and equalization during the pauses on the other. Neglecting such conditions in aging tests unintentionally intensifies cell aging, resulting in manipulation and superelevation of cell degradation compared to real-world usage and, consequently, a high likelihood of underestimating the real battery lifetime.

(3) Dedicated strategies for cell relaxation as a countermeasure.

Moreover, our study provides viable insights for optimizing LIB performance for vehicle applications. Regular pauses during operation emerge as a beneficial strategy for preserving cycle life performance over the long term and extending battery lifespan. Even better results were achieved with intermediate low-current charge cycles, which promoted cell homogeneity and doubled the cycle life. Implementing these insights into the design of cycle aging tests holds the potential to enhance their overall reliability by maintaining short test periods.

Looking ahead, future research should focus on a comprehensive understanding of the occurring inhomogenization and relaxation mechanisms. Exploring acceleration methods for intermediate cell relaxation could pave the way for a more realistic and reliable lifetime prognosis. These advancements are pivotal for the ongoing development of battery technology, ensuring sustainable and efficient electric vehicle batteries in the long run.

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Appendix A. Correlation Between end of Discharge Voltage and Cell Temperature

Figure A1 illustrates the correlation between end of discharge voltage and cell temperature, exemplarily shown for the cell in test case 20–100% DOD within the cycle interval between 900 and 1000 cycles. The observed behavior is consistent across other cycle intervals and between different cells. As evident from the plot, the cell temperature increases during the first few cycles after approaching the ambient temperature of 25 °C in the climate chamber during CU and resting. This temperature rise is accompanied by an increase in end-of-discharge voltage, as cell polarization decreases.

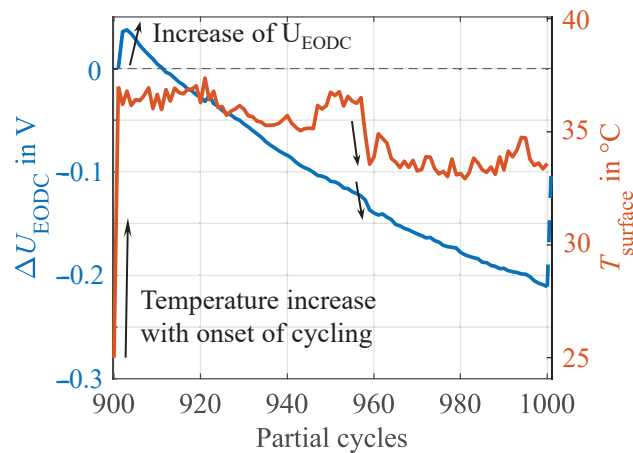


Figure A1. Correlation between U_{EODC} and cell temperature: blue indicates the difference in U_{EODC} relative to the first cycle of the interval, while red represents the cell surface temperature.

Appendix B. Progression of the Cell Surface Temperatures During Cycling

Figures A2–A5 show the progression of cell surface temperatures during the cycle aging test. The temperatures at the end of charge and end of discharge are presented, as these represent the highest cell temperatures within each cycle.

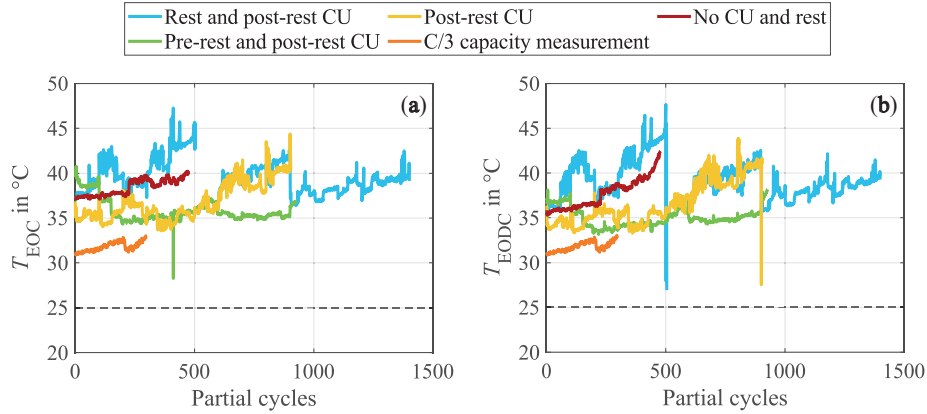


Figure A2. Temperature progression of the cells in the cycle interruption study over the course of the experiment: end of charge temperature (a) and end of discharge temperature (b). The climate chamber temperature of 25 °C is indicated by the black dashed line.

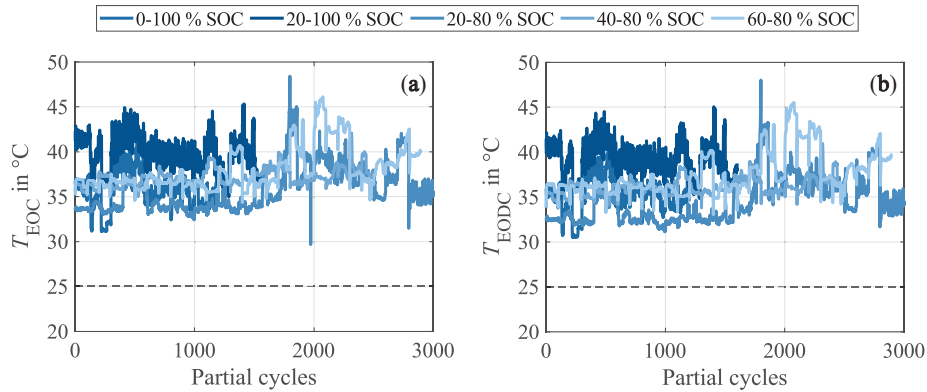


Figure A3. Temperature progression of the cells in the DOD test cases over the course of the experiment: end of charge temperature (a) and end of discharge temperature (b). The climate chamber temperature of 25 °C is indicated by the black dashed line.

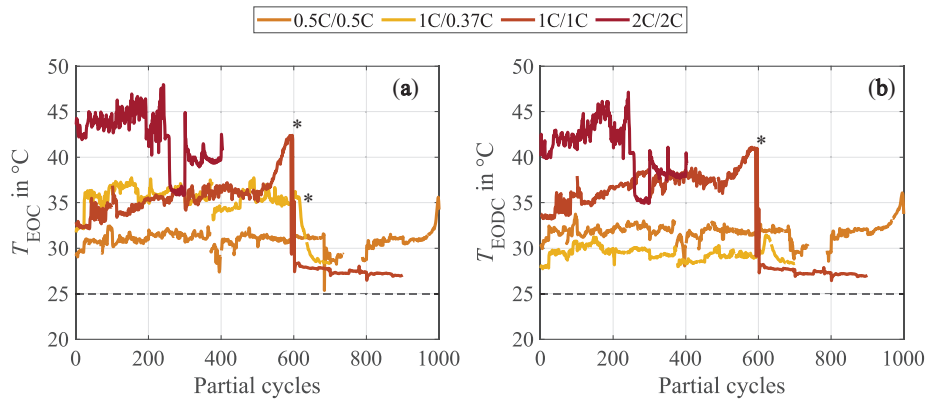


Figure A4. Temperature progression of the cells in the C-rate study over the course of the experiment: end of charge temperature (a) and end of discharge temperature (b). The climate chamber temperature of 25 °C is indicated by the black dashed line. The asterisk markers indicate the point in time at which the charge throughput during cycling significantly decreased.

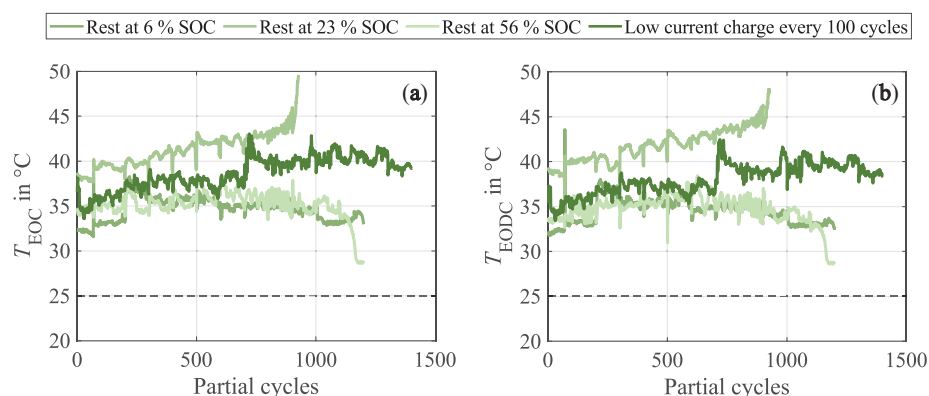


Figure A5. Temperature progression of the cells in the recovery study over the course of the experiment: end of charge temperature (a) and end of discharge temperature (b). The climate chamber temperature of 25 °C is indicated by the black dashed line.

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Article

A Passive Experiment on Route Bus Speed Change Patterns to Clarify Electrification Benefits

Yiyuan Fang *, Wei-Hsiang Yang and Yushi Kamiya

Faculty of Science and Engineering, Waseda University, Tokyo 169-8555, Japan

* Correspondence: fyy@aoni.waseda.jp

Abstract: In addition to the widely recognized benefits of reducing carbon emissions and protecting the environment, the authors believe that bus electrification has potential advantages in enhancing driving safety, improving passenger comfort, and reducing driver fatigue—areas that have not yet been sufficiently studied and emphasized. Safety and comfort are fundamental objectives in the continuous development of transportation systems. They are directly and closely related to both passengers and drivers and are among the top priorities when individuals choose their mode of transportation. Therefore, these aspects deserve broader and more in-depth attention and research. This study aims to identify the potential advantages of route bus electrification in terms of safety and comfort. The results of a passive experiment on the speed profile of buses operating on actual routes are presented here. Firstly, we focus on the acceleration/deceleration at the starting/stopping stops, specifically for regular-route buses, and obtain the following information: I. Starting acceleration from a bus stop is particularly strong in the second half of the acceleration process, being suitable for motor-driven vehicles. II. The features of the stopping deceleration at a bus stop are “high intensity” and “low dispersion”, with the latter enabling the refinement of regenerative settings and significantly lowering electricity economy during electrification. And we compare the speed profile of an electric bus with those of a diesel bus and obtain the following information: III. Motor-driven vehicles offer the advantages of “high acceleration performance” and “no gear shifting”, making them particularly suitable for the high-intensity acceleration required when route buses depart from stations. This not only simplifies driving operations but also enhances lane-changing safety. And by calculating and analyzing the jerk amount, we could quantitatively demonstrate the comfortable driving experience while riding on this type of bus where there is no shock due to gear shifting. IV. While the “high acceleration performance” of motor-driven vehicles produces “individual differences in the speed change patterns”, this does not translate to “individual differences in electricity consumption”, owing to the characteristics of this type of vehicle. With engine-driven vehicles, measures such as “slow acceleration” and “shift up early” are strongly encouraged to realize eco-driving, and any driving style that deviates from these measures is avoided. However, with motor-driven vehicles, the driver does not need to be too concerned about the speed change patterns during acceleration. This characteristic also suggests a benefit in terms of the electrification of buses.

Keywords: electric vehicle; motor characteristics; speed change pattern; acceleration and deceleration; gear shifting; eco-driving; starting and stopping; safety and comfort fuel cell bus; diesel bus

1. Introduction

In recent years, global climate change has become increasingly severe, with frequent occurrences of extreme weather events. Phenomena such as glacier melting and rising sea levels have escalated into global crises, with greenhouse gas emissions—particularly carbon dioxide—being one of the primary causes of this issue [1–3]. At the same time, the consumption of fossil fuels such as oil, natural gas, and coal is far exceeding their formation rate, leading to an increasing risk of resource shortages [4–6]. The interconnection between energy consumption and environmental change has made global warming and fossil fuel shortages intertwined issues, positioning them as central challenges for sustainable development worldwide [7,8].

Concerns over climate change and fossil fuel depletion have driven global efforts to reduce carbon emissions and conserve energy [9,10]. The transportation sector, responsible for 25% of global CO₂ emissions, plays a key role, especially road transport [11,12]. To meet the Paris Agreement targets, significant reductions are needed in this sector [13,14]. Consequently, vehicle electrification has been accelerating worldwide [15,16].

At present, the development of electric vehicles has achieved remarkable progress, with key technologies such as lithium batteries and energy replenishment making critical advancements in recent years [17–19]. Meanwhile, fuel cell engineering technology and commercialization, which are crucial to the electrification of heavy-duty vehicles, are also continuously progressing [20,21]. The development of renewable energy has also driven the progress of vehicle electrification. The large-scale adoption of renewable energy further enhances the ability of electric vehicles to reduce overall CO₂ emissions. Conversely, the advancement of electric vehicles can also promote the development of renewable energy. In addressing the issue of intermittent power generation from renewable sources, the batteries of electric vehicles can serve as energy storage devices, working in coordination with the power grid to stabilize the output of solar and wind energy. This, in turn, increases the share of renewable energy in the grid and facilitates its further development [22–24].

In previous related studies, most research has focused on energy-saving, carbon reduction, and environmental benefits of electrification. Extensive and in-depth studies have been conducted on topics such as energy consumption comparisons between electric vehicles and internal combustion engine vehicles [25–28], differences and effectiveness of eco-driving strategies [29–31], and energy consumption comparisons of hybrid and electric vehicles under real-world driving conditions [32].

Additionally, a smaller number of studies have examined other aspects of electric bus adoption, such as scheduling, battery performance, and charging speed [33], vehicle availability and failure rates [34], as well as route planning and energy management [35], highlighting additional advantages of bus electrification.

The findings of these past studies have significantly contributed to the advancement of vehicle electrification. However, the authors have observed that the potential benefits of electric bus adoption in terms of enhancing driving safety, reducing driver fatigue, and improving passenger comfort have not yet received sufficient attention or exploration. Safety and comfort are critical aspects of transportation development, directly and closely related to both passengers and drivers. They are also among the highest-priority considerations for individuals when evaluating electric transportation options. Therefore, these factors deserve broader and more in-depth research.

Based on this perspective, the present study focuses on the suitability between specific driving conditions and vehicle electrification as its central theme. Specifically, it investigates how the transition from internal combustion vehicles (ICVs) to electric vehicles (EVs) affects factors such as powertrain configuration and acceleration performance and how these changes influence driving safety, driver fatigue, and passenger comfort under certain

driving conditions. As previously discussed, the benefits of vehicle electrification in terms of energy savings, carbon reduction, and environmental protection have been extensively studied in much research work [27,28,31]; therefore, this study does not delve deeply into these aspects.

Different types of vehicles operate under vastly different driving conditions, which implies that different usage scenarios demand varying vehicle performance characteristics. For example, urban transit buses operating in busy city areas frequently start from bus stops due to passengers boarding and alighting. In such cases, slow and smooth acceleration is required to prevent passengers from losing balance or experiencing discomfort. However, once the bus merges into a high-speed traffic lane, rapid acceleration is necessary to avoid rear-end collisions with other vehicles. This situation highlights the dual requirement for high acceleration performance during lane merging (to prevent rear-end collisions) and smooth acceleration when starting (to ensure passenger safety and comfort).

At the same time, the powertrain systems of EVs differ significantly from those of conventional ICVs, leading to notable changes in vehicle performance due to electrification. In terms of powertrain composition, EVs primarily consist of batteries and electric motors, whereas ICVs rely on internal combustion engines and transmissions. Consequently, EVs exhibit significant advantages in acceleration performance (particularly at low speeds), precision in torque output control, and smooth acceleration due to the absence of a transmission system.

Ideally, the performance changes introduced by electrification should precisely align with the performance requirements of specific driving conditions. If the changes brought about by electrification contradict the demands of a particular driving scenario, efficiency may decline, making the adoption of EVs impractical. Conversely, if electrification results in excessive performance improvements that far exceed the requirements of the driving scenario, it will lead to unnecessary resource consumption, making such an approach suboptimal for the widespread adoption of EVs.

By investigating the suitability of electrification for specific driving conditions (particularly speed change patterns), we can better understand the benefits of vehicle electrification beyond the widely discussed macro-level impacts on carbon reduction, energy conservation, and environmental protection. Specifically, electrification may enhance driving safety, reduce driver fatigue, and improve passenger comfort in certain applications. Furthermore, the authors believe that clarifying the benefits of electrification in specific driving scenarios, beyond the general discussion of carbon reduction and energy efficiency, can further promote the adoption and expansion of EVs across various transportation applications.

The potential benefits of electric vehicle adoption, such as energy savings, emission reduction, and increased renewable energy utilization through power storage technology, have been extensively discussed in numerous studies. However, there has been relatively limited discussion on the impact of EV adoption in terms of enhancing driving safety, improving passenger comfort, and reducing driver fatigue. These previously overlooked benefits may have a positive impact on various societal groups.

Therefore, the objective of this study is to analyze speed data obtained through experimental investigations to achieve the following: first, to clarify the differences in speed variation patterns between roads near bus stops and general roadways; and second, to identify the differences in driving performance between motor-driven electric buses and engine-driven conventional fuel-powered buses due to their distinct powertrain characteristics. Ultimately, based on these differences in speed patterns and driving performance, this study aims to elucidate the potential benefits of bus electrification in terms of increasing driving safety, enhancing passenger comfort, and mitigating driver fatigue.

Specifically, this study focuses on a route bus that operates commercially within Tokyo [36]. EVs are said to be particularly suitable for public transportation, such as buses, because they generally have a low carbonization effect and contribute to an improved driving environment, with minimal impact on the surrounding area [37–39]. In addition to these benefits, as mentioned earlier, the authors consider the speed change pattern, which is unique to regular route buses, to be particularly well-suited for EVs. Therefore, this paper reports on the results of a passive experiment analyzing the speed change patterns of commercially operating buses on real regular routes, conducted to further clarify the benefits of route bus electrification.

For example, the speed variation patterns of route buses indicate that high-intensity acceleration is required after departing from a bus stop. This is because route buses need to rapidly accelerate to cruising speed to ensure driving safety and reduce the risk of rear-end collisions after lane changes. This characteristic aligns well with the superior acceleration performance and gearless operation of electric buses. Therefore, the electrification of route buses can enhance driving safety. Improving driving safety is a potential benefit of electrification that has not been widely discussed. Additional benefits include improved passenger comfort and reduced driver fatigue. This study provides a detailed analysis of these potential benefits based on passive experimental data.

In the first part (Section 3), the results of the analysis focused on acceleration when starting from a bus stop and deceleration when stopping, which is unique to route buses, are summarized. Through this analysis, the authors aim to highlight the specific driving performance requirements of route buses based on their operational characteristics. In the second part (Section 4), the results of the comparative analysis between the speed change pattern of an electric bus, which was chosen as an example of a motor-driven vehicle, and a diesel bus, which was chosen as an example of an engine-driven vehicle, are summarized. Through this analysis, the authors aim to further clarify the suitability of electrification for route buses in terms of improving driving safety, reducing driver fatigue, and enhancing passenger comfort. Additionally, based on the operational characteristics of route buses, this study proposes recommendations for regenerative braking settings and driving strategies specifically tailored for electric route buses.

2. Passive Experiment Method

2.1. Regular Routes and Buses Being Measured

The regular route studied in this passive experiment is the “To 05-2” line of the Toei Bus operated by the Tokyo Metropolitan Bureau of Transportation, Japan [36]. The route shown in Figure 1 connects Tokyo Station Marunouchi South Exit and Tokyo Big Sight. The return trip distance is 17 km, and it takes approximately 80 min to complete.

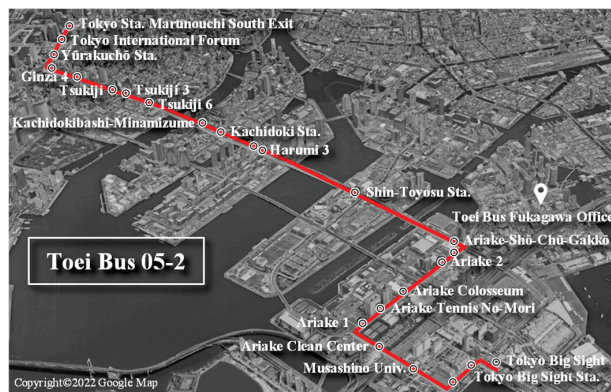


Figure 1. Route profile of Toei Bus 05-2 shuttle route.

Both electric buses [40] and diesel buses [41] are used on this route and have been measured. Their basic specifications are listed in Table 1.

Table 1. Specifications of tested vehicles.

	Name	Toyota Fuel Cell Bus SORA
	Capacity	79 persons
	Motor	226 kW/670 Nm
	Transmission	Fixed
	Driver	A, B, C, D
	Name	Mitsubishi Fuso MP38FK
	Capacity	78 persons
	Engine	199 kW/785 Nm
	Transmission	Six-speed AT
	Driver	E, F, G, H

2.2. Passive Experiment Period and Equipment Used

In this study, the data collection process lasted approximately four weeks. The first two weeks were dedicated to preparatory experiments, including the design and development of the measurement device, preliminary measurements, and accuracy adjustments. The formal experiments were conducted during the final two weeks, and all data used in this study were obtained from this period.

During the formal experiments, the main measurement device was securely fixed inside the vehicle cabin, while the signal reception antenna was positioned near the window. The measurement equipment operated on an independent power source, ensuring continuous operation throughout the day regardless of whether the vehicle was running. From early morning departure from the depot to evening return, one to two experiment monitors were always present on the vehicle. Their responsibilities included real-time monitoring of the collected data, recording operational conditions, and handling unexpected situations if necessary.

An electric bus was chosen as an example of a motor-driven vehicle, and a diesel bus was chosen as an example of an engine-driven vehicle for speed measurements. Both types of buses run on the route. The measurements for the former were conducted on the journeys taken between 14 and 17 December 2021 by drivers A, B, C, and D, while the measurements for the latter were conducted on the journeys taken between 22 and 25 December 2021 by drivers E, F, G, and H.

We prepared a GPS-type device ourselves that was used for measuring speed (Figure 2). This equipment consisted of an antenna, receiver (GPS module circuit board: UBLOX/C099-F9P [42]), and smartphone. It was devised to realize higher precision than common GPS devices through reference station compensation. Figure 3 shows an example of the measured data.

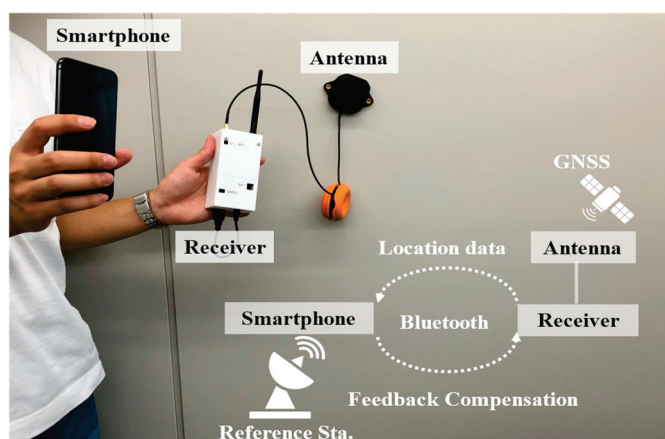
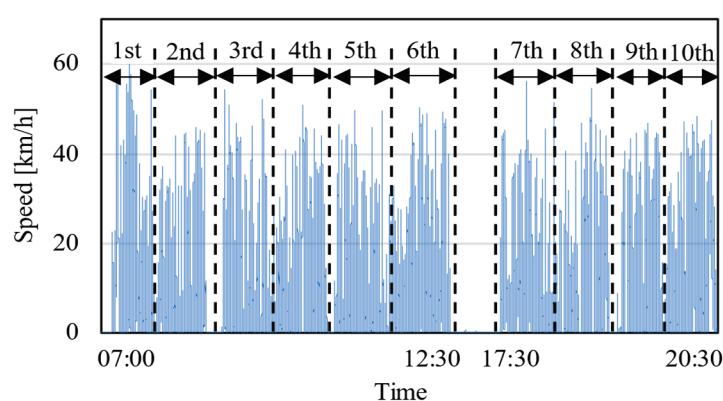
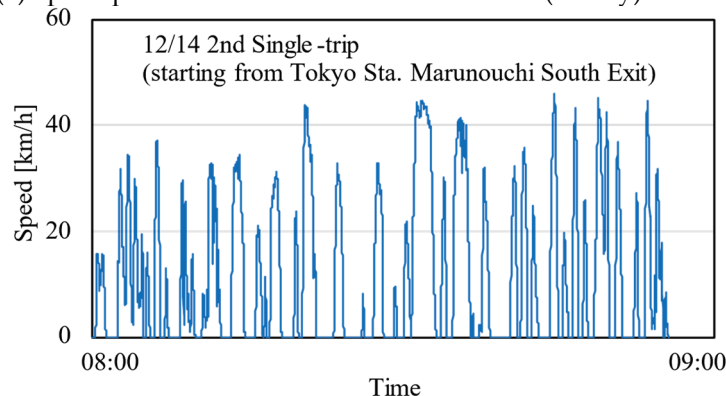


Figure 2. Measuring equipment and measuring method.



(a) Speed pattern of FC bus on December 14th (all day)



(b) Speed pattern of FC bus on December 14th (2nd)

Figure 3. Measured data example of speed pattern.

3. Passive Experiment Results and Analysis Focusing on the Acceleration/Deceleration of Route Buses When Starting and Stopping at Bus Stops

3.1. Separation and Extraction of Different Types of Starts and Stops (Bus Stop/Traffic Signal/Other)

As the analysis in this paper focuses on the acceleration when starting from a bus stop and the deceleration when stopping at a bus stop, such information must be separated and extracted from the speed measurement data. Herein, we discuss how that has been achieved.

Table 2 shows the result of performing this separation on the second bus (departing from Tokyo Station Marunouchi South Exit) on 14 December, and Table 3 shows the same

separation performed on all the buses on the same day. First, the continuously measured speed data are separated into individual trips, each consisting of one continuous trip from start to stop (trip number (a) in the same table). Next, the starts and stops of all the trips are categorized into starting from/stopping at a bus stop, starting from/stopping at a traffic signal, and other starts/stops through visual examination of the GPS travel trajectory. After that, only the starts/stops at bus stops and starts/stops at traffic signals were extracted; those that were to be affected by the surrounding traffic (e.g., traffic jams) were excluded. More specifically, all the trips that were less than 100 m were removed first (remaining start/stop number: (b) in the same table). Then, those wherein the speed at the end of acceleration or the start of deceleration was less than 30 km/h were excluded (remaining start/stop number: (c) in the same table).

Table 2. Details of measured data separation (2–14 December).

	Bus Stop	Signal	Total
(a) The number of total trips	-	-	35
(b) The number of starts and stops (≥ 100 m)	31	15	-
(c) The number of starts and stops (≥ 100 m, ≥ 30 km/h)	15 (68%)	7 (32%)	-

Table 3. Details of measured data separation (14 December).

	Bus Stop	Signal	Total
(a) The number of total trips	-	-	395
(b) The number of starts and stops (≥ 100 m)	295	165	-
(c) The number of starts and stops (≥ 100 m, ≥ 30 km/h)	118 (61%)	75 (39%)	-

The following analysis is performed on the data extracted through the operation discussed above. Note that the number of start accelerations/stop decelerations at bus stops, unique to regular route buses, exceeds the number of start accelerations/stop decelerations at traffic signals.

3.2. Comparative Analysis of Start Acceleration at Bus Stops and Start Acceleration at Traffic Signals

Figure 4 shows all speed change pattern measurements for the start of acceleration at bus stops and the start of acceleration at traffic signals by Driver A. Moreover, Figure 5 (Driver A) shows the same data summarized as the acceleration values for each speed region. In the first half of acceleration (in the low-speed region), the start of acceleration at bus stops is weaker than the start of acceleration at traffic signals. The main reasons for this are the consideration given to preventing passengers from falling and checking the flow of traffic in the driving lane. Meanwhile, during the second half of acceleration (in the medium-speed region), the start of acceleration at bus stops is stronger. The reason for this was the desire to reach cruising speed quickly after entering the driving lane to prevent rear-end collisions.

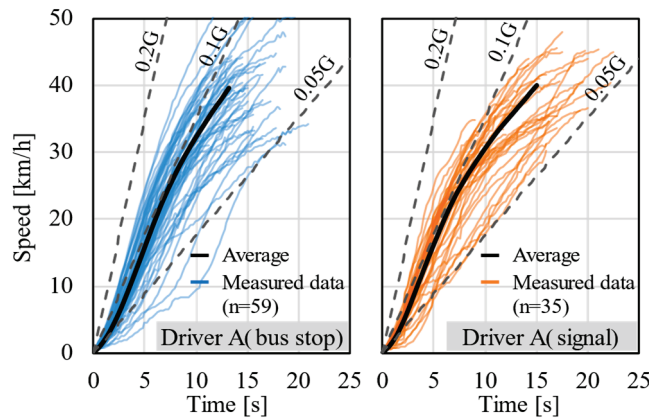


Figure 4. Comparison of acceleration speed patterns starting from bus stops (left)/from signals (right).

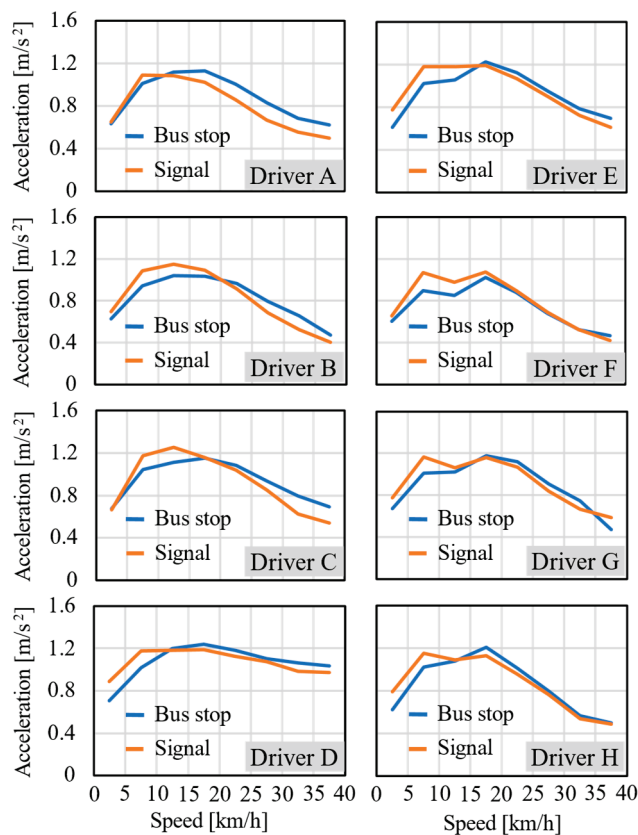


Figure 5. Comparison of starting acceleration (each driver).

Generally, the acceleration performance of motor-driven vehicles is superior to that of engine-driven vehicles. Therefore, the characteristics of start acceleration at bus stops discussed above are considered more suitable for the former than the latter. A similar analysis was performed on the operations of every driver to verify the generality of this phenomenon (Figure 5 (Driver B–H)). The results remained the same.

3.3. Comparative Analysis of Stop Deceleration at Bus Stops and Stop Deceleration at Traffic Signals

Figure 6 shows all the speed change pattern measurements for stop decelerations at bus stops and stop decelerations at traffic signals by Driver A. Additionally, Figure 7 (Driver A) displays the same data reorganized as the accelerations (decelerations) according to each speed region. During the first half of deceleration (the high-speed region), the

strength of deceleration to stop at bus stops (still in the driving lane at this point) and that of deceleration to stop at traffic signals were the same. However, during the second half of deceleration, the increase in the strength of the former (having left the driving lane at this point) was notable. This is because, in general, the distance to a bus stop after leaving the driving lane is short, requiring faster deceleration to come to a stop. A similar analysis was performed for every driver to verify the generality of this phenomenon (Figure 7 (Driver B–H)). The results were the same for all cases.

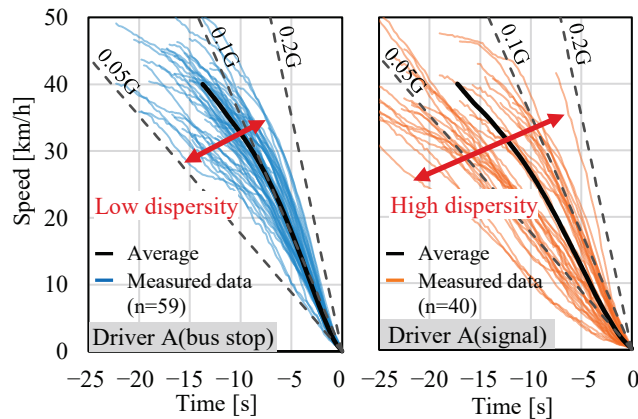


Figure 6. Comparison of deceleration speed patterns stopping to bus stops (left)/to signals (right).

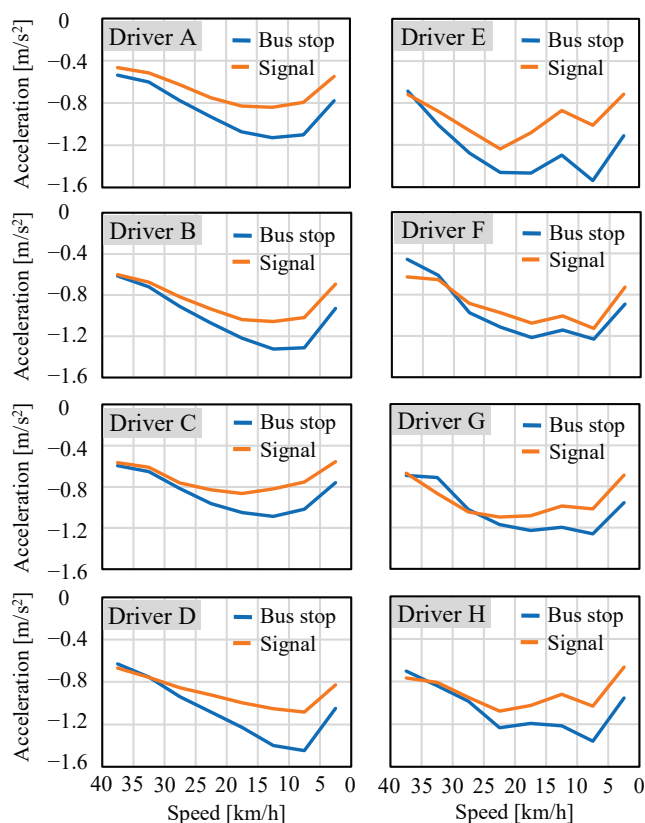


Figure 7. Comparison of stopping deceleration (each driver).

Next, we compare the degrees of dispersion between stop decelerations at bus stops and stop decelerations at traffic signals. From Figure 6 above, the former has a lower degree of dispersion in the speed change pattern than the latter. Figure 8 shows the same data reorganized as the probability distribution of the average acceleration (deceleration). The same phenomenon can also be observed in normal distribution curves and standard

deviations in this figure. This was because stop decelerations at bus stops tend to be less easily affected by the traffic, which makes it possible for the drivers to decelerate out of their own volition, resulting in similar speed change patterns. Meanwhile, we concluded that there are discrepancies in stop decelerations at traffic signals because these are easily affected by the traffic.

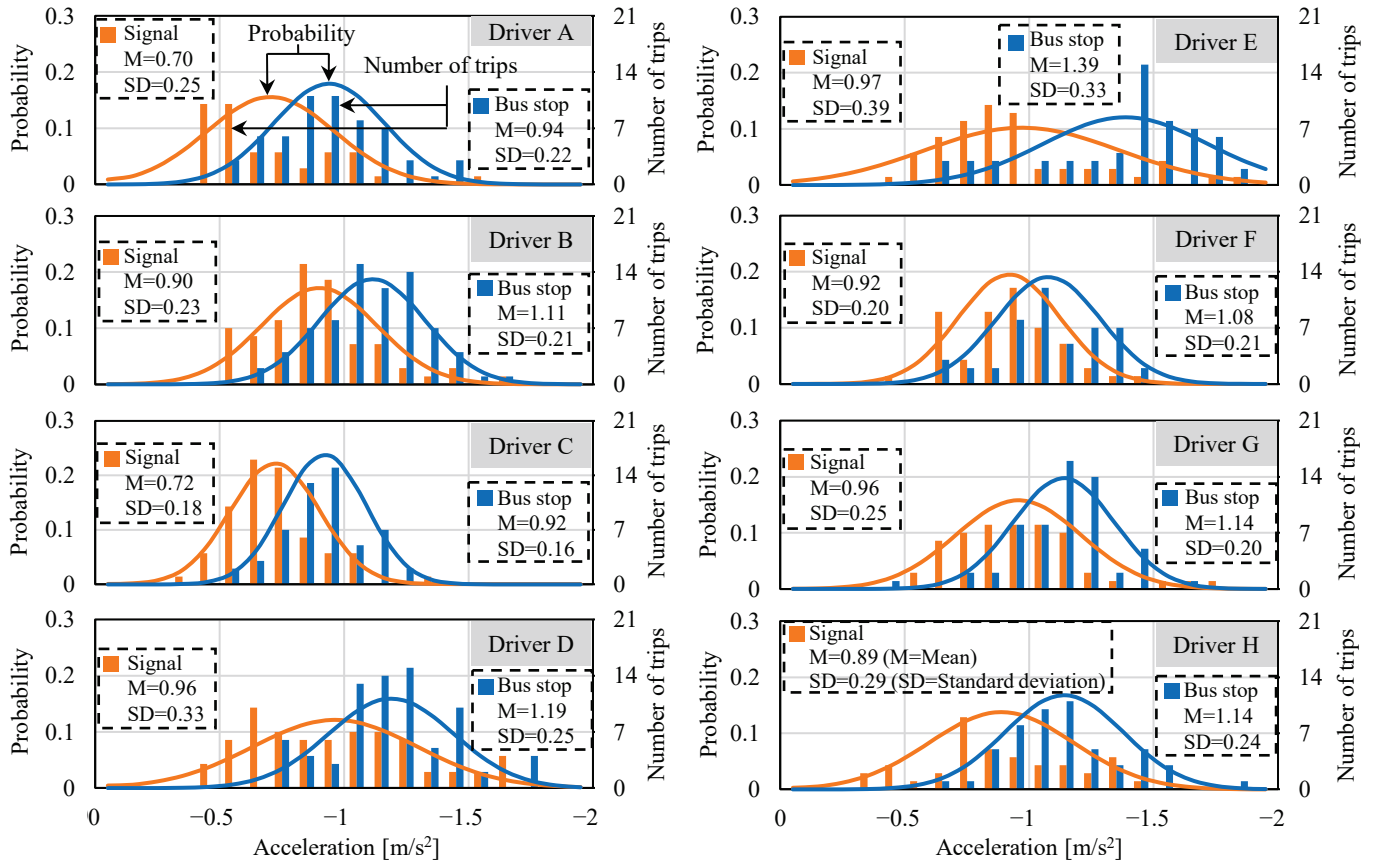


Figure 8. Comparison of the probability distribution at deceleration section stopping to bus stops/signals (each driver).

The examination in this section elucidated the characteristics of deceleration for route buses, namely the fact that there is “strong deceleration when stopping at bus stops” and a “low degree of dispersion when stopping at bus stops”. The latter has the potential to facilitate the narrowing down of the regeneration setting, which contributes to improving electricity consumption during electrification to a significant degree.

4. Passive Experiment Results and Comparative Analysis of Speed Change Patterns Between Electric Buses and Diesel Buses

4.1. Comparative Analysis of Acceleration Intensity at the Start

First, we focused on the acceleration when starting from a bus stop that is unique to route buses. Figure 9 shows the compilation of the speed change pattern for every driver (electric bus: Driver A, B, C, and D/diesel bus: Driver E, F, G, and H). Moreover, Figure 10a shows the same data as the acceleration intensity for each speed region. One can observe that at every speed band (particularly at 30 km/h or more), the acceleration intensity of electric buses is higher than that of diesel buses. Although the main reason for this result is the difference in the output characteristics of the motor and the engine, low acceleration (acceleration work) applied on diesel buses to reduce gear-shifting shock revealed during separate interviews is also assumed to influence the results.

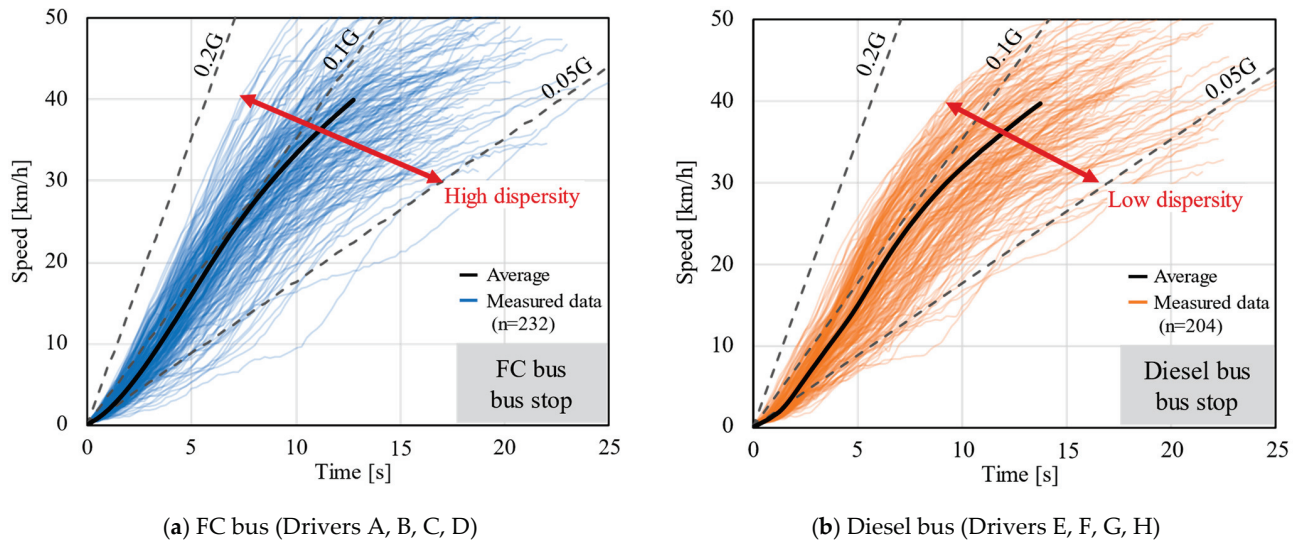


Figure 9. Comparison of acceleration speed change patterns between FC buses and diesel buses (acceleration from bus stops).

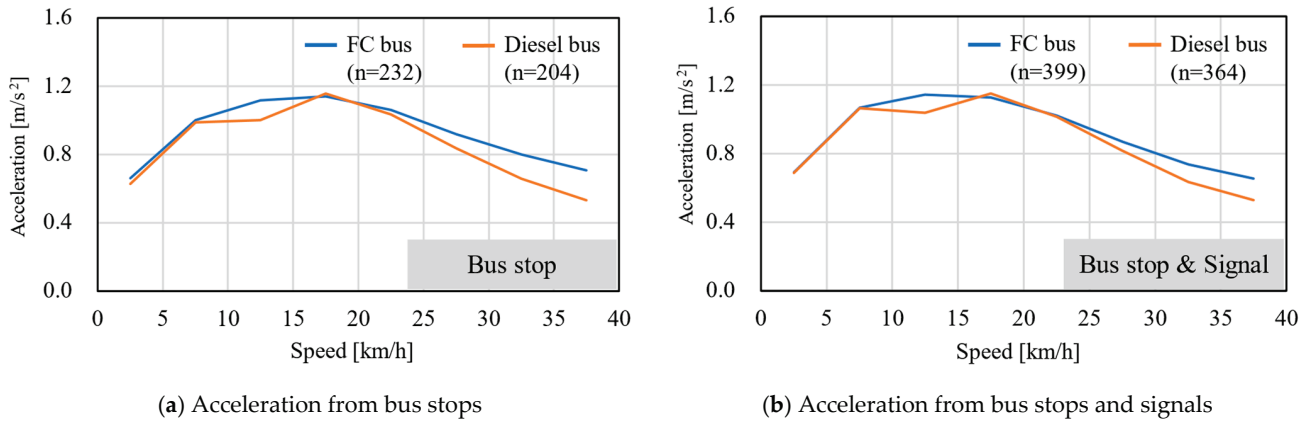


Figure 10. Comparison of acceleration intensity between FC buses and diesel buses.

Next, acceleration data when starting at traffic signals were added, and a similar analysis was performed. This yielded similar results, as shown in Figure 10b.

In addition to the phenomena discussed above, the stalling of diesel buses at medium speeds (10–15 km/h) and large individual differences in electric buses among the drivers (high degree of dispersion) were observed in the measurement results. These are analyzed in detail in the following sections.

4.2. Analysis of the Negative Impact of Gear Shifting During the Start of Acceleration of Diesel Buses

As mentioned earlier, the acceleration of diesel buses slowed in the 10–15 km/h speed band. This was due to the interruption of acceleration caused by gear-shifting operations. Figure 11a shows a diagram representing the acceleration–speed profile during the start of acceleration that was prepared to clarify this phenomenon. It shows the interruption of acceleration in the diesel buses, which does not exist in the electric buses. In the previous sections, we pointed out that, as a characteristic of the start/stop acceleration unique to route buses, strong acceleration occurs during the latter half of acceleration (the medium-to-high speed region) to quickly reach cruising speed to avoid a rear-end collision by the vehicle in the rear. As the abovementioned speed band corresponds to the initial stage of

this acceleration, one can claim that an electric bus, wherein acceleration does not slow, has characteristics that facilitate easy driver operation.

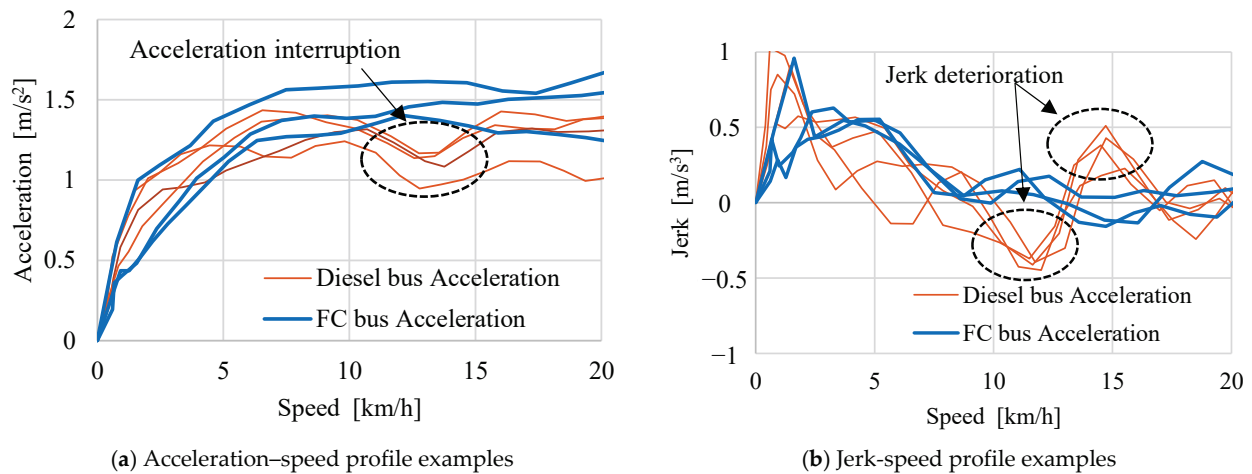


Figure 11. Comparison of acceleration and jerk between FC buses and diesel buses.

Gear shifting also makes riding more uncomfortable. The change pattern of the jerk amount was also compiled in Figure 11b to quantitatively understand this phenomenon [43–45]. While both types of buses had the same amount of jerk on startup, the deterioration of jerk when shifting gears in the diesel bus was notable.

The high acceleration performance and riding comfort can be said to be the primary advantages of motor-driven vehicles, and this phenomenon was reconfirmed in these actual measurement data. Moreover, we would like to add that many drivers agreed with these benefits.

4.3. Comparative Analysis of Individual Differences in the Speed Change Pattern When Starting

As indicated earlier, there are considerable differences among individuals in terms of the speed change patterns when starting electric buses. This phenomenon was particularly notable in the speed band of 30 km/h or more. Herein, we will proceed with a detailed analysis of this phenomenon.

Figure 12 shows the averages of the acceleration strength in each speed band as a bar graph, with the addition of the maximum and minimum values. This shows a particularly large discrepancy in the high-speed range of the electric buses. Figure 13 reorganizes the appearance frequencies of the acceleration average as a distribution diagram. Furthermore, individual differences can be recognized here.

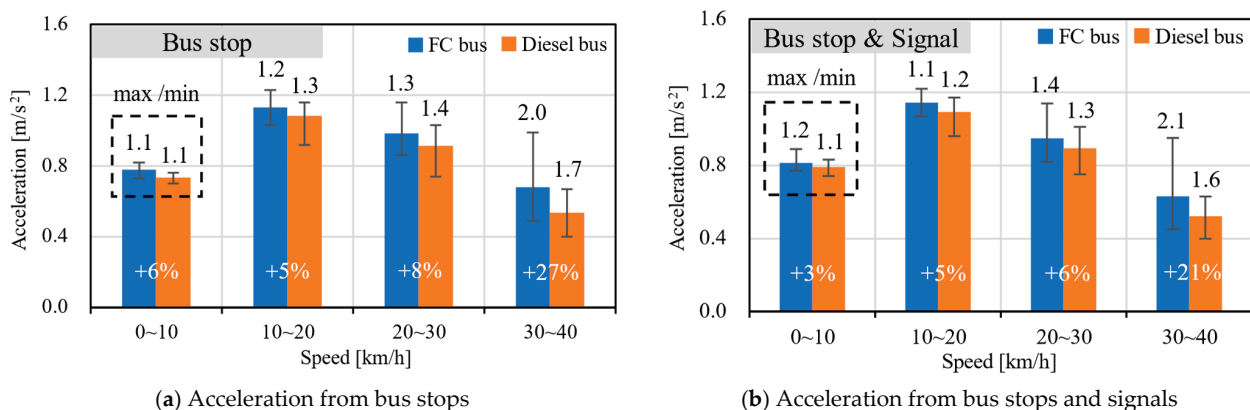


Figure 12. Comparison of acceleration intensity between FC buses and diesel buses (maximum value/minimum value).

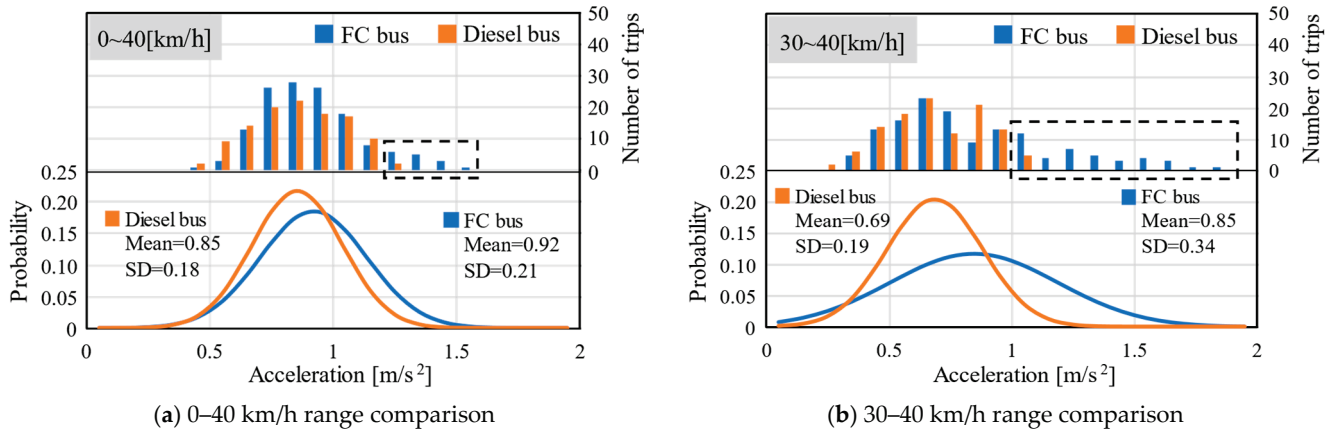


Figure 13. Comparison of acceleration probability distribution between FC buses and diesel buses (limited to the acceleration from bus stops).

The reason why the individual differences in the speed change history become notable during the acceleration of electric buses is because of the high acceleration performance of this type of bus. Meanwhile, the limitations in the acceleration performance of diesel buses result in nearly identical driving operations among the drivers, making it more difficult for individual differences to occur.

4.4. Comparative Analysis of the Speed Change Pattern When Stopping

Figure 14 compiles the speed change patterns of all drivers during deceleration while stopping at bus stops. No differences in behavior between the two types of buses, similar to those observed during startup, were identified.

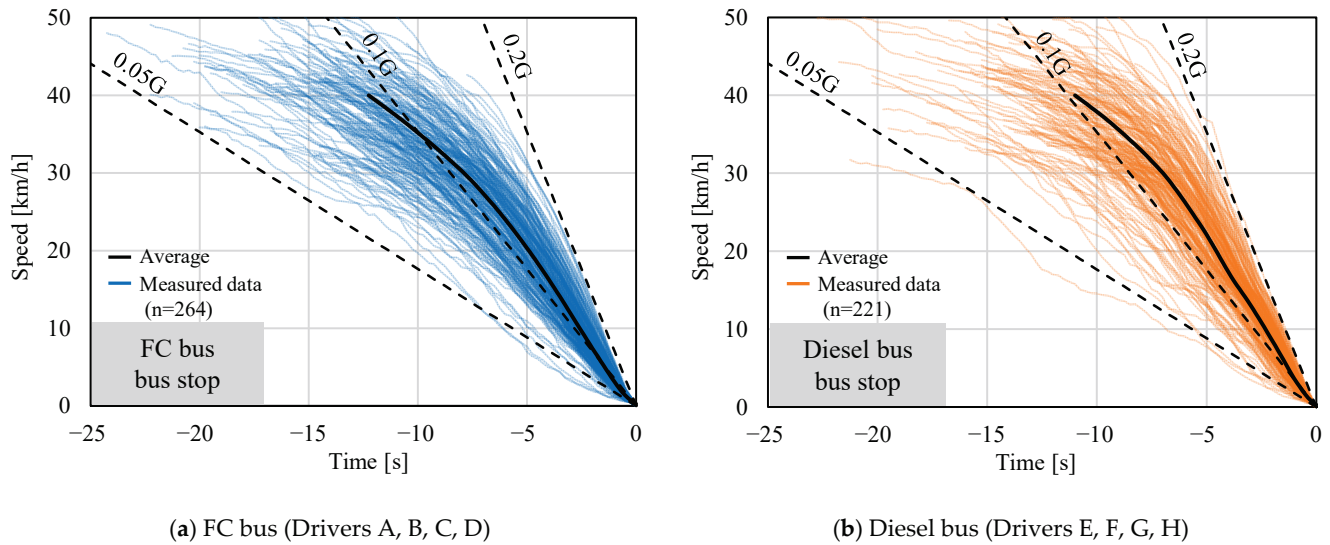


Figure 14. Comparison of deceleration speed change patterns between FC buses and diesel buses (deceleration to bus stops).

5. Conclusions

The findings obtained through this study are summarized as follows:

- I. Regarding the start of acceleration at bus stops, unique to regular route buses, it was pointed out that the start of acceleration at bus stops is weaker than the start of acceleration at traffic signals during the first half of acceleration (in the low-speed region), and the reasons for this were clarified. Furthermore, it was elucidated that during the second half of the start of acceleration at bus stops (in the medium-speed

region), acceleration is stronger, and the reason for this was due to the desire to reach cruising speed quickly to prevent rear-end collisions. Generally, the acceleration performance of motor-driven vehicles is superior to that of engine-driven vehicles, and it is widely understood that this characteristic is well-liked by bus drivers. Moreover, the difference in performance was verified, primarily during the second half of the start of acceleration at bus stops (in the medium-speed region).

- II. This study suggests that the observed stronger acceleration of electric buses during lane changes may be attributed to three key factors: (1) Higher torque and a wider high-torque operating range of electric motors, which provide more robust acceleration capabilities. (2) The absence of gear shifting during acceleration in electric vehicles, which eliminates power interruptions caused by gear changes in conventional vehicles, resulting in smoother and more consistent acceleration performance. (3) A more favourable driving experience for bus drivers, as they can execute high-intensity acceleration more easily without concerns about the shift shocks and engine noise associated with conventional vehicles. This allows drivers to focus on safe driving and utilize the vehicle's acceleration potential more effectively, when necessary, without worrying about the negative impacts of aggressive acceleration on passenger comfort.
- III. Regarding the stop deceleration at bus stops, unique to regular route buses, the characteristics of "strong deceleration when stopping at bus stops" and a "low degree of dispersion when stopping at bus stops", as well as their reasons, were elucidated. It was pointed out that the latter has the potential to facilitate the narrowing down of the regeneration setting, which contributes to improving electricity consumption during electrification to a significant degree.
- IV. We concluded that the "no gear shifting" characteristic makes acceleration easy when departing from a bus stop in addition to the "high acceleration performance" of motor-driven vehicles. Furthermore, by calculating and analyzing the jerk amount, we could quantitatively demonstrate the comfortable driving experience while riding on this type of bus where there is no shock due to gear shifting.
- V. While the "high acceleration performance" of motor-driven vehicles produces "individual differences in the speed change patterns", this does not translate to "individual differences in electricity consumption", owing to the characteristics of this type of vehicle [30,46]. With engine-driven vehicles, measures such as "slow acceleration" are strongly encouraged to realize eco-driving, and any driving style that deviates from these measures is avoided. However, with motor-driven vehicles, the driver does not need to be too concerned about the speed history during acceleration. This characteristic also suggests a benefit in terms of the electrification of buses.
- VI. The measurement device used in this study requires both satellite and network signals. Therefore, the proposed passive experiment method cannot be applied in areas where satellite signals are disrupted or unavailable, such as tunnels and high-rise building areas, or in locations without network coverage. Additionally, the electric vehicle used in this study (the fuel cell bus SORA) has certain limitations compared to conventional vehicles (diesel buses) in terms of driving range and refuelling. The driving range of the fuel cell bus is approximately 200 km, with a hydrogen refuelling time of about 15 min [47,48]. While this design is generally sufficient to meet the daily operational requirements of the target route, it is still inferior to traditional vehicles such as diesel buses. Moreover, it is important to note that hydrogen refuelling stations are significantly fewer in number compared to conventional fuelling stations, and the stability of the hydrogen supply remains an open question. Therefore, improving

the refuelling infrastructure is a critical challenge in the electrification of public transportation.

This study demonstrates that, in addition to the widely recognized advantages of reducing carbon emissions and protecting the environment, the electrification of buses has previously overlooked potential benefits, such as enhancing driving safety, improving passenger comfort, and reducing driver fatigue. These findings may have positive implications for various societal groups. For passengers, these findings can help them better understand the technological advancements and improve their experience of public transportation, potentially encouraging more active use of public transit. For bus operators, a comprehensive understanding of the diverse benefits of electric bus adoption can help them reduce safety risks and labor costs while improving service quality. For electric bus manufacturers, these findings can be leveraged to highlight “enhanced safety”, “improved passenger comfort”, and “reduced driver fatigue” as new market advantages, fostering differentiated competition, strengthening brand image, and expanding market share. For government agencies, incorporating these new findings into policy discussions can lead to more comprehensive policymaking and facilitate greater acceptance among key stakeholders, including passengers, drivers, and labor unions. Additionally, a clearer understanding of the long-term benefits of electric buses—such as reducing traffic accidents, improving traffic efficiency, lowering healthcare costs, and increasing operational efficiency—can provide stronger justification for public financial support, encouraging government agencies to prioritize electric bus projects in budget allocation.

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Article

A Case Study on Gas Venting Events in NCM523 Batteries During Thermal Runaway Under Different Pressures in a Sealed Chamber [†]

Cheng Li, Hewu Wang *, Yalun Li and Minggao Ouyang

School of Vehicle and Mobility, Tsinghua University, Beijing 100084, China; licheng76@mail.tsinghua.edu.cn (C.L.)

* Correspondence: wanghw@tsinghua.edu.cn

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Abstract: The venting process is one of the most important events during the thermal runaway (TR) of lithium-ion batteries (LIBs) in determining fire accidents, while different ambient pressures will exert an influence on the venting events as well as the TR. Ternary nickel–cobalt–manganese (NCM) batteries with a 75% state of charge (SOC) were employed to conduct TR tests under different ambient pressures in a sealed chamber with dilute oxygen. It was found that elevated ambient pressure results in milder ejections in terms of jet temperature and mass loss. Gas venting characteristics were also obtained. Additionally, the amount of carbon dioxide (CO₂), hydrogen (H₂), methane (CH₄), and ethylene (C₂H₄) released increase with ambient pressure, while carbon monoxide (CO) varies inversely with ambient pressure. The higher the ambient pressure is, the greater the flammability risk is. The molar amount of C, H, O, and total gases released shows a positive correlation with the maximum battery temperature and ambient pressure. This study will support the design of safety valves and help reveal the effects of venting events on the evolution of TR.

Keywords: LIBs; TR; gas venting characteristics; gas compositions; different pressures

1. Introduction

LIBs have been widely employed in the field of new energy vehicles and energy storage power stations operating at various altitudes because of their huge advantages, such as their long life cycles, high specific energy density, and low self-discharge rate [1–3]. However, under abuse conditions, including electrical abuse, thermal abuse, and mechanical abuse, LIBs may suffer from TR, one of their most important safety issues [4–6]. The TR of LIBs has attracted public attention, and establishing how to mitigate or prevent thermal hazards is becoming more and more crucial. During the process of TR, a venting event is another way that matter and energy can be exchanged between the interior of the battery and the external environment, resulting in the release of a large number of combustible gases [5–8]. In addition, vented particles at elevated temperatures are also potential sources of arc failure in the battery system, as they could ignite combustibles and possibly lead to fire accidents or explosions [9,10]. Local atmospheric pressures can vary with different altitudes; therefore, venting events should be different during the process of TR.

The venting process is a necessary pressure relief design in order to avoid the collapse of the battery shell. When a battery is involved in the evolution of TR, several exothermic reactions may occur successively among its cathode materials, anode material, electrolyte, and other components [4,6]. Gases released from these reactions will accumulate gradually inside the sealed battery until the battery valve opens, resulting in a venting event, when

the internal pressure of the battery reaches a certain value [11]. Some solid materials and unreacted liquid electrolyte are eventually ejected out of the battery along with these gases during the process of venting. These ejections possess a large amount of heat and flammability and are considered a source of extremely hazardous combustions or explosions [12,13]. Therefore, research on the venting behavior of batteries is of great importance.

There has been abundant research on the characteristics of venting behaviors, such as the composition of ejections and the total amount of gas vented. Vented ejections were described as appearing gaseous, liquid, and solid based on the sampling temperature and detection temperature [11,14–16]. The TR gas analysis of a 50 Ah prismatic NCM622 battery with a 100% SOC revealed at least 31 chemical compositions in the vented ejections, which were discovered in a sealed chamber initially filled with nitrogen, while 17 compounds were found to have a boiling temperature below 25 °C, accounting for approximately 90% of the detected gases [15]. Most of the vented gases were H₂, CO, CO₂, and short-chain hydrocarbons such as CH₄, ethane (C₂H₆), and C₂H₄. TR tests of 51 ternary nickel–cobalt–manganese (NCM) batteries in a gas-tight autoclave filled with air were conducted and the seven most common gas species—H₂, CO, CO₂, CH₄, C₂H₆, C₂H₄, and propylene (C₃H₆)—were summarized, with these making up over 99% of the total gases released [17]. Similar conclusions were also reached about the gas compositions of nickel–cobalt–aluminum (NCA), lithium cobalt oxide (LCO), and lithium iron phosphate (LFP) batteries at different SOC levels in a sealed vessel that was filled with nitrogen before the TR tests [16,18]. Besides the gaseous and liquid ejections, metallic and nonmetallic elements were found in the vented particles, most of which were Ni, Co, Mn, Li, Al, Cu, C, H, P, and O [9,19–22]. In terms of the total amount of gas released, roughly 0.03 mol/Ah, 0.08 mol/Ah [16,18], and 0.09 mol/Ah [17] were obtained from LFP, NCA, and NCM batteries with a 100% SOC at normal temperature and pressure, respectively. By taking most of the species of vented gases into account and adopting Le Chatelier's mixing rule, upper and lower flammability limits were calculated to evaluate the flammability characteristics of LIBs with different cathodes [23–25].

A venting event is mainly shaped by pressure differences between the inside and outside of the battery. Therefore, different ambient pressures should result in different gas venting behaviors during TR. TR tests of 2.6 Ah LCO batteries with 0, 50%, and 100% SOC under 64.3 kPa and 100.8 kPa were carried out in an open environment and their jet behavior and combustion hazards were characterized [26]. The results showed that a lower pressure could lead to a faster ignition and a smaller mass loss and heat release rate during TR. Nevertheless, venting behaviors in the open environment may depend on the content and concentration distribution of oxygen to some extent, because oxygen can participate in several reactions during the venting event.

Although sufficient efforts have been made towards studying venting behaviors with regard to battery type, SOC, capacity, etc., limited studies have investigated venting behaviors under different pressures. Furthermore, a comprehensive understanding of the whole venting process without the influence of oxygen is yet to be achieved.

In this study, TR tests of 50 Ah NCM523 batteries with a 75% SOC were carried out in a sealed chamber filled with nitrogen. The tested batteries were prompted to enter TR by lateral heating and the ambient pressure inside the chamber was set to 20 kPa, 100 kPa, or 260 kPa of absolute pressure. Thermocouples (TCs) and pressure sensors were adopted to monitor thermodynamic parameters. After the TR tests terminated, the released gases were collected and analyzed by a gas chromatography analyzer (GC). Thermal parameters, venting characteristic parameters and gas compositions were mainly adopted to describe gas venting behaviors. This research will benefit pressure relief design of the

safety valves and provide reference to battery safety evaluation for application scenarios at different altitudes.

2. Experiment

Compared to pouch cells, the safety valve on prismatic batteries enables a relatively vertical jet flow during gas discharge. Moreover, the burst pressure of the safety valves in the same batch of batteries is consistently uniform, ensuring reliable performance under critical conditions [11,27,28]. In this study, prismatic batteries were selected to investigate venting behaviors. As shown in Table 1, the tested battery with a $\text{Li}(\text{Ni}_{0.5}\text{Co}_{0.2}\text{Mn}_{0.3})\text{O}_2$ cathode has a nominal capacity of 50 Ah, a nominal weight of 865 g, and a specific energy density of 212 Wh/kg. Before each test, the examined battery was discharged to 0% SOC and then charged to 75% SOC using a constant current mode. If the SOC of the examined battery is significantly below the required threshold (e.g., 0% SOC), violent TR reactions will not occur even if a venting event takes place. By contrast, if the SOC is extremely high (e.g., 100% SOC), TR will occur once the safety valve opens, which complicates the analysis of the relationship between the venting event and the TR.

Table 1. Information of the tested battery.

Parameters	Value
Nominal capacity (Ah)	50
State of charge (%)	75
Nominal weight (g)	865
Size (mm)	$148 \times 27 \times 102$
Type	Prismatic
Cathode	$\text{Li}(\text{Ni}_{0.5}\text{Co}_{0.2}\text{Mn}_{0.3})\text{O}_2$
Anode	Graphite
Specific energy density (Wh/kg)	212
Ambient pressure (kPa)	20, 100, 260

To comprehensively understand the characteristics of the entire venting process in LIBs, TR tests were conducted on 50 Ah NCM523 batteries with a 75% SOC within a sealed chamber filled with nitrogen. It facilitates the precise adjustment of ambient pressure and, to a significant extent, prevents subsequent reactions with oxygen, thereby enabling the observation of the intrinsic venting event. During the TR process, combustible emissions released from LIBs pose a high risk of fire accidents or explosions. Given that the oxygen concentration and its distribution can significantly influence the combustion process, different operation conditions are expected to lead to varying thermal hazard behaviors. Therefore, an inert and sealed piece of equipment was constructed to avoid the effects of oxygen and enhance comparability of test results. The tested batteries were triggered to undergo TR by lateral heating with a heating power of 400 W. Prior to each test, the chamber was evacuated to a pressure of 20 kPa to control the residual oxygen content. Subsequently, the internal pressure was adjusted to the desired value. To simulate diverse pressure conditions, the ambient pressure inside the chamber was set to 20 kPa, 100 kPa, and 260 kPa in terms of absolute pressure, respectively. TCs and pressure sensors were adopted to monitor the thermodynamic parameters inside the chamber, as well as the jet temperature. Both pressure and temperature were detected throughout the entire process in order to calculate the total gas amount. In addition to analyzing the variations in battery temperature and jet temperature, gas compositions as well as mass loss ratios were investigated at different pressures. By introducing a real-time gas amount calibration method, the venting characteristics were systematically evaluated.

As shown in Figure 1, a sealed and gas-tight chamber with a volume of 230 L was adopted to carry out TR tests and collect the vented gases. On the outside surface of the chamber, at least 3 K-type TCs were arranged to measure the battery temperature, the jet temperature (approximately 30 mm above the safety valve) and the ambient temperature, while pressure sensors with a full-scale error of 0.5% were installed to monitor the internal pressure of the sealed chamber. The tested battery was placed in the chamber by a fixture initially. A total torque of 4 N·m was applied uniformly at the four corners to create a consistent gap structure between the tested battery and the fixture for each test, in order to ensure that the heat conduction and heat dissipation conditions remained nearly unchanged. After the chamber was locked, a vacuum pump and a pure nitrogen cylinder were utilized to exchange the atmosphere inside the chamber. Firstly, the air inside the chamber was slowly removed with the vacuum pump until the vacuum degree reached 0.8. A few minutes were required to reach an equilibrium state, and the chamber was filled with fresh nitrogen with the pure nitrogen cylinder to the given pressure, typically atmospheric pressure. The atmosphere exchange operation was repeated to control the oxygen concentration below 1%. Then, the heating plate was turned on to initiate the thermal runaway process in the examined battery. The signals of the temperature and pressure were recorded with a data acquisition instrument for the whole process with a frequency of 1 Hz. When the venting event eventually terminated, gases inside the chamber were collected with gas collection bags for subsequent gas analysis. The gas chromatography analyzer, Trace 1300 (Thermo Fisher, Singapore), was primarily calibrated for H_2 , CO , CO_2 , CH_4 , C_2H_6 , C_2H_4 , and C_3H_6 , which were the most common gas species of the vented gases. Two thermal conductivity detectors (TCDs) were utilized to detect common permanent gases, while two flame ionization detectors (FIDs) were employed to analyze short-chain hydrocarbons. Argon (Ar) and helium (He) served as carrier gases. By calculating the total gas amount, the influence of ambient pressures on elemental contents of C, H and O in the vented gases were also explored. Additionally, flammability characteristics were analyzed based on gas analysis.

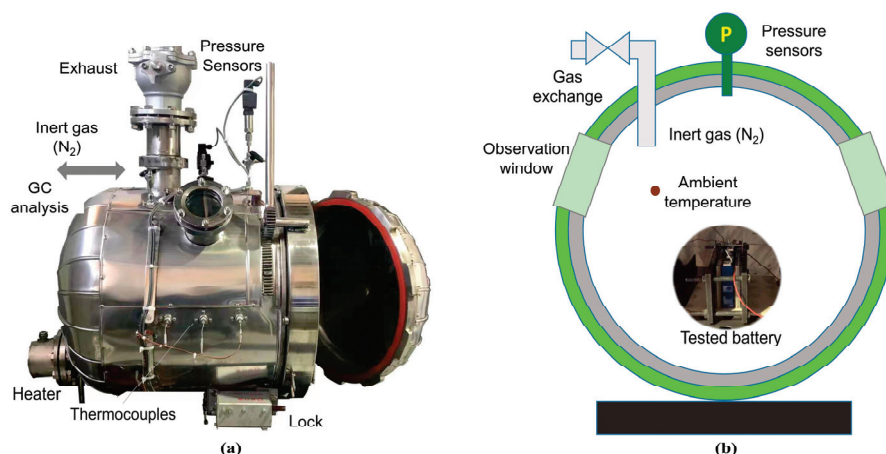


Figure 1. Experimental setup. (a) The sealed chamber; (b) a schematic diagram and the tested battery.

3. Results

3.1. Thermal Behavior

It has been observed that the beginning of a venting event during the process of TR is primarily governed by the pressure difference between the inside and outside of the battery, because the burst pressure of the safety valve is approximately consistent. Consequently, the venting event will appear earlier at a lower ambient pressure. However, owing to manufacturing variations in the burst pressure of the safety valve and potential discrepancies

in the reaction process under varying pressure, the evolution of internal pressure inside the battery may exhibit slight differences. Therefore, it is crucial to recognize that the start time of venting events is not the only judgement for determining venting behaviors.

As the tested battery was laterally heated to the TR, it is evident that the battery temperature on the heating side is more sensitive than that on the opposite side. Figure 2 presents the temperature curves on the heating side of the tested batteries under different pressures. For comparison, the moment when the heating plate was activated was set to $t = 0$ s. Approximately 20 min elapsed before the venting event occurred. The tested battery under 260 kPa reached the maximum temperature (827 °C) of the TR at $t = 1381$ s, while the maximum temperature of the tested battery under 100 kPa achieved the lowest value (749.9 °C) at $t = 1447$ s. The maximum temperature shows a positive correlation with ambient pressure, suggesting that a higher pressure results in a more violent TR, consistent with the previous results [18]. Compared with the case at 20 kPa, although the tested battery under 100 kPa achieved the maximum temperature at the latest, the maximum temperature was elevated. Meanwhile, the onset of the venting event under 20 kPa was significantly earlier than the other two cases. Hence, it may imply that the lower burst pressure of the safety valve can mitigate the hazards of the TR and provide earlier warning signals, such as characteristic gases. However, the internal pressure of the examined battery will increase to a certain degree during normal cycles. As a consequence, an optimal value of the burst pressure should exist in terms of early warning and hazard prevention for the TR.

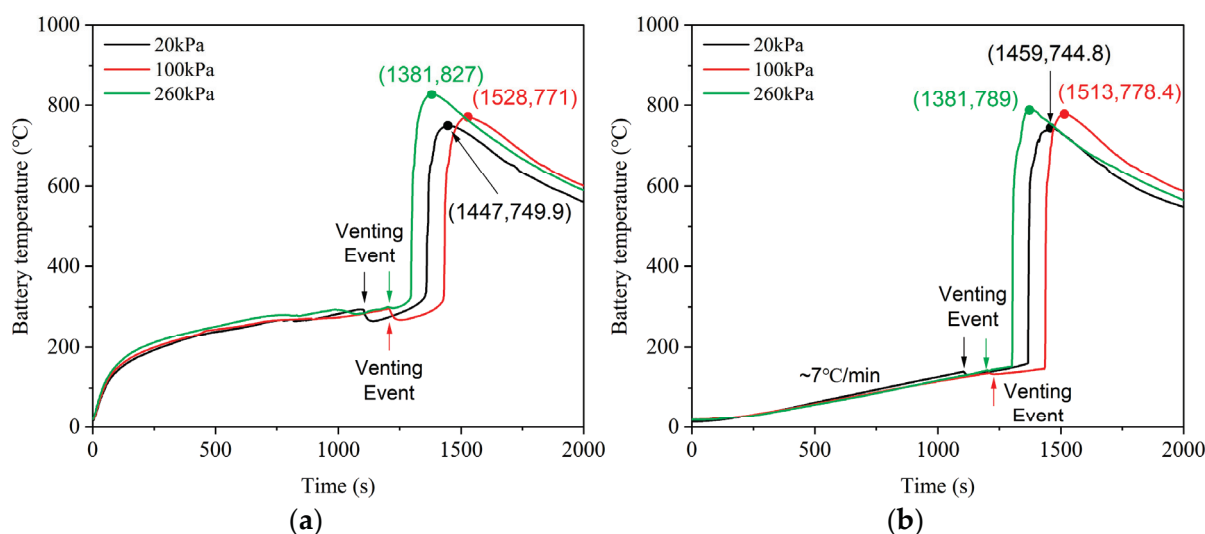


Figure 2. Temperature curves of tested batteries under different pressures. (a) Heating side; (b) opposite side.

Figure 3 illustrates the variations of jet temperature approximately 30 mm above the safety valve under different pressures. It is worth noting that it is difficult to avoid measurement errors as a result of the location of the measurement point and the heat capacity of the TCs. For the case at 20 kPa, jet temperature was first detected at $t = 1105$ s and reached the first peak (113.5 °C) at $t = 1194$ s and the second peak (309.2 °C) at $t = 1368$ s. For the case at 100 kPa, the jet flow appeared at $t = 1209$ s and its temperature reached the first peak (107.7 °C) at $t = 1237$ s and the second peak (239.4 °C) at $t = 1440$ s; for the case at 260 kPa, the significant rise in jet temperature appeared at $t = 1201$ s and reached the first peak (135.8 °C) at $t = 1209$ s and the second peak (200.2 °C) at $t = 1305$ s. It seems that the maximum jet temperature decreases with the elevated ambient pressures. The reason why all cases exhibited two peaks in the jet temperature curves was that two ejections occurred during the venting process. During the first ejection, the saturated

vapor pressure of electrolyte contributed the most, but TR was not triggered. With the elevated battery temperature, the main triggering reactions commenced and released a great number of gases; thus, the second ejection took place. The time interval between the second peak and the onset of the jet was employed to describe the response time, which varied conversely with the ambient pressure, namely 263 s under 20 kPa, 231 s under 100 kPa and 104 s under 260 kPa. The variations of jet temperature implied an earlier warning and a longer response time under a lower pressure. Characteristic temperatures of the tested battery and the jet during the TR are listed in Table 2.

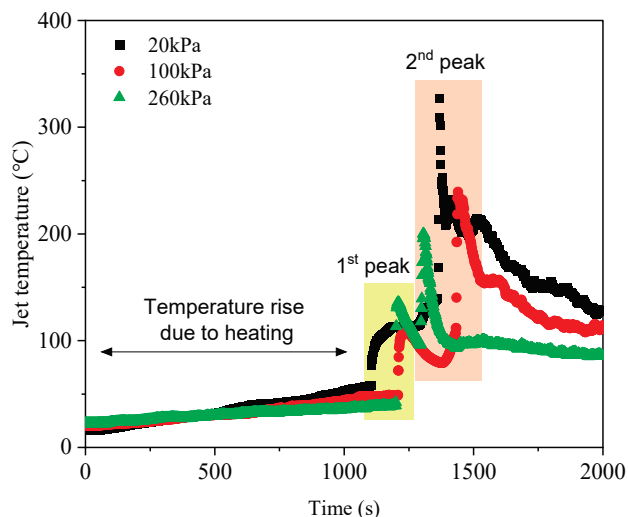


Figure 3. The time variation of jet temperature (about 30 mm above the safety valve).

Table 2. Characteristic temperature of the battery and jet field during TR.

Parameters	$P_0 = 20 \text{ kPa}$	$P_0 = 100 \text{ kPa}$	$P_0 = 260 \text{ kPa}$
Maximum battery temperature ($^{\circ}\text{C}$)	749.9	778.4	827
Maximum jet temperature of 1st peak ($^{\circ}\text{C}$)	113.5	107.7	135.8
Maximum jet temperature of 2nd peak ($^{\circ}\text{C}$)	309.2	239.4	200.2

3.2. Gas Venting Behavior

3.2.1. Evolution of Pressure in the Chamber

For the lithium-ion battery with an SOC near 50%, TR may not occur when the safety valve opens, because the battery temperature is still below the critical point to trigger TR reactions. Therefore, the burst of the safety valve and the TR event lead to two distinct venting processes. The first venting event is primarily driven by the increasing internal pressure of the battery as a consequence of continuous electrolyte evaporation, while the second venting event is probably induced by violent reactions of the TR. The battery samples adopted in this study conform to this scenario.

The pressure variations in the sealed chamber represent the intensity of the venting process to a degree. Figure 4 illustrates the diagrammatic sketch of a typical pressure curve of the examined batteries and defines several parameters to describe the whole venting process from the aspect of pressure variations inside the chamber. Prior to the opening of the safety valve, the pressure within the chamber is approximately equal to the initial pressure, P_0 . Similar to Figure 3, there are two pressure peaks, namely P_{P1} and P_{P2} , which may result from the dynamic pressure and the rapid cooling. After each pressure peak,

the pressure inside the chamber gradually approaches a constant value, P_1 and P_2 . The pressure variation between the peak pressure and the onset pressure is defined as the pressure impact to represent the venting intensity, such as ΔP_{P1} and ΔP_{P2} . Two parameters calculated at the stable stage, ΔP_1 and ΔP_2 , are positively correlated with the amount of gas released and represent the pressure effects of each venting process.

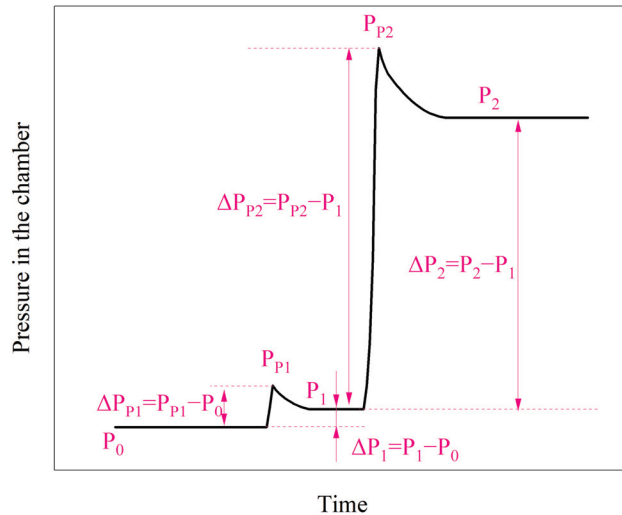


Figure 4. Diagrammatic sketch of typical pressure curve and parameter definition of pressure variation.

Figure 5 presents the four parameters, ΔP_1 , ΔP_2 , ΔP_{P1} and ΔP_{P2} , against ambient pressure inside the chamber. During the first venting process, exothermic or gas-producing reactions were weak, and as a result, only a few gases were released from the battery. Hence, the pressure effects of the first venting event under various ambient pressures were significantly smaller than those of the second venting event. It should be noted that the interval between the two venting events was much shorter for the case of 260 kPa. This could explain why ΔP_1 at $P_0 = 260$ kPa was lower. In terms of pressure effects, ΔP_1 was only 9.3%, 9.5%, and 6.8% of ΔP_1 for 20 kPa, 100 kPa, and 260 kPa, respectively, implying that most of the vented gases were produced by TR reactions and the pressure rise of the first venting event could hardly serve as a signal for the early warning of TR. However, organic electrolyte vapor and a small number of vented gases may serve as better indicators for predicting the occurrence of TR. In contrast, there is a great difference in the pressure impact between the two venting events. For the first venting peak, the pressure impact ΔP_{P1} was approximately 2~3 times the pressure effect ΔP_1 , while the value was approximately 1.5~3 for the second venting peak. The venting intensity of the second venting event was much more violent than that of the first venting event. Dynamic pressure shocks and ejections with the elevated temperature significantly contribute to the second pressure peak. In addition to the pressure rise due to the accumulated gases during the venting process, it is necessary to consider the margin of safety design to improve structure design and pressure relief design of the battery pack in consideration of pressure impacts. It is evident from Figure 5 that the pressure effect is considered as a weakly positive correlation with ambient pressure, while the pressure impact is strongly correlated with ambient pressure. The influence of ΔP_{P2} is greater than that of ΔP_{P1} . At low ambient pressures, both the pressure effect and pressure impact are at a lower level. Protection design against pressure rise becomes more complicated at a higher ambient pressure.

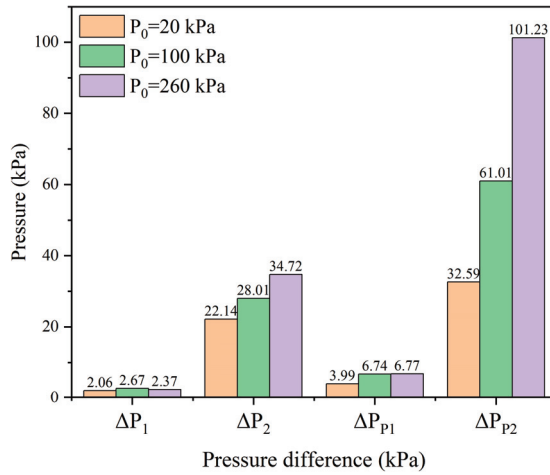


Figure 5. Comparison of pressure variation under different ambient pressure.

3.2.2. Evaluation of Gas Amount

Thermodynamic parameters of the chamber interior, pressure and temperature, are potentially influenced by test conditions and heat dissipation conditions. The variations of pressure and temperature could be disparate without given situations. Instead, the gas amount versus time, calculated by the ideal gas law based on the pressure and temperature in the chamber as expressed in Equation (1), represents the venting behaviors.

$$n = \frac{P_a V_0}{RT_a} \quad (1)$$

n is the total gas amount inside the chamber, in mol; P_a denotes the average of ambient pressure, in kPa; V_0 is the effective volume of the chamber, 230 L; R is the universal gas constant, 8.314 J/mol/K; T_a denotes the average of ambient temperature, in K.

The venting characteristic parameters are derived from the gas amount curve in Equation (1). Nevertheless, according to the pressure curve inside the chamber, the pressure peak means a non-equilibrium state. Near this point, the ideal gas law may not be applicable; hence, an evaluation method was proposed to calibrate the real-time gas amount, as shown in Figure 6. Before the venting event, the total gas amount was approximately a constant due to the gas-tight chamber, and the ideal gas law was satisfied. For each venting event, it could be further divided into two stages, namely the non-equilibrium stage and the quasi-equilibrium stage. Take the second venting process induced by the TR, for instance, in the non-equilibrium stage; the uneven temperature field and dynamic pressure led to an inaccuracy of the gas amount. At the point (t_2, n_2) , the first venting process adequately weakened, and the gas amount by the ideal gas law was reliable. The situation was also applicable after $t = t_3$. Based on the gas amount calculated directly by Equation (1), valuable datasets were available, namely (t_2, n_2) , (t_3, n_3) and (t_3, n_3') , where n_3' is the slope at $t = t_3$. A unique formula of quadratic polynomial was determined as Equations (2)–(4). In Figure 6, the black solid line and blue dotted line describe the whole real-time gas amount together, and corresponding venting characteristic parameters are acquired, such as the gas amount of each venting, the maximum gas release rate, the total gas amount, and the venting duration. Compared to the linear fitting method, the quadratic fitting method can satisfy the decaying tendency of each venting event in practice.

$$n(t) = a_i(t - t_{2i-2})^2 + b_i(t - t_{2i-2}) + n_{2i-2}, t_{2i-2} < t < t_{2i-1}, i = 1, 2 \quad (2)$$

$$a_i = \frac{n_{2i-2} - n_{2i-1} + n'_{2i-1}(t_{2i-1} - t_{2i-2})}{(t_{2i-1} - t_{2i-2})^2}, i = 1, 2 \quad (3)$$

$$b_i = \frac{2(n_{2i-1} - n_{2i-2})}{(t_{2i-1} - t_{2i-2})} - n'_{2i-1}, i = 1, 2 \quad (4)$$

n is the total gas amount inside the chamber, in mol; t denotes time, s; a_i and b_i are undetermined coefficients, in mol/s² and mol/s, respectively, and i denotes the first and second venting processes. In most cases, b_2 denotes the maximum gas release rate during TR.

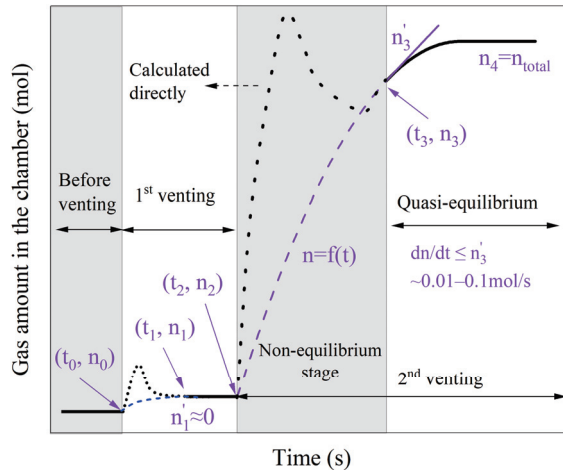


Figure 6. Method for evaluation of the gas amount during the process of venting [29].

3.2.3. Venting Characteristic Parameters

The primary venting characteristic parameters employed in this study encompass the maximum gas release rate, the total gas amount, and the venting duration. Table 3 lists the critical points employed in Section 3.2.2 under various ambient pressures, defined as Figure 6. The safety valve of LIBs opened at $t = t_0$, and the initial gas amount was mainly decided by the initial pressure inside the chamber. Therefore, the real-time gas amount could be calibrated to describe and predict venting behaviors.

Table 3. Critical points under various ambient pressures.

Parameters	$P_0 = 20 \text{ kPa}$	$P_0 = 100 \text{ kPa}$	$P_0 = 260 \text{ kPa}$
$t_0 \text{ (s)}$	0	0	0
$n_0 \text{ (mol)}$	2.28	9.75	24.54
$t_1 \text{ (s)}$	66	57	51
$n_1 \text{ (mol)}$	2.42	9.89	24.63
$n'_1 \text{ (mol/s)}$	0.00018	0.0011	0.0024
$t_2 \text{ (s)}$	250	219	94
$n_2 \text{ (mol)}$	2.48	9.99	24.69
$t_3 \text{ (s)}$	289	269	148
$n_3 \text{ (mol)}$	4.09	11.58	26.42
$n'_3 \text{ (mol/s)}$	0.0075	0.015	0.016
$n_4 \text{ (mol)}$	4.43	12.17	27.18

Figure 7 displays the comparison of the gas amount during each venting process and the predicted maximum gas release rate under different ambient pressures. For the first venting event, the total gas amount was around $0.20 \pm 0.05 \text{ mol}$ regardless of the dramatically changed ambient pressures. The amount of vaporized electrolyte and other produced gases was small, and the gases released in the first venting event over several minutes were limited. In comparison, the total gas amount during the second venting process was relatively large and presented a positive correlation with ambient pressure. Therefore, the second venting event is the dominant gas release process. The maximum gas

release rate depends on the fitting method to a degree, and the predicted maximum gas releasing rate is 0.075 mol/s for the case of 20 kPa in this study, obviously larger than that of other two cases. The maximum gas release rate should appear at $t = t_2$ for most cases. Although the gas amount increases with ambient pressure, the maximum gas release rate exhibits an inverse trend.

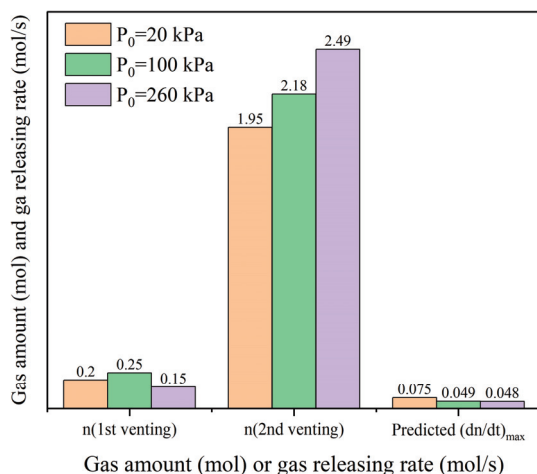


Figure 7. Comparison of gas amount and predicted maximum gas release rate under different ambient pressure.

Another important venting characteristic parameter is the venting duration, as shown in Table 4. Free cooling of the examined battery remains with the elevated temperature requires a long period, and gas-producing reactions continuously proceed; therefore, it is challenging to precisely define the venting duration for the whole venting process. In this research, t_{50} , $t_{50,1}$, and $t_{50,2}$, which are defined as the time intervals to release 50% of the total gas amount for the whole venting process, first venting event, and second venting event, respectively, are utilized to describe the venting duration and represent the average venting rate. $t_{50,2}$ is counted from $t = t_2$. Once the safety valve opens, all vented gases release from the examined battery more violently against ambient pressure in terms of t_{50} . The first venting event contributes slightly to the total gas amount, and $t_{50,1}$ is hardly influenced by TR reactions; hence, it is not discussed in detail in this research. As for the second venting event, the average venting rate on the basis of $t_{50,2}$ is much faster at a low ambient pressure. Although the duration of the entire failure process is longer at low pressure, the venting intensity induced by TR is more violent. Different venting modes should be applied under various ambient pressures.

Table 4. Venting duration under different ambient pressures.

Parameters	$P_0 = 20$ kPa	$P_0 = 100$ kPa	$P_0 = 260$ kPa
t_{50} (s)	264	243	124
$t_{50,1}$ (s)	32	24	45
$t_{50,2}$ (s)	16	28	33

3.3. Gas Analysis

3.3.1. Compositions of Vented Gases

The gas generation inside the battery due to the evolution of TR is one of the most essential processes to determine the venting behaviors. The identification of vented gases is of great importance to reveal the intrinsic mechanism of TR reactions and provide reference for hazard prevention. Both the proportion and content of the vented gases are crucial parameters to describe the venting behaviors.

Figure 8 gives the compositions and molar amount of the vented gases under different ambient pressures. In total, the six most common gas species, accounting for more than 1% by volume, were detected in all cases, including CO, CO₂, H₂, C₂H₄, CH₄, and C₃H₆, according to the order of proportion. As for the proportion by volume of the main vented gases, CO and C₃H₆ are negatively correlated with ambient pressure, while CO₂, H₂, C₂H₄, and CH₄ present a positive correlation with ambient pressure. There are significant changes in the gas proportion of CO and H₂. The molar amount which can be expressed by the product of the gas proportion and the total gas amount reflects the absolute content of each gas species, showing a consistent trend with the gas proportion. The content of CO₂ presents a strongly positive correlation with ambient pressure as the total gas amount increases. Meanwhile, there is a drop in the ratio of CO to CO₂, implying that the redox reactions among battery materials during TR are more complete under a higher ambient pressure. This can be attributed to the increased ejections of reactants under a lower pressure. On the whole, by adjusting ambient pressure, the main components of the vented gases can hardly change, while the relative proportion and absolute content of these gases significantly dissimilate. For instance, the concentration of CO drops by 12.6% (0.15 mol), while that of H₂ increases by 5.6% (0.24 mol).

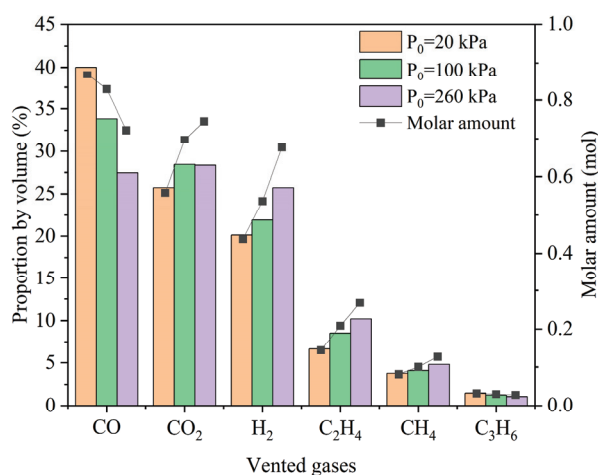


Figure 8. Vented gases under different ambient pressures.

The vented emissions are mainly composed of gases, particles, and liquid electrolyte or its reaction products (if any), which contributes to the mass loss together during the process of TR. In this study, gaseous emissions were mainly focused on. The total gas amount, the total mass loss and the total elemental contents of C, H and O are the overall parameters to characterize the gas venting event. Maximum battery temperature as a variable was recalculated by the average of the battery temperature, and 747.4 °C, 774.7 °C, and 808.1 °C were obtained for 20 kPa, 100 kPa, and 260 kPa, respectively, showing a strongly positive relation with ambient pressure. Figure 9 illustrates the influence of maximum battery temperature on the above parameters. The horizontal axis represents the average of the maximum temperatures for both sides of the tested battery. The mass loss varies inversely with the maximum battery temperature, while the total gas amount increases obviously with the maximum battery temperature from 2.15, 2.43 to 2.64 mol. Figure 3 points out that there are two ejections during the process of TR for each tested battery. Each ejection is made up of a fast ejection and a subsequently continuous stream. Under a lower ambient pressure, the earlier opening of the safety valve allows more liquid electrolyte to be ejected out of the tested battery during the first ejection before the TR. Under 260 kPa, the duration of the first ejection was relatively insufficient, which could explain the decrease in the mass loss ratio. Meanwhile, the total gas amount can describe

the intensity of TR to some extent, satisfying the positive relation. All the most common gas species are composed of C, H and O, and the molar amount of these elements shown in Figure 9 was calculated by the detected compositions in Figure 8. Element H significantly increases with ambient pressure, potentially implying that more decomposition reactions occur under an elevated ambient pressure because of a relatively long period prior to the onset of the safety valve. Furthermore, C and O show a weakly positive trend with the maximum battery temperature as a consequence of the increasing total gas amount. The average molar weight of the vented gases, defined as the proportion of the gas mass to the gas molar amount, also represents the degree of decomposition during the whole TR process, 26.30, 26.18, and 24.64 g/mol, respectively, with the increase in the maximum battery temperature, signifying more thorough reactions during the TR process. In other words, under a lower ambient pressure or for a lower burst pressure of the safety valve, some reactants are released from the tested battery at the initial stage prior to the TR; hence, less energy is released in a series of exothermic reactions, mitigating the intensity of the TR. However, more attention should be paid to the remaining battery materials and the vented emissions in order to prevent further energy release.

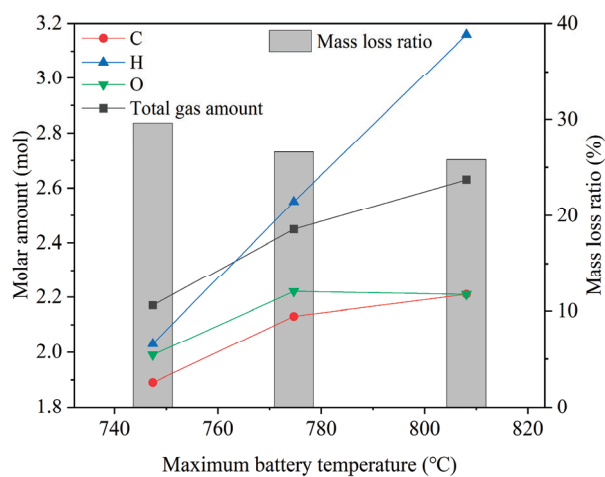


Figure 9. The overall parameters versus maximum battery temperature.

3.3.2. Flammability Characteristics of Vented Gases

Flammability characteristics, including the upper flammability limit (UFL), lower flammability limit (LFL), flammability range (R_F), and flammability hazard index (H_F), can effectively represent the flammability risk of vented gases to a great extent [25]. Equation (5) provides the calculation method for flammability limits of mixed combustible gases. When an inert gas, such as CO_2 , is present in the mixture, CO and CO_2 are treated as a new synthetic gas in this study. This synthetic gas is considered as a new component and substituted into Equation (5). R_F and H_F are expressed by Equations (6) and (7). The larger the R_F and H_F are, the greater the probability and hazards of combustion are. As mentioned in Section 3.3.1, CO, CO_2 , H_2 , C_2H_4 , CH_4 , and C_3H_6 are the most common species and normalized to calculate flammability characteristic parameters. Table 5 shows the results of flammability characteristics. Both UFL and LFL decrease slightly with ambient pressure. Based on R_F and H_F , although the probability of combustion reduces, the potential hazards increase significantly once a fire or explosion occurs.

$$\text{XFL}_{\text{mix}} = \frac{1}{\sum_i \frac{\varphi_i}{\text{XFL}_i}} \times 100\% \quad (5)$$

$$R_F = \text{UFL} - \text{LFL} \quad (6)$$

$$H_F = \frac{UFL - LFL}{LFL} \quad (7)$$

XFL denotes UFL or LFL and φ_i is the volume fraction of species i .

Table 5. Flammability characteristics of the vented gases.

Parameters	$P_0 = 20 \text{ kPa}$	$P_0 = 100 \text{ kPa}$	$P_0 = 260 \text{ kPa}$
UFL (%)	53.41	52.37	50.81
LFL (%)	8.53	8.20	7.49
R_F (%)	44.88	44.17	43.33
H_F	5.26	5.39	5.79

4. Discussion

Ambient pressure and burst pressure of the safety valve influence gas venting behaviors by altering the occurrence of venting events. Gas venting behaviors could be characterized by numerous parameters. In this study, the main characteristic parameters include maximum battery temperature, jet temperature, pressure shock, total gas amount, gas release rate, venting duration, early warning, and flammability risk, as summarized in Table 6. The ‘+’ symbol indicates beneficial effects for safety design of battery systems, while the ‘−’ symbol denotes poor performance. Additionally, the ‘o’ symbol represents reference values under normal pressure conditions. Overall, lowering ambient pressure or burst pressure of the safety valve leads to a relatively safe condition.

Table 6. Summary of main gas venting behaviors.

Parameters	$P_0 = 20 \text{ kPa}$	$P_0 = 100 \text{ kPa}$	$P_0 = 260 \text{ kPa}$
Maximum battery temperature	+	o	−
Jet temperature	−	o	+
Pressure shock	+	o	−
Total gas amount	+	o	−
Gas releasing rate	−	o	+
Venting duration	+	o	−
Early warning	+	o	−
Flammability risk	+	o	−

5. Conclusions

In this study, TR tests of 50 Ah prismatic NCM523 batteries with a 75% SOC were carried out using a 400 W heating plate in a sealed chamber filled with nitrogen under different ambient pressures. Thermal parameters, venting characteristics, gas compositions, and flammability characteristics were investigated to elucidate the gas venting behaviors. The vented gases were analyzed by GC and compared in terms of the composition and molar number of main elements. By comparing the characteristics of venting behaviors under different ambient pressures, the mechanism of external pressure on the process of TR was explored. The research can assist in optimizing the burst pressure of safety valves for prismatic batteries and provide guidance for battery safety evaluation under various operating pressures.

The primary conclusions are as follows:

- (1) Different ambient pressures significantly affect the TR process and gas venting behaviors.
- (2) In this study, lower ambient pressure leads to an earlier venting event, mitigates the intensity of TR in terms of maximum battery temperature, and reserves more response time for hazard prevention. Simultaneously, lower ambient pressure reduces the total gas amount and increases the mass loss ratio.

- (3) Pressure effects and shocks are remarkable at elevated ambient pressures, particularly during the second venting event. The first venting event contributes minimally to the overall venting process, except for providing early warnings for TR.
- (4) The six most common gas species above 1% by volume were detected under different pressures, including CO, CO₂, H₂, C₂H₄, CH₄, and C₃H₆, accounting for over 97% of all vented gases by volume. Lower ambient pressure implies more incomplete reactions during the process of TR and releases less CO₂.
- (5) Among the main vented gases, element H increases significantly with ambient pressure, indicating that electrolytes and separators contribute more to gas generation during TR under higher pressures.
- (6) Reducing ambient pressure or burst pressure of the safety valve enhances the safety design of battery systems.

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Article

Cloud-Enabled Reconfiguration of Electrical/Electronic Architectures for Modular Electric Vehicles

David Kraus *, Daniel Baumann, Veljko Vučinić and Eric Sax

Institut fuer Technik der Informationsverarbeitung (ITIV), Karlsruhe Institute of Technology (KIT), Engesserstr. 5, 76131 Karlsruhe, Germany; daniel.baumann@kit.edu (D.B.); veljko.vucinic@kit.edu (V.V.); eric.sax@kit.edu (E.S.)

* Correspondence: d.kraus@kit.edu

Abstract: Modern mobility faces increasing challenges, like carbon-free transportation and the need for flexible transportation solutions. The U-Shift II project addresses these problems through a modular electric vehicle architecture, a drive unit (Driveboard) and a vehicle body (Capsule). This separation offers high flexibility in different use cases. Current architecture paradigms, like AUTOSAR, face limitations in cost and development speed. To address these issues, this paper introduces a hybrid software architecture that integrates signal-oriented architecture (e.g., CAN bus) with service-oriented architecture for enhanced flexibility. A integral component of the hybrid architecture is the dynamic link system, which bridges these architectures by dynamically integrating Capsule-specific components into the Driveboard software stack during runtime. The performance of the developed system and its functionality were evaluated using a hardware setup integrated into a Driveboard prototype. The dynamic link system was evaluated including latency measurements, as well as functionality tests. Additionally, a cloud-based reconfiguration process enhances the versatility of the Driveboard by allowing for over-the-air software updates and resource allocation. The results show a promising hybrid, reconfigurable E/E architecture that aims to enable a robust transition towards a pure service-oriented architecture required in future electric autonomous vehicles.

Keywords: electric connected vehicles; e/e architecture; software architecture; service-oriented architecture; cloud computing

1. Introduction

In an era characterized by rapid urbanization and technological innovation, the global transportation landscape is undergoing a profound transformation. Urban mobility is being reshaped by three key trends, namely, the sharing economy, electrification, and the advent of autonomous vehicles, fundamentally altering how people and goods move within and between cities [1]. Traditional paradigms of personal vehicle ownership and conventional public transportation face significant challenges as urban centers grapple with congestion, environmental sustainability, and equitable accessibility. Amid these challenges, the concept of shared modular mobility emerges as a viable and innovative solution, offering a flexible and adaptive framework to address the dynamic needs of modern societies. The interplay between shared mobility models and advanced electrical/electronic (E/E) architectures redefines vehicles as intelligent and interconnected systems rather than mere modes of transportation. Through the prioritization of signal-based communication, vehicles achieve seamless interaction with their components and dynamically respond to their surroundings, creating a safe, efficient, and responsive network. Furthermore,

the integration of service-based software enhances modularity, enabling vehicles to deliver tailored functionalities based on their current configuration. As this trend gains momentum, established automotive manufacturers are adapting to meet the demands of modularity and scalability. For instance, Daimler has announced plans to mass-produce a modular and scalable “Van Electric Architecture” [2], which decomposes the vehicle into three interchangeable units during manufacturing. Similarly, Kia introduced its “Platform Beyond Vehicle” at CES 2024 [3], adopting a comparable approach. These innovations enable the creation of modular vehicles with interchangeable components, allowing for a diverse range of hardware configurations.

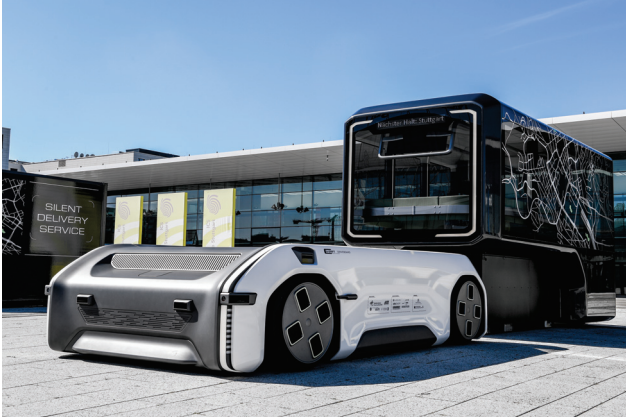
However, traditional software architectures, typically designed for fixed hardware setups, face significant challenges in accommodating the variability introduced by modular components. Signal-oriented software architectures are by design limited in their ability to efficiently adapt to the dynamic requirements of modular vehicles, particularly when unique software adaptations are necessary for different configurations.

Service-oriented architecture offers a promising solution to address these challenges. By decoupling software functionality from specific hardware configurations, Service-Oriented Architecture (SOA) enables greater flexibility, scalability, and adaptability in managing the complexity of modular and scalable vehicle architectures, paving the way for more efficient and innovative automotive solutions. An SOA approach is already well established in consumer web and cloud services where APIs based on HyperText Transfer Protocol (HTTP) are typically used for exchanging information. However, due to the fundamental differences of the consumer cloud and automotive applications, HTTP cannot be used in the automotive industry [4]. As a solution, current standard architecture solutions like AUTOSAR Adaptive are already focusing on an automotive, service-based architecture with Scalable Service-Oriented Middleware over IP (SOME/IP). Combined with AUTOSAR Classic via a gateway Electrical Control Unit (ECU), it is already possible to combine bus systems with SOA. However, this system lacks two major points. First, as AUTOSAR is economically driven, the annual fee for using a AUTOSAR Basic Software stack by a provider is well above EUR 10.000, depending on the company size and volume. Secondly, of significant importance is to mention that the AUTOSAR documentation is in need of improvement [5]. Therefore, frameworks like ROS2 are a promising alternative to the current popular software architecture solutions like AUTOSAR, as there are already some efforts towards automotive applicable ROS2 versions [6]. Furthermore, the field of connectivity has emerged in the automotive sector. Most modern vehicles are connected to a cloud, and some vehicles, like the Volkswagen ID.3, are leveraging Vehicle-to-Vehicle (V2V) to enhance the overall awareness through messages like Cooperative Awareness Message (CAM) [7] and Decentralized Environmental Notification Message (DENM) [8] defined by the European Telecommunications Standards Institute (ETSI). This article is an extended version of the authors’ contribution to the International Electric Vehicle Symposium and Exhibition (EVS37), held from 23 to 26 April 2024, in Seoul, Republic of Korea [9]. Building on that work, Section 3 has been revised and expanded with Section 3.2, which provides a more detailed description of the cloud reconfiguration process. Additionally, the evaluation has been extended to incorporate the new content in Section 5.

1.1. Problem

The U-Shift II platform represents a solution for modular electric autonomous vehicles tackling challenges of modern mobility [10], similar to the vehicle concept from the first U-Shift project (see Figure 1). Within U-Shift II, an on-the-road modular vehicle, which has to seamlessly integrate different capabilities and dependencies, and which comes equipped with the current Capsule topology, is developed. With that flexibility, the conception of

a suitable E/E architecture becomes a major challenge. Besides the power supply needs, the Capsule could also provide a prior unknown set of sensors and actors, which the Driveboard has to accommodate within the current system configurations. With that in mind, typical automotive E/E architectures of modular vehicles quickly reach their limits, endangering their potential (benefits) to the overall mobility.



(a) Driveboard and Capsule separated



(b) Driveboard with attached Capsule

Figure 1. U-Shift vehicle concept [11].

1.2. Aim

The transition towards a native automotive SOA needs to be initiated with hybrid software architectures. Hybrid software architectures are an emerging system bridging the gap between current technical standards and future software-defined cars by exploiting the flexibility and fast development cycles enabled through SOA systems while still being able to have a failure-proof and cost-efficient way to distribute information within set time constraints. Considering the fully autonomous functionality combined with high modularity achieved with different Capsules, U-Shift presents the unique demonstrator for implementing and evaluating a hybrid and modular software architecture.

1.3. Contribution

We provide a detailed understanding of our developed E/E architecture for automated modular vehicles. This is achieved through the development of a prototype Driveboard and its construction within the U-Shift II project. Within that prototype, the proposed concepts for a hybrid software architecture, combining service- and signal-oriented architectures, are implemented and tested. Through a dynamic software coupling mechanism, namely, the dynamic link, the signal- and service-oriented architectures enable a seamless transition between Capsule topologies and therefore its use cases, leading to new requirements to the overall E/E architecture. Through 5G connectivity, the Driveboard itself can leverage cloud computing capabilities and over-the-air updates to enhance the overall performance, reliability, and adaptability towards new Capsule technologies. In Section 5, measurements are conducted to show the capability of the proposed dynamic link concept. We provide performance benchmarks to evaluate the necessity and suitability of the cloud-based reconfiguration mechanisms.

2. State of the Art

The automotive industry is undergoing a significant transformation as it shifts from traditional signal-oriented architectures to more flexible service-oriented architectures. Signal-oriented architectures have historically been the backbone of automotive E/E systems and they rely on predefined communication protocols, such as Controller Area Net-

work (CAN). This approach has limitations in the sense of modular vehicles, particularly in terms of scalability and flexibility, as it requires static configurations that can slow down the rapid development and adaptation of new functionalities [12].

Recent research explores various aspects of SOA implementation in automotive systems, focusing on resource allocation, network architecture, timing predictability, and communication protocols. A method for optimization-based resource allocation in SOA was proposed in [13]; it utilizes mathematical optimization to schedule service parameters while considering dependencies between data flows and computations within services. The research focused on optimizing resources locally inside vehicle ECUs and across multiple services and ECUs. The integration of Software-Defined Networks (SDNs) with service-oriented architectures was investigated in [14] through a simulation environment as a means to support dynamic network configurations in vehicles. This research demonstrated the use of SDNs to support a dynamic, service-oriented network architecture using the SOME/IP protocol. Furthermore, a formal timing analysis of the discovery phase in SOME/IP was developed in [15]. This work highlighted the importance of the SOA discovery phase in determining the readiness of vehicle sub-systems, as the time required to complete this phase is a critical parameter for overall system performance. A case study [16] discussed the implementation of an SOA distributed feedback control loop automotive application using SOME/IP and programmable data planes, and demonstrated the potential benefits of incorporating SOME/IP awareness of overall automotive SOA applications and network devices. Efforts to improve the performance and platform independence of SOA implementations have also been made. Bitroute SOME/IP, a new implementation of the SOME/IP communication protocol, focuses on execution performance and deployment platform independence, addressing the need for scalable and efficient communication middleware in modern automotive systems in [17]. These advancements in SOA applications for automotive systems represent significant progress towards more flexible, scalable, and efficient vehicle software architectures. The UNICARagil research project is based on a scalable drive platform and various usage units [18], similar to the U-Shift project. Compared to U-Shift, the authors used a native SOA approach for their autonomous vehicle solutions [19,20].

Currently, hybrid signal- and service-oriented architectures that include a combination of Ethernet, CAN, and FlexRay, are more realistic in practice, as stated in [13]. One of the first efforts of hybrid service-oriented architectures with a practical case study was shown in [21]. Applications of hybrid software architectures were also discussed in the context of the classical signal-based, CAN and ECU-driven AUTOSAR Classic and the Adaptive platforms that form a SOA using Ethernet [22]. The state of the art indicates that in order to fully leverage the advantages of a pure SOA required for modular autonomous electrical vehicles, a controlled transition of hybrid architecture presents itself as an intermedial solution for the current state of industry based on signal-oriented approaches.

In the cross-section area of SOA and cloud technologies for automotive applications, there is a significant shift towards more dynamic, flexible, and interconnected systems. The authors of [23] introduced an Orchestrator for dynamically extending automotive E/E architectures to the cloud, enabling Control Over the Air (COTA) capabilities for non-safety-critical functions. This approach aligns with the growing trend of service orchestration across edge and cloud environments, as exemplified by the study on object detection in industrial vehicles [24]. Further work carried out in [25] shows a multi-layered SOA which provides abstractions for heterogeneous computing hardware and facilitates the integration of cloud computing and big data analysis for advanced autonomous driving technologies. To ensure high availability and enhance Quality of Service (QoS) in cloud computing, various replication strategies have been developed, categorized into data-oriented and

service-oriented approaches in [26]. Furthermore, a demonstration of the vehicle update management systems connecting in-car communication networks with out-car services, including cloud vehicle services, was provided in [27].

The utilization of cloud technologies in the automotive sector spreads towards the online reconfiguration of automotive software architectures. The expansion of on-board computing and storage capacity through cloud computing has given rise to the concept of cloud-based vehicle functions, which use cloud capabilities to enhance vehicle control strategies and enable new functionalities that would otherwise not be feasible with on-board resources [28]. The authors of [29] emphasized the potential of cloud connectivity in vehicles, enabling computationally intensive machine learning models to be executed in the cloud, with applications such as reducing the energy impact of air conditioning in city buses. By leveraging the scalability and computing power of the cloud, a mixture-of-experts approach can be used [30], where a gating mechanism dynamically selects specialized models based on context-specific data to optimize vehicle functions and adapt to different scenarios. The authors of [31] proposed a reconfiguration protocol for Ethernet TSN in automotive systems, which enables dynamic over-the-air network operation using the cloud with features like traffic isolation, fault recovery, and performance adjustments, enhancing both safety and user experience with reconfiguration. Furthermore, Ref. [32] introduced a cost-aware multifaceted reconfiguration approach for dynamic routing applications, leveraging infrastructure-as-code modules for efficient resource allocation and the rescheduling of idle components. Finally, Ref. [33] presents a smart cloud management system using a knowledge base to model cloud resources, manage service-level agreements, and optimize resource allocation through RESTful services.

3. Hybrid E/E Architecture Concept

3.1. Dynamic Link System Architecture

For the use case of the Driveboard, a dynamic link system architecture emerges as a viable solution to address the challenges associated with the evolving landscape of Capsule technologies. Due to the inherently static nature of signal-based systems, such as CAN bus, a well-defined information flow interface is required to bridge the service-oriented and signal-based components of the hybrid software architecture. In addition, updates to the signal-oriented ECU occur infrequently and are typically performed during major maintenance in a workshop. To ensure a universally applicable Driveboard, a universal dynamic link system message becomes essential.

The Dynamic Link System (DLS) message comprises two essential parts: the Universal Information Field (UIF) and a corresponding Rule Identifier (RID). The UIF acts as a unique identifier that dictates how to interpret the data within the DLS message. Essentially, the RID serves as an interface definition for the Orchestrator's Dynamic Link X service. It creates a standardized communication protocol between the Driveboard and Capsule. This design ensures both backward and forward compatibility. This means that the Driveboard can understand messages from Capsules built with different technologies and functionalities. An RID-based design enables the DLS architecture to support modular and extensible interactions. As new Capsule features or functionalities are developed, corresponding RIDs can be introduced to define these advancements without requiring modifications to the Zone Controller ECU's software. This modularity ensures that the Driveboard remains versatile and capable of supporting a wide array of Capsules without necessitating fundamental redesigns or software updates. The UIF within the DLS message acts as a container for transmitting various types of data, including sensor readings, control commands, and status updates. Capsule services leverage the DLS message to interface with the signal-oriented components of the Driveboard, such as CAN bus and

other communication buses. The encapsulated information within the UIF is translated and bidirectionally routed, enabling efficient and standardized communication between the Driveboard and the Capsule. This architecture ensures a robust and adaptable platform for seamless interaction across diverse Capsule technologies.

A key factor of the DLS is the dynamic integration of Capsules during runtime. Therefore, a Plug-and-Play compatibility is needed to process of connecting and disconnecting Capsules. The overall DLS architecture is displayed in Figure 2. As can be observed on the left side, one Capsule X of a variety of Capsules connects the DLS to the Driveboard, where it initially shares the Capsule type with the Driveboard Orchestrator, as can be seen in Figure 3. The Orchestrator then contacts the Capsule Service Backend to download the corresponding Dynamic Link X service and integrates it into the already operating SOA. As soon as the new Capsule connects with the Driveboard, it announces itself with its Capsule type. After a handshake process, the Driveboard first downloads the new service and starts the Capsule-specific Dynamic Link X service. Once this Dynamic Link X is ready to operate, it also sends an announcement message. After receiving a final acknowledgment flag from the Capsule X, the Dynamic Link X service starts to operate. This Dynamic Link X can then be used for a wide variety of applications. For example, the Capsule can have, depending on the Capsule type, a battery storage of its own, which can be used to either support the battery storage of the Driveboard or, vice versa, to balance out the state of charge (SoC). By exchanging information on the SoC, encoded with a specific RID, the Driveboard can dynamically adjust power distribution to balance the SoC between the Capsule and the Driveboard. This ensures the optimal utilization of energy resources, prolongs the range, and can prevent deep discharges of the batteries, therefore extending the battery life. Another application would be a Capsule weight-based motor controller adjustment. With the ability to communicate weight information from sensors within the Capsule to the Driveboard, the DLS enables adaptive motor controller adjustments based on the Capsule's weight. For example, in a Capsule carrying varying payloads, the motor controller can dynamically adjust torque output or regenerative braking settings to optimize performance and efficiency based on the current load. Taking safety into account, the DLS enables the coupling of safety-critical elements of the Capsule and the Driveboard (e.g., the door interlocks of the people mover Capsule with the motor enable signal of the Driveboard). Other applications synchronize similar actuators of the Capsule and Driveboard, such as light controls, enabling the real-time monitoring of the overall system, among others. To maintain robust operation within the CAN bus by ensuring timely message transmission while preserving the flexibility of SOA, the system retains the most recent successful transmission between the two domains.

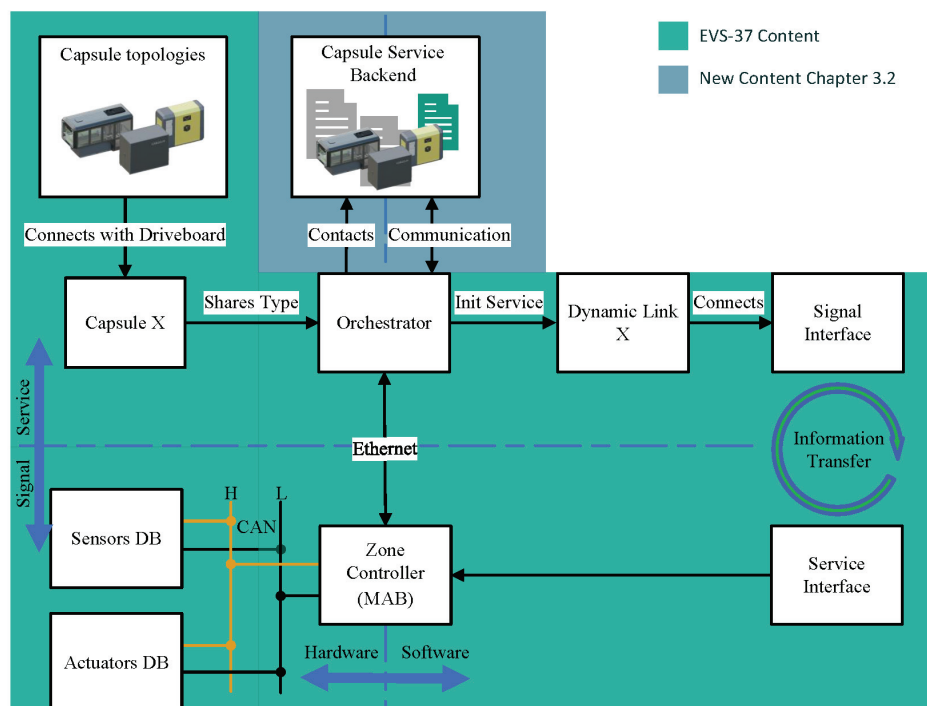


Figure 2. System architecture of dynamic link system based on [9].

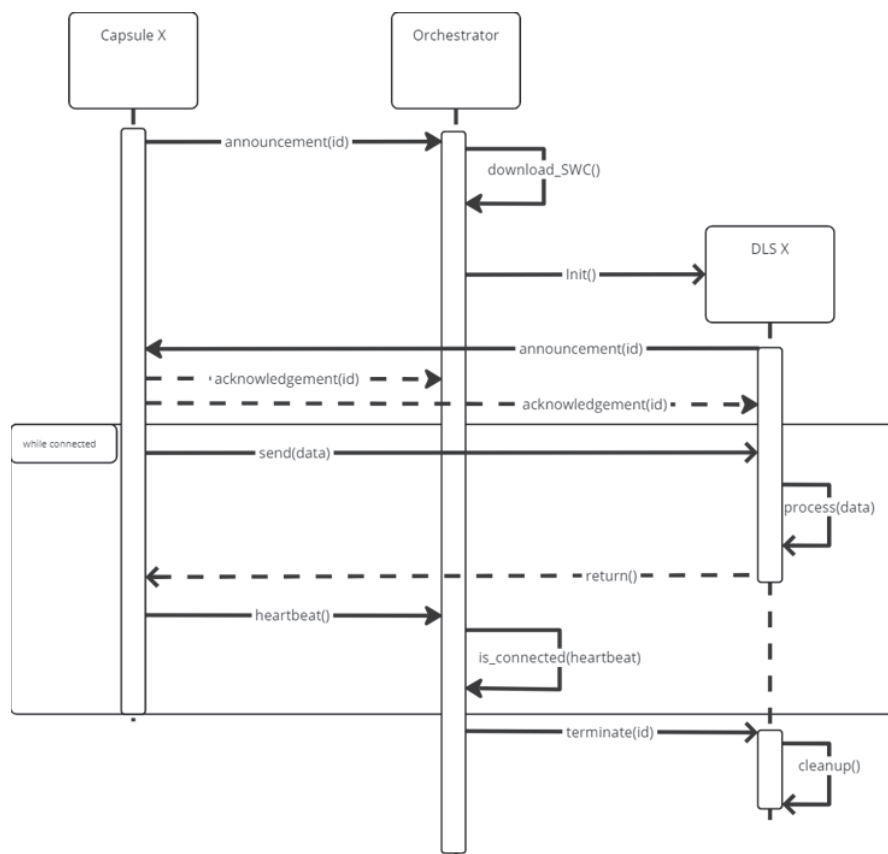


Figure 3. Startup sequence of new DLS X-Software Component (SWC) and exemplary interaction between Capsule and Driveboard.

3.2. Cloud-Enabled Software Reconfiguration

Running an SWC in the cloud offers a number of advantages. A key advantage of integrating the cloud is the ability to dynamically include real-time data and external information

in the SWC. Relevant data include, for example, current weather data or traffic forecasts, which can be processed in real time and adapted to the individual requirements of individual vehicles. Furthermore, the cloud enables the creation of a comprehensive fleet database that centrally stores and aggregates information from all vehicles in a fleet. Another advantage of outsourcing to the cloud is that it overcomes the resource limitations imposed by the hardware within a vehicle. Cloud systems offer virtually unlimited computing and storage capacities, so that computing and data-intensive applications can be executed without using up the capacities of the on-board systems. Finally, the cloud architecture ensures the global availability of outsourced functions and data. Relevant information can be provided, updated, and used regardless of the vehicle's location, which is particularly advantageous for globally operating fleets. Before an SWC can be executed in the cloud, it must first be evaluated for its feasibility to be offloaded (see Figure 4). Preliminary work on this subject has already been conducted in [34] and can be incorporated into this process. The evaluation process consists of two steps. The first stage determines the operational relevance of the function based on criteria such as real-time requirements or Automotive Safety Integrity Level (ASIL). If a function is deemed not operationally relevant, its suitability for offloading to the cloud can then be assessed. This suitability is determined by a combination of quantitative and qualitative criteria. Quantitative criteria include potential energy savings at the hardware compute level and potentially faster response times due to faster processing in the cloud. The potential added value of outsourcing a function, such as the benefits of fleet learning, is assessed qualitatively and is also included in the evaluation process. At the end of this process, each function is assigned a suitability score that is normalized to a range between 0 and 1, with higher scores indicating greater suitability for cloud offloading. The main advantage of running SWC in the cloud is the ability to have not just one general model for a functionality, but different experts. An expert model is a specialized machine learning model that has been trained on a specific context or dataset and thus achieves particularly high performance in its area of application. However, a general base model is still required to serve as a fallback solution if no suitable expert is available. The use of a general base model as a fallback solution is essential to ensure that the system remains operational even when no suitable expert model is available or applicable. This base model can serve as a versatile solution capable of providing acceptable results across a wide range of contexts. However, it may offer lower performance compared to the specialized expert models. The combination of expert models and a base model allows the system to achieve both flexibility and efficiency, dynamically adapting to various requirements and data contexts.

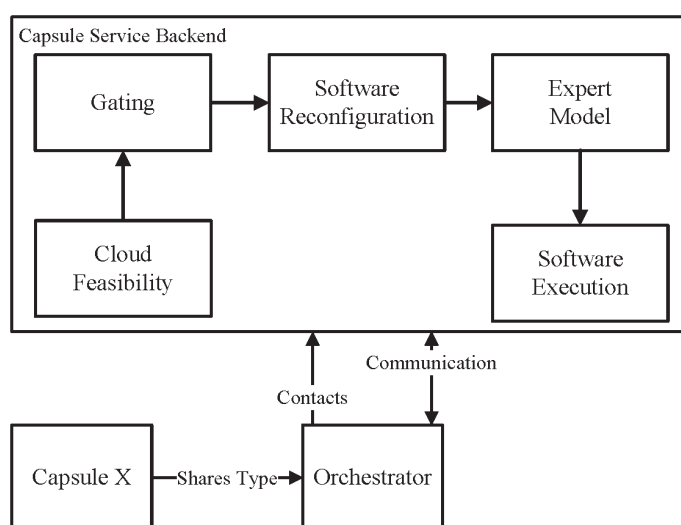


Figure 4. Reconfiguration of a software component in the cloud with a gating mechanism and the context for selecting expert networks.

A general machine learning model that offers a broad coverage of all possible context areas serves as a starting point. In addition, a number of expert models are required, each of which has been trained for specific contexts. These expert models should have clear areas of application that can be adapted depending on the context. Furthermore, these expert models can be gradually learned and incorporated during the system's operation. As new contexts emerge or existing ones evolve, the system can continuously refine its expertise by training and integrating new specialized models. This dynamic approach allows the system to improve its performance over time. When a request is made to the cloud, the appropriate expert must be selected via a gating (see Figure 4). The gating can be a simple lookup table or a trainable mechanism such as a neural network or a decision tree. Based on the input data, a decision is made as to which expert is relevant for the given task. If no expert model is suitable or available, the general model or the model with the greatest coverage is selected. Depending on the expert selected, the software is reconfigured accordingly and executed in the cloud (see Figure 4). The reconfiguration process involves dynamically loading the required model, adapting the processing pipeline, and ensuring compatibility with the incoming data format. Software execution is then orchestrated by allocating the necessary computational resources. The result is sent back to the vehicle via the communication channel.

4. Prototypical Setup

The goal of sustainable mobility can be achieved through modular electric vehicle architectures, in which fewer vehicles with a higher daily usage time complete the necessary journeys. In order to achieve the highest possible modularity, the U-Shift II vehicle concept breaks up existing structures and divides the vehicle into a drive unit (Driveboard) and a vehicle body (Capsule), as can be seen in Figure 1a,b, where a prototype Driveboard with a people mover Capsule from a predecessor project can be seen.

The Driveboard integrates all the components required for fully automated electric vehicle operation, including electric drives, a battery system, control units, and environmental sensors. Automation is achieved using the novel hybrid A* path planning algorithm proposed by Schumann et al. [35], which integrates the unique driving characteristics of the Driveboard. The specific application of the vehicle is determined by selecting an appropriate Capsule. Depending on the chosen Capsule, the vehicle can support diverse use cases such as passenger transport, food delivery, bicycle collection, or cargo logistics. A lifting mechanism embedded within the chassis enables the vehicle to autonomously pick up and dock with Capsules without external assistance.

A key design requirement for the Driveboard is its adaptability to the varying architectures of different Capsules, addressing the challenges of modern mobility. This adaptability ensures compatibility with ongoing advancements and dynamic developments in Capsule technologies. Since new Capsule designs, functionalities, and configurations are likely to emerge after the Driveboard's production, it must accommodate these changes to remain effective and versatile across diverse vehicle applications. This adaptability is essential for sustaining the Driveboard's relevance in an evolving technological landscape. The hardware setup implemented in the U-Shift II system for dynamic linking is illustrated in Figure 5. This setup is divided into two primary sections. The main section is located at the front of the Driveboard and houses components facilitating the integration of service-oriented and signal-oriented architectures, highlighted in blue. This section also includes the Capsule coupling mechanism, which interfaces with key Driveboard components, such as the Orchestrator. The Orchestrator manages communication and operates the service-oriented architecture. The dSpace MicroAutoBox (MAB) serves as the Zone Controller, functioning as a real-time-capable rapid prototyping system that manages the control and

communication of most sensors and actuators on the Driveboard. Communication in this system occurs via signal-oriented methods, utilizing various CAN bus components to meet hard real-time requirements.

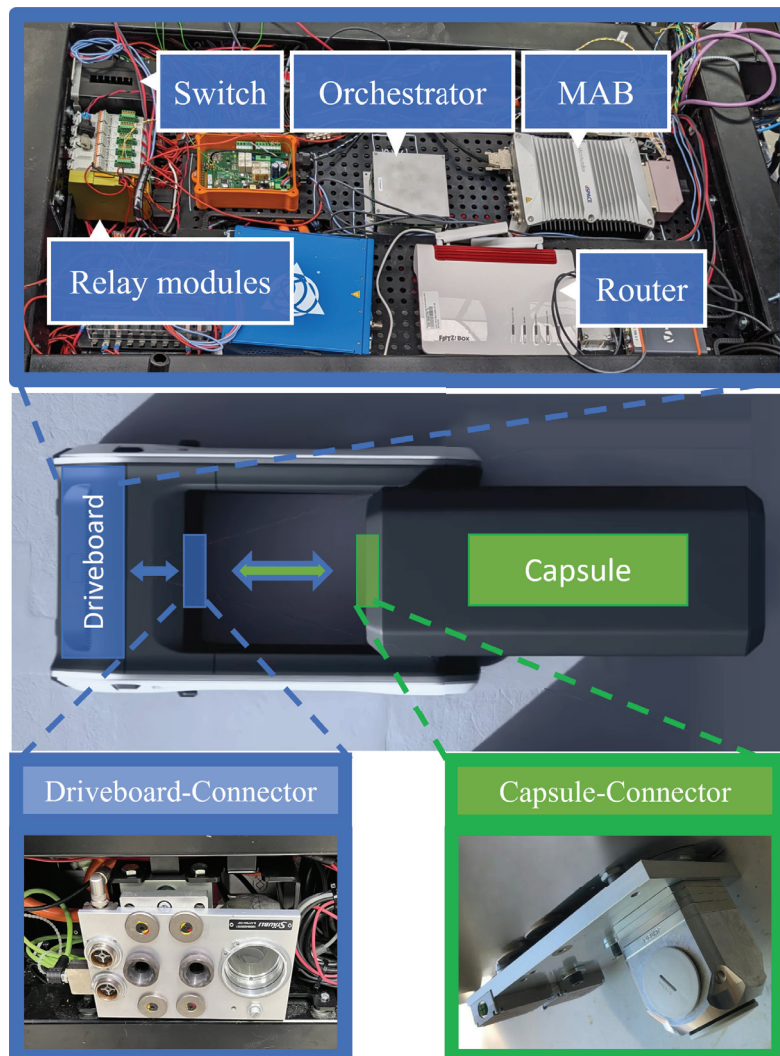


Figure 5. U-Shift II prototype hardware setup.

The MAB and the Orchestrator execute software components designed to facilitate dynamic integration between signal-oriented and service-oriented architectures. To meet the real-time performance requirements of the Driveboard and ensure the execution of safety-critical functions within specified temporal constraints, the MAB operates at a clock frequency of 1 kHz. This configuration ensures that all essential tasks for controlling the Driveboard are executed reliably. Communication between the MAB and other control units within the network is established through the Ethernet interface using the UDP protocol. This approach enables the seamless integration of service-oriented architecture elements into the signal-oriented framework of the Driveboard. The switch is used as a physical interface between Orchestrator, MAB and possibly connected Capsules. The time synchronization in normal operation is established between the MAB, Orchestrator, and Capsules through a high-precision Precision Time Protocol (PTP) Grandmaster. The second part of the hardware setup is indicated in green and represents the Capsule and its coupling mechanisms between the Driveboard and Capsules, respectively. They offer mechanical, power, and networking coupling that ensures the full modularity of U-Shift II. Within the Capsule, there is at least one small ECU that acts as an interface between the Orchestrator

and the Capsule itself. As a cloud provider, we use our in-house server infrastructure to create a dedicated Virtual Machine (VM) for U-Shift II as the Capsule Service Backend (CSB). The VM is vertically and horizontally scalable as needed for the deployment of updates to the Driveboard and the execution of other SWCs. The Driveboard initiates an IPSec-secured VPN connection with Advanced Encryption Standard (AES) to the CSB if needed. This ensures the authenticity and security of the communication between the Driveboard and CSB.

5. Measurements and Evaluation

For the experiment, an implementation of the DLS architecture was evaluated by taking two of the aforementioned scenarios into account. Firstly, there was the shared weight information of the Capsule attached, which could then be used to optimize control parameters within the MAB, and, secondly, to measure the transmission delay from synchronizing signals from the Dynamic Link X service to the signal-oriented CAN bus, we controlled the light actuators of the Driveboard which are components of the CAN bus system. For the measurements including latency information, the Orchestrator PC and the MAB were first synchronized directly with PTP, where the MAB serve as master clock.

The performance of the PTP synchronization was observed with approximately 9000 measurement points and can be seen in Figure 6, with a median time deviation of the MAB and Orchestrator of $56 \mu\text{s}$, where the maximum outlier peaked at $246 \mu\text{s}$. Therefore, the worst case approximation of the synchronization in our hardware setup in the measurements can be assumed at $250 \mu\text{s}$. The results shown in the Figure 6 reflect the specific hardware setup used in the case of the U-Shift II demonstrator, but the reasoning and performance will be scaled to this solution. The average transmission times from the Orchestrator to the MAB were 1.23 ms , which is below 2.5 ms , which therefore can be assumed as the worst case transmission time between two control units in the vehicle. This opens up the possibility of controlling even, as aforementioned, safety-critical functions like battery shutdown or emergency stopping, via the dynamic link interface, although these were not explicitly considered in the current work. The variance in the transmission times depending on the direction resulted from the constant clock of the MAB, which was firmly defined to maintain real-time capability and was not further reduced due to the computing time required for other tasks. For further processing and sending the corresponding message on the CAN bus, an additional 1.25 ms was required on average until the message arrived on the CAN bus and the lights were activated. Once the weight had been successfully transmitted from the Orchestrator to the MAB, the MAB set various model variables, such as control parameters for trajectory tracking, depending on the weight.

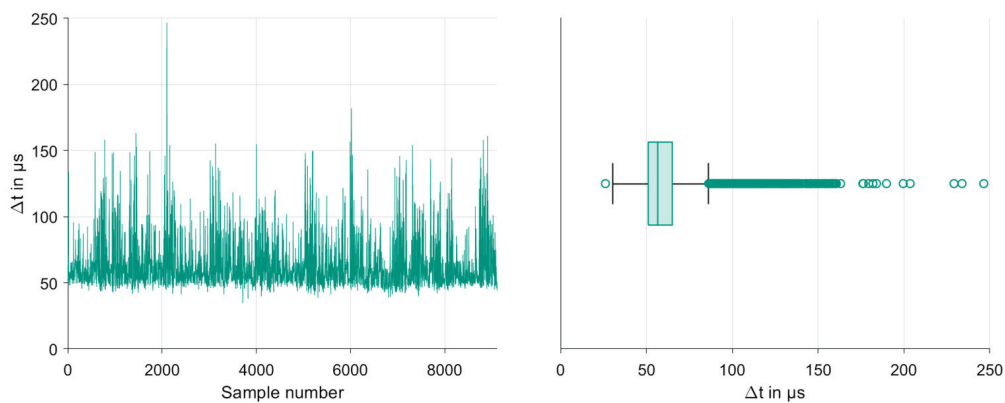


Figure 6. PTP synchronization of MAB and Orchestrator.

Within Figure 7, a sequence of message frames and the corresponding information extraction can be seen, which is executed by the MAB and the Orchestrator. In the upper measurement, the raw UIF message frame, not yet separated (but for clarity already colored properly), can be observed. Note that there are two axes, as the scale deviates too much otherwise. In the second measurement is the corresponding RID, which is needed to interpret the information correctly. The MAB receiving the DLS message can use the RIDs as context markers to determine how to interpret the information contained within the UIF. This contextual interpretation ensures that each component processes the data according to its specific requirements and functionalities. This process can be seen in the lower two measurements, where the separation is performed and processed accordingly. While the RID value is 11, the Driveboard shares the information to synchronize the left turn signal from the CAN bus to the Orchestrator (and therefore the Capsule's Dynamic Link X service), whereas within the time RID equals 10, the Capsule shares its current weight. This weight can then be used further to adjust controller parameters to gain a higher performance.

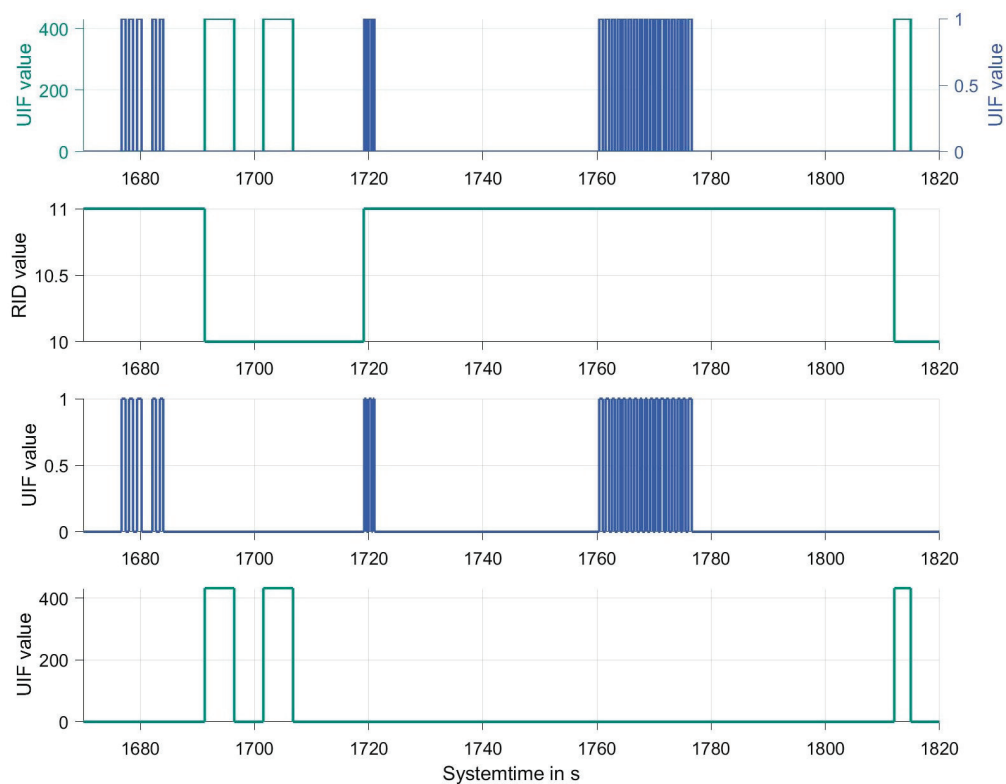


Figure 7. Received raw UIF message and separated information based on RID.

Figure 8 presents the relationship between the CPU utilization and the message frequency measured over time. Within the measurement, a benchmark is conducted to better understand the effects of a high CPU load. The red line indicates the start of the benchmark, where the CPU load is slowly raised from basic load utilization at roughly 5%, linearly increasing within 30 s up to 100%. During the increasing utilization, a steep drop in the service frequency from well above 90 Hz to 40 Hz occurs. The reduced frequency stays well below the target frequency of 100 Hz until the CPU utilization decreases again to the base load. Both the drop and rise in the service frequency happen at roughly 60% CPU utilization, and therefore a correlation between CPU utilization and service frequency becomes evident. More precisely, the correlation between CPU utilization and service frequency is -0.39 , which therefore hints towards a moderate negative correlation. Consequently, a high CPU load should be avoided during operation. The growing computational demands of

additional software components, such as Capsule-specific SWCs, can negatively impact the performance of sensor data processing as shown in Figure 8, potentially compromising the effectiveness of automated driving functions. In the worst case, this could result in a failure to execute these functions successfully. To prevent this, resource-intensive, non-safety-critical tasks should be offloaded to the cloud whenever possible. By reallocating only non-time-critical SWCs, this limitation can be effectively mitigated.

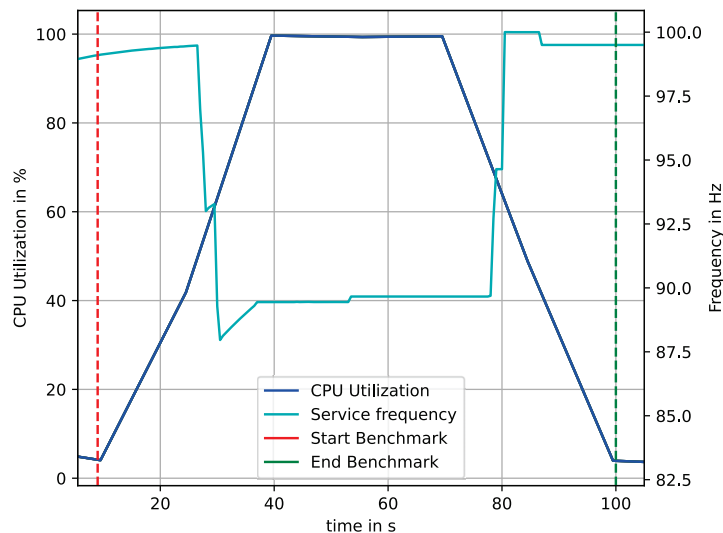


Figure 8. Impact of CPU utilization on the frequency of an SWC.

6. Conclusions

In summary, the novel DLS architecture demonstrates its potential to address key challenges in developing a modular, on-the-road vehicle concept. By enabling seamless communication, adaptability, and integration among diverse Capsule and Driveboard components, the DLS facilitates advanced functionalities, including safety-critical features. These include coupling motor control with safety mechanisms in the Capsule or dynamically balancing the state of charge between the Driveboard and, if available, the Capsule's battery storage. In collaboration with our partners, we developed a full-sized Driveboard prototype featuring the proposed hybrid E/E architecture. Our initial testing confirmed that the DLS enables a low-latency connection between the signal-oriented architecture and SOA. The measurements included various bidirectional messages, demonstrating promising results—most notably, a dynamic link message that meets hard real-time requirements. The DLS offers the flexibility to adapt to new Capsule technologies, even after the Driveboard is already on the road. Through the Orchestrator and MAB, interactions can be dynamically adjusted using the proposed RIDs that define universal information fields. Additionally, the cloud-enabled software reconfiguration allows for offloading SWCs to the cloud, offering advantages such as enhanced computational power, real-time data processing, and global availability. This reconfiguration process is facilitated by expert models and a gating mechanism that dynamically selects the most suitable model for a given context, optimizing performance and resource usage. In the context of hybrid software architectures, our focus on a single bus protocol in the signal-oriented architecture aligns with the prototype-driven nature of this research. While the prototype is built around a single bus protocol, the methodology remains flexible. This enables future research to investigate alternative protocols for broader feasibility in automotive applications. In order to transfer our cloud-based reconfiguration methodology to other E/E architectures, an individual study must be carried out to determine the system capabilities. This is due to the fact that

different bus protocols, physical transmission layers, and processing units can result in different behavior, for example, in terms of latency.

Further research is needed to address connectivity failures, security challenges, the integration of new Capsule topologies, and a comparison of different E/E architectures. To improve robustness against connectivity failures, our current system keeps the last successful transmission between the service- and signal-oriented architectures. The proposed system could be enhanced through internal redundancies or fallback functionalities in the event of transmission errors. Regarding cybersecurity, while IPSec with AES encryption provides a solid foundation, additional measures for cyberattack detection and mitigation can improve secure operation. Furthermore, an evaluation of our system through different Capsule topologies is necessary to assess the feasibility and scalability of the DLS. To support this, we are actively collecting extensive data, enabling further analysis and direct comparisons with alternative technologies.

For the comparison of different E/E architectures, we aim to focus our research on examining how multiple CAN domains and other in-vehicle networks interact with the DLS architecture. In parallel, we are actively collecting data from our prototype to evaluate system performance and will explore strategies for integrating safety-critical communication within the Capsule.

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Conflicts of Interest: The authors declare no conflicts of interest.

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Article

The Development and Characteristics of an In-Wheel Assembly Using a Variable Speed-Reducing Device

Kyeongho Shin *, Kyoungjin Ko and Junha Hwang

Hyundai Mobis Uiwang Technical Center Advanced E-Drive System Development Team, 37
Cheoldobangmulgwan-ro, Uiwang-si 16082, Gyeonggi-do, Republic of Korea; kyoungjin.ko@mobis.com (K.K.);
1669jh@mobis.com (J.H.)

* Correspondence: kyeonghoshin@mobis.com; Tel.: +82-1075110112

Abstract: This study proposes an in-wheel assembly with a variable speed-reduction device designed to maximize torque and vehicle speed, enabling high-performance vehicle-level driving characteristics in front-engine, rear-wheel drive (FR), internal combustion engine (ICE) vehicles, where conventional EV motors cannot facilitate e-4WD. The proposed system integrates a motor and speed reducer within the wheel while avoiding interference from braking, steering, and suspension components. Through various innovative approaches, concepts for an integrated wheel-bearing planetary reducer and a variable speed planetary reducer were derived. The developed system achieved twice the maximum torque and a 35% increase in top speed compared to previously developed in-wheel systems, all without altering the front hard points. Multi-body dynamic analysis and component testing revealed wheel lock-up issues during reverse driving, and instability in the one-way clutch at high speeds. To address these issues, the power transmission structure was improved, and the type of one-way clutch was modified. Additionally, deficiencies in lubrication supply to the friction surface of the one-way clutch were identified through flow analysis and visualization tests, leading to design improvements. The findings of this study demonstrate that even in in-wheel systems where the application of large and complex transmission devices is challenging, it is possible to simultaneously enhance both maximum torque and top vehicle speed to achieve high-performance vehicle-level driving dynamics. Consequently, implementing an in-wheel e-4WD system in ICE FR vehicles is expected to improve fuel efficiency, achieve high-performance vehicle capabilities, and enhance market competitiveness.

Keywords: in-wheel; e-4WD; one-way clutch; planetary gear trains; variable reducer; gear dynamics; hub bearing; multibody system dynamics

1. Introduction

Recently, automotive manufacturers have been making significant efforts to develop electrification technologies to gain a competitive edge in the electric vehicle (EV) market. Among these technologies, the in-wheel system is gaining attention as a promising future technology. The in-wheel system integrates a motor and a speed reducer within the wheel, in addition to the suspension, steering, and braking components, to drive the wheel directly. By eliminating the drive shaft, this system enables independent driving and regenerative braking at each wheel, thereby improving both driving performance and energy efficiency [1,2]. From a vehicle packaging perspective, the in-wheel system may be the only viable solution for implementing e-4WD in front-engine, rear-wheel drive (FR),

internal combustion engine (ICE) vehicles and fuel cell electric vehicles (FCEVs) without interference from the engine or hydrogen tank.

Due to these advantages, various companies have been actively researching and developing in-wheel systems for many years [3]. Toyota has developed an in-wheel system with a power output of 55 kW and a maximum wheel torque of 1200 Nm, which can be integrated with a front-wheel caliper in a 17-inch wheel. The company is also developing various control logics for four-wheel in-wheel vehicles [4]. Schaeffler developed the E-Wheel Drive system by further integrating the drive motor, electrical equipment, and braking and cooling systems [5]. Protean proposed the concept of integrating the motor and brake and connecting the motor directly to drive the wheels [6].

As presented in Table 1, Hyundai Mobis has been developing in-wheel systems since 2010, validating in-wheel e-4WD performance across various vehicle models. In 2013, an in-wheel system was installed in the rear wheels of the Ray EV, enhancing cornering stability and low-friction split escape performance, thereby achieving 6+ to 7– 4WD performance. In 2015, the system's e-4WD performance was tested at a winter proving ground in China [7]. In 2016, the in-wheel system was applied to the front wheels of the Genesis G80, demonstrating improved yaw stability in one-circle turns, step steer, sine sweep, and double lane change tests, as well as enhanced climbing performance on low-friction surfaces compared to mechanical 4WD systems [8,9]. In 2017, an in-wheel system was developed for the rear wheels of the NEXO, achieving 6 to 6+ 4WD performance, which was 1.5 levels superior to 2WD, and enabling an 8% gradient ascent on snowy roads. The in-wheel system developed in 2019 featured a motor output of 30 kW, a maximum torque of 650 Nm, and a top speed of 200 km/h. It was installed on the front wheels of the high-performance G70 without modifying the hard points. As presented in Figure 1, in 2021, Hyundai Motor Company's high-performance vehicle development team verified that in-wheel torque vectoring control could enhance the agility and responsiveness of high-performance vehicles [10].

Table 1. Developed in-wheel e-4WD specifications.

	Ray EV	SONATA	G80	NEXO	G70
Mounting	Rear	Front	Front	Rear	Front
Power (kW)	16	35	23	6.4	30
Torque (Nm)	500	630	650	180	650
4WD Rate	6+~7–	-	-	6~6+	-

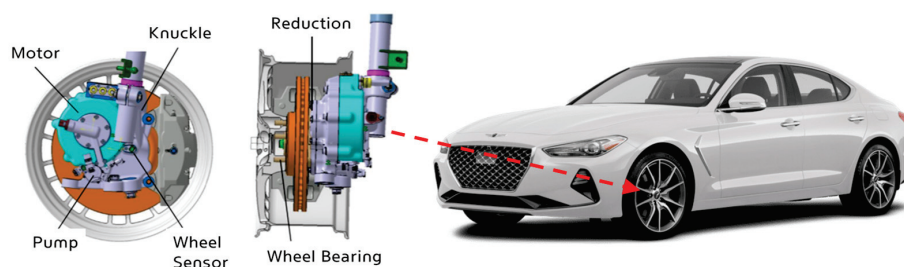


Figure 1. In-wheel e-4WD configuration of G70.

Previous in-wheel e-4WD systems have faced challenges in achieving sufficient 4WD performance due to motor size limitations within the confined wheel space. To achieve maximum torque equivalent to mechanical 4WD without increasing motor size, a higher reduction ratio is required. However, in in-wheel gearboxes composed of planetary gears and external gears, the external gear reduction ratio is constrained by the center distance between the wheel shaft and the motor shaft, while the planetary gear reduction ratio is

limited by the diameter of the ring gear, which is located inside the motor end coil. These constraints make it difficult to increase the overall reduction ratio.

In this study, a novel variable speed-reduction device is proposed to enhance both torque and vehicle speed simultaneously within the limited space of the wheel, without increasing motor size. The study further explores the entire process of design, analysis, and testing to assess the characteristics of the variable speed-reduction device and address any identified issues.

2. Structure and Characteristics

2.1. Hub Bearing Integrated Planetary Gear Set

The in-wheel motor and reduction ratio applied to the front wheels of the G70 were insufficient to meet the high-speed cornering performance requirements targeted by Hyundai Motor Company (HMC) for high-performance vehicles, necessitating more than a twofold increase in wheel torque. However, as shown in the rear view of the in-wheel motor within the wheel in Figure 1, increasing the motor size within the limited wheel space would interfere with the steering and braking systems. Therefore, instead of increasing the motor size, torque was enhanced by incorporating a reduction gear into the existing motor. However, adding a reduction gear increases the overall width of the assembly, causing the motor to protrude further inward toward the vehicle. As shown in the side view of the in-wheel system in Figure 1, this results in interference with the damper strut. To accommodate a reduction gear within these stringent packaging constraints, a hub bearing integrated planetary gear set (HB-PGS) was developed. The concept and block diagram of this HB-PGS are illustrated in Figure 2a,b.

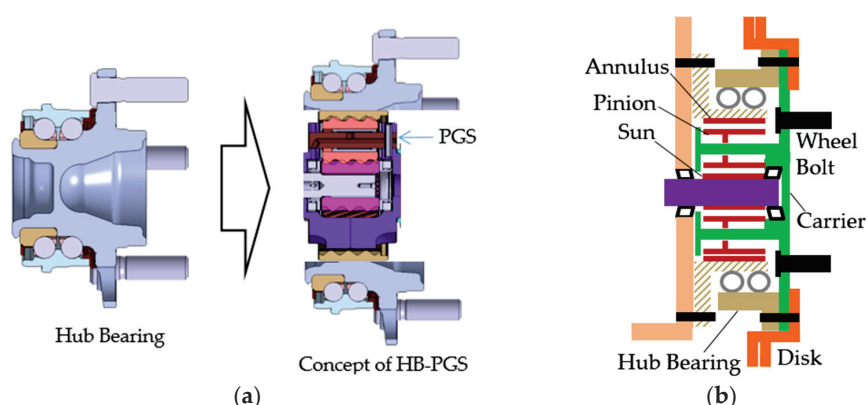


Figure 2. (a) Concept of hub bearing integrated PGS. (b) Block diagram of HB-PGS.

As shown in Figure 2a, the proposed concept involves integrating a planetary gear set—comprising a sun gear, planetary gears, a carrier, and a ring gear—within the hub bearing. To fit the PGS within the hub bearing, the ball pitch circle diameter (PCD) of the hub bearing was maximized within the available space inside the front disk hat. Additionally, instead of attaching the wheel bolts directly to the hub bearing, they were press-fitted into the PGS carrier. By maintaining the wheel bolt PCD identical to that of conventional systems, existing wheels could be used without modification. The carrier was bolted to the hub bearing, enabling the hub bearing to support both the wheel load and the output load from the carrier. This configuration effectively distributes the structural functions between the hub bearing and the carrier, with the hub bearing primarily supporting the wheel load while also assisting in output transmission.

Unlike conventional, third-generation hub bearings, in which the inner race rotates and the outer race is fixed, the proposed design features a fixed inner race and a rotating outer race. The ring gear was fixed to the hub bearing's inner race, allowing the input

power from the sun gear to be transmitted through the carrier to the wheel, thereby achieving the maximum reduction ratio. Additionally, to prevent the leakage of lubricating oil for the gears and bearings from the hub bearing integrated PGS, seals were carefully designed. The structural rigidity of the hub bearing, PGS assembly process, concentricity maintenance, and oil flow characteristics were all considered in the design process to ensure optimal performance.

2.2. Variable One-Way Clutch with PGS

When the HB-PGS is applied to the G70 in-wheel system to increase the reduction ratio, the maximum vehicle speed decreases due to motor speed limitations. Doubling the reduction ratio would result in a twofold increase in wheel torque, but it would also reduce the maximum vehicle speed by half. Therefore, to incorporate a reduction gear while still achieving the top high speed required for high-performance vehicles, a gear-shifting mechanism is necessary. However, conventional multi-speed transmission systems, such as hydraulic or shift fork-based transmissions, have complex structures and require additional actuators, making them unsuitable for integration within the constrained space of an in-wheel system.

Since the G70 in-wheel system is used as an auxiliary drive system rather than a primary propulsion system, unlike the main engine, it is not required to deliver driving performance under all conditions. Therefore, a new, efficient, and compact clutch solution was needed—one that would provide maximum torque to assist during vehicle launch and hill climbing while enabling freewheeling rotation at high speeds to prevent exceeding the motor's maximum speed. To address this challenge, a variable speed-reduction device was devised by combining two OWCs with the PGS. This mechanism ensures a high reduction ratio during driving and a low reduction ratio during freewheeling or regenerative braking.

The variable one-way clutch (VOWC), which enables the transition between reduction ratios, consists of two OWCs arranged in opposite orientations on the rotor, with one OWC connecting the rotor to the sun gear and the other connecting the rotor to the carrier in a symmetrical configuration. The rotor extends through the sun gear to the carrier, with both OWCs linking the rotor to the respective components. During torque transmission, only one of the two OWCs locks, while the other remains in a freewheel state, thereby altering the reduction ratio. The block diagram illustrating the entire power transmission system, including the VOWC, PGS, and external gears, as well as the target T-N (torque–speed) curve for the real vehicle when this system is applied, is shown in Figure 3a,b.

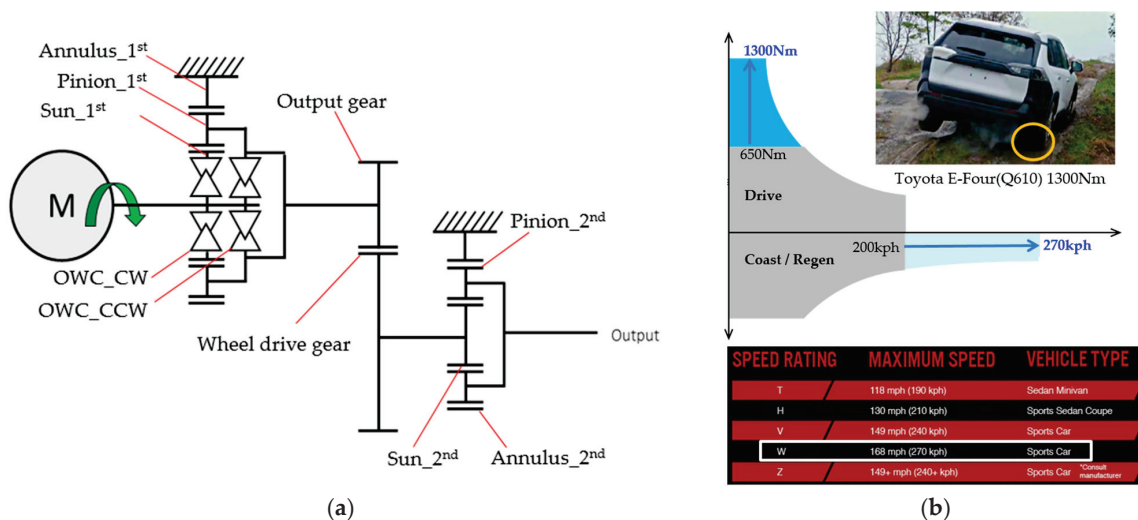


Figure 3. (a) The block diagram of power transmission. (b) The target T-N (torque–speed) curve.

2.3. Gear Shifting Process of VOWC and PGS

The gear ratio shifting process through the combination of the PGS and VOWC can be explained as follows. When torque is generated by the motor, the transmission sequence is as follows: rotor $\rightarrow$ sun gear OWC lock (rotor rotational speed $>$ sun gear rotational speed) $\rightarrow$ sun gear $\rightarrow$ planetary gears (reduction) $\rightarrow$ carrier. As a result, the torque is amplified according to the reduction ratio. Conversely, when torque is generated at the wheel, the transmission sequence is as follows: carrier $\rightarrow$ carrier OWC lock (rotor rotational speed $<$ carrier rotational speed) $\rightarrow$ rotor. In this case, the torque is directly transmitted to the rotor. Figure 4 illustrates the operational state of each OWC based on the location of torque generation and the relative rotational speeds of the components.

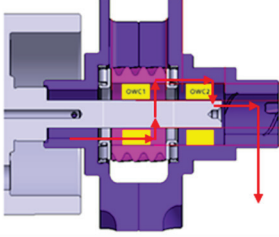
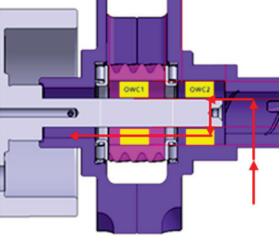
Forward by Motor	Relative speed			OWC A		OWC B		
				CCW	CW	CCW	CW	
Rotating Speed (CCW)	Rotor	$>$	Sun Gear	Lock	Free	-	-	
				-	-	-	-	
	Rotor	$>$	Carrier	-	-	Free	Lock	
Forward by Wheel	Relative speed			OWC A		OWC B		
				CCW	CW	CCW	CW	
Rotating Speed (CCW)	Rotor	$<$	Sun Gear	Free	Lock	-	-	
				-	-	-	-	
	Rotor	$<$	Carrier	-	-	Lock	Free	

Figure 4. The operational state of each OWC based on the location of torque generation and the relative rotational speeds of the components in forward.

The gear ratio shifting process during driving consists of two phases: the torque transmission phase and the speed synchronization phase.

- **Torque Transmission Phase:** In this phase, the rotor shaft engages with one of the two OWCs to transmit torque. This phase ends once the required torque is achieved.
- **Speed Synchronization Phase:** In this phase, the rotor shaft is not engaged with either OWC, and its speed transitions between the rotational speeds of the sun gear and the carrier. This phase ends once the speed difference between the rotor and either component is eliminated.

The transition between the torque transmission phase and the speed synchronization phase is controlled entirely through motor speed and torque control, eliminating the need for an additional actuator. The rotor speed varies only within the range between the carrier speed (minimum) and the sun gear speed (maximum), and since it is proportional to the reduction ratio of the PGS, the speed difference increases at higher speeds. Therefore, precise rotor speed control is required in the low-speed range to ensure smooth synchronization.

When transitioning from 2WD to 4WD to provide auxiliary driving force, the rotor is initially connected to the carrier OWC and synchronized with the carrier speed in the 2WD driving state. To shift to 4WD, the rotor speed is first increased until it matches the rotational speed of the sun gear. Once synchronization with the sun gear is achieved, the motor torque is increased to lock the sun gear OWC, completing the transition to the 4WD mode. Conversely, when transitioning from 4WD to 2WD at high vehicle speeds, the rotor—initially connected to the sun gear OWC—has its rotational speed reduced to a level between the speeds of the carrier and the sun gear. This ensures that at high speeds, the

motor does not act as a resistance force. During regenerative braking in either the 2WD or 4WD mode, the rotor speed is first synchronized with the carrier speed, after which reverse torque is generated to lock the carrier OWC, enabling effective energy recovery.

2.4. Resolving the Interlock Issue in the PGS and VOWC Combination

A key issue with the combination of the PGS and the VOWC arises during clockwise (CW) rotation, where both OWCs lock simultaneously regardless of the torque generation point. As illustrated in Figure 5, when torque is generated at the rotor in the CW direction, the rotor's rotational speed exceeds that of the carrier, causing the carrier OWC to lock first. As the carrier rotates, it accelerates the sun gear, eventually making the sun gear rotate faster than the rotor, thereby locking the sun gear OWC as well. This results in an interlock of both OWCs. Similarly, when torque is generated at the wheel in the CW direction, the carrier rotation accelerates the sun gear, causing the sun gear OWC to lock as the sun gear's rotational speed exceeds that of the rotor. As the rotor then synchronizes with the sun gear's speed, it eventually surpasses the carrier's speed, causing the carrier OWC to lock, again leading to an interlock of both OWCs.

Backward by Motor	Relative speed			OWC A		OWC B	
				CCW	CW	CCW	CW
Rotating Speed (CW)	Rotor	<	Sun Gear	Free	Lock	-	-
						Interlocking	
	Rotor	>	Carrier	-	-	Free	Lock

Backward by Wheel	Relative speed			OWC A		OWC B	
				CCW	CW	CCW	CW
Rotating Speed (CW)	Rotor	<	Sun Gear	Free	Lock	-	-
						Interlocking	
	Rotor	>	Carrier	-	-	Free	Lock

Figure 5. The operational state of each OWC based on the location of torque generation and the relative rotational speeds of the components in backward.

To resolve the OWC interlock issue during reverse rotation, the output gear was decoupled from the carrier and instead connected to a separate shaft. The OWC, which was previously linked to the carrier, was relocated to the new output gear shaft. Additionally, power transmission between the carrier and the output gear shaft was modified using a roller, magnet, and wedge mechanism.

- When torque is generated by the motor, the carrier rotates, inducing a centrifugal force on the roller. When the centrifugal force exceeds the magnetic force, the roller detaches from the magnet and becomes engaged in the wedge structure, thereby transmitting driving force.
- When torque is generated at the wheel, the output gear shaft rotates, but since the roller is not subject to centrifugal force, it remains fixed by the magnet and does not engage with the wedge structure. As a result, the PGS does not rotate, and the rotor, which is connected to the OWC and the output gear shaft, rotates together.

This design modification effectively prevents the OWC interlock issue, ensuring stable power transmission and improved system reliability. The structure of the new design is shown in Figure 6.

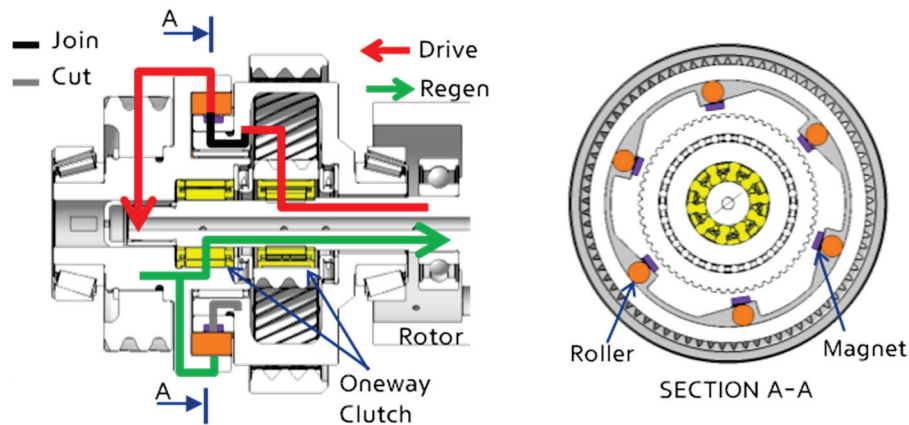


Figure 6. The structure of the new design of preventing OWC interlock.

2.5. Overall Structure and Characteristics

By integrating the hub bearing planetary gear set (HB-PGS) and the variable one-way clutch planetary gear set (VOWC-PGS) into the existing in-wheel system, it was possible to achieve both the maximum torque and top speed required for high-performance vehicles without modifying the suspension, steering, or braking systems. The one-way clutch (OWC) was designed by analyzing Hertzian stress at the sprag contact points, hoop stress in the inner (rotor shaft) and outer (sun gear) components, rollover torque, and service life to ensure optimal performance. The two PGS units were designed to provide maximum reduction ratios while ensuring sufficient gear strength and bearing durability. Additionally, the external gear reduction ratio was adjusted to set the overall reduction ratio at 1:18.7, as shown in Figure 7. As presented in Table 2, the proposed system achieves higher torque and greater vehicle speed compared to Toyota's in-wheel system, highlighting its superior performance.

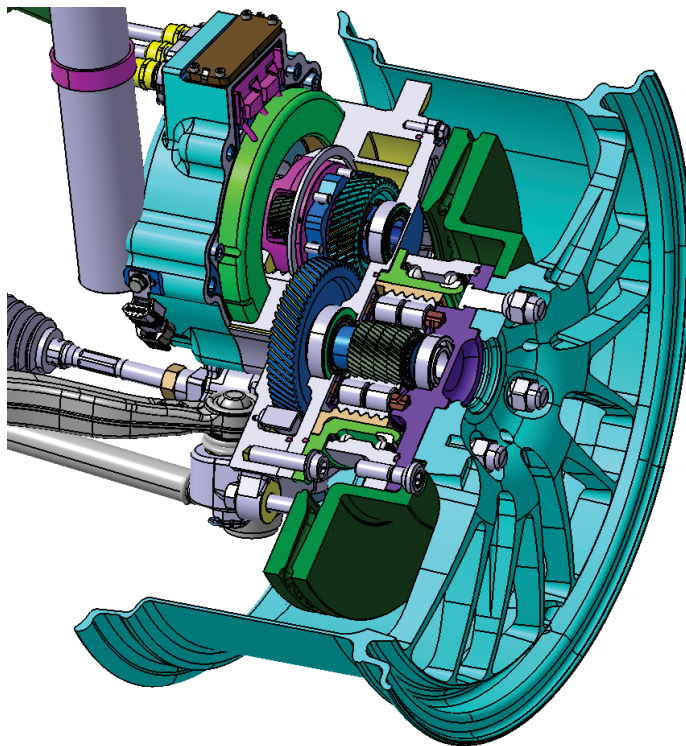


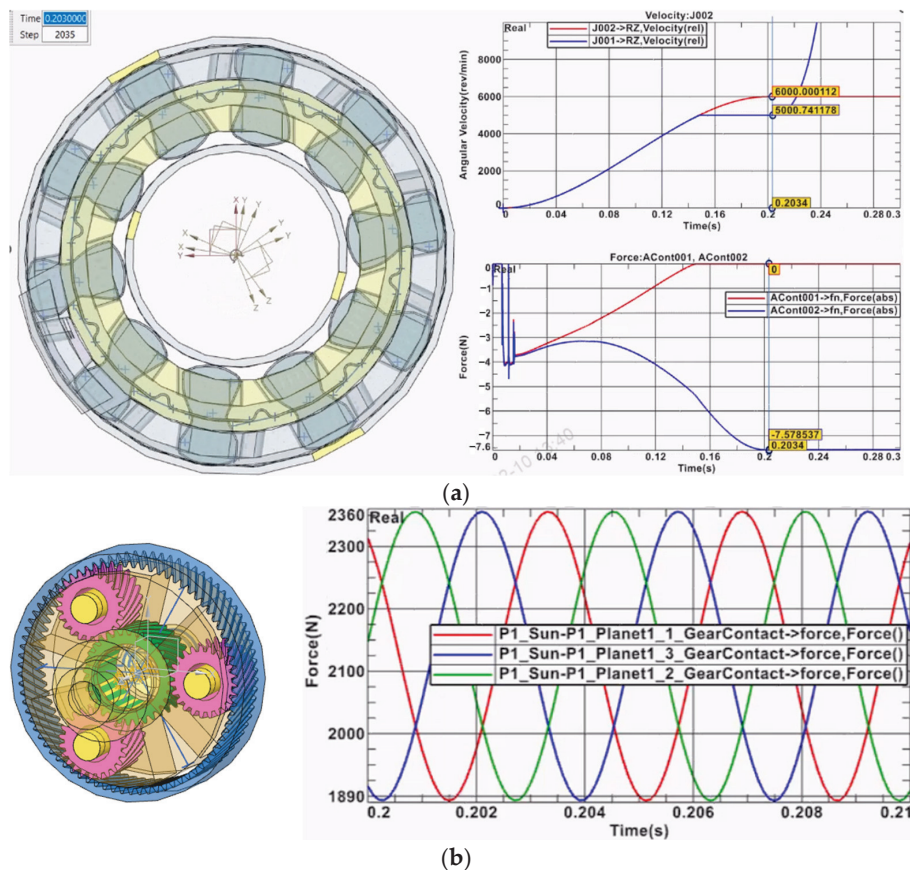
Figure 7. Overall structure of in-wheel assembly with the HB-PGS and VOWC-PGS.

Table 2. Comparison of the main technical parameters.

	MOBIS_IW	TOYOTA_IW	Unit
Maximum output power	30 (Air cooling)	55 (Oil cooling)	kW
Maximum output torque	1300 (3 stage)	1200 (2 stage)	Nm
Maximum vehicle speed	270 (2 stage)	180 (2 stage)	KPH
Minimum wheel size	18 (Front)	17 (Rear)	Inch

3. Simulation Model and Test Results

To verify whether the engagement between the inner and outer races of the one-way clutch (OWC) remains stable under centrifugal force and to analyze variations in the meshing load between the sun gear and planetary gears, a dynamic analysis model of the OWC and planetary gear set (PGS) was developed. The OWC model includes the inner race, outer race, sprag, and ribbon spring, while the PGS model consists of the sun gear, planetary gears, carrier, and ring gear. All components were modeled as flexible bodies to capture realistic deformation and interaction effects. The initial ribbon spring force in the OWC was determined based on X-ray imaging of the OWC structure and the drag torque in the freewheel state. The ribbon spring stiffness and preload were adjusted accordingly. A simulation of the sprag and inner race separation speed under centrifugal force was conducted, and the results are illustrated in Figure 8a. As shown, when the OWC rotates, the inner and outer races initially rotate together. However, at rotational speeds above 5000 rpm, the contact force between the sprag and inner race reaches zero, causing a relative speed difference between the components. After this point, even when a 1 Nm locking torque is applied to the inner race, it fails to engage and continues freewheeling.

**Figure 8.** (a) Dynamic analysis of the OWC. (b) Dynamic analysis of the PGS.

Additionally, a PGS analysis model was developed to investigate the meshing behavior of planetary gears. When a 100 Nm input torque was applied to the sun gear, the mesh phasing effect among the planetary gears caused the gear contact forces to be sequentially distributed, as illustrated in Figure 8b.

3.1. Dynamic Behavior Analysis of VOWC in Low Speed

To analyze the dynamic behavior of gear meshing and the one-way clutch (OWC) under conditions where the reduction ratio increases (18.72:1) when auxiliary drive engagement is required during freewheeling, a simulation study was conducted. As shown in Figure 9a, in the initial freewheeling state, the planetary carrier (red) and rotor shaft (green) rotate together at a low speed (1000 rpm), while the sun gear (blue) rotates at a relatively high speed (3484 rpm) in a freewheel state. When a 6 Nm torque is applied to the motor, the rotor speed increases until it surpasses the sun gear speed (3484 rpm), at which point the rotor and sun gear engage, transmitting driving force to the sun gear. During this process, the carrier speed remains constant at 1000 rpm, while only the rotor speed increases (from 1000 rpm to 3484 rpm).

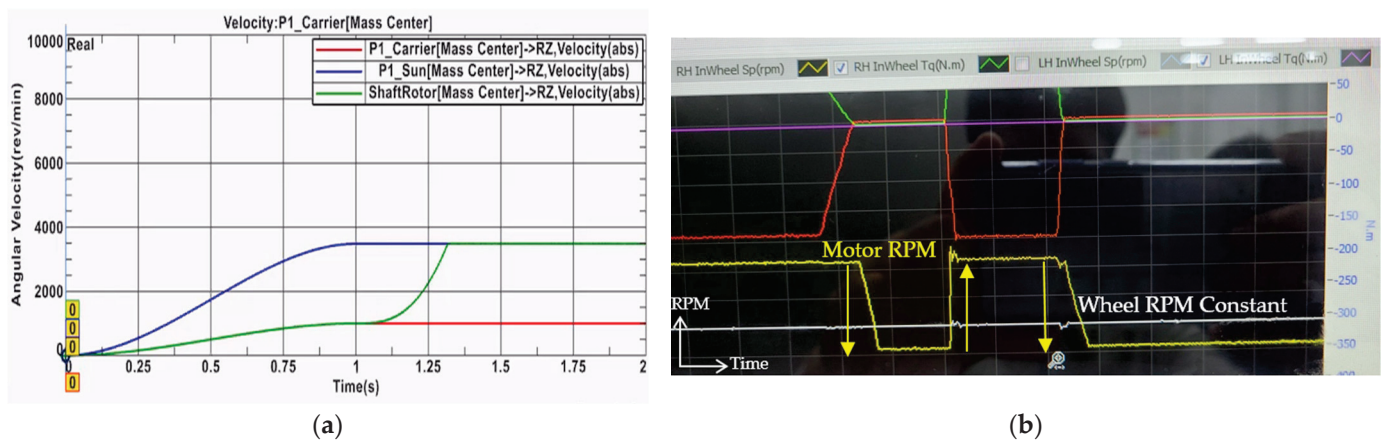


Figure 9. (a) Dynamic analysis of the VOWC in low speed. (b) Test results of the VOWC.

Furthermore, the test results shown in Figure 9b confirmed the same behavior. When motor torque was applied and removed, the wheel rotation speed remained constant, while only the motor speed either increased or decreased, demonstrating the effectiveness of the proposed system in controlling gear engagement and speed variation.

3.2. Dynamic Behavior Analysis of VOWC in High Speed

An experimental study was conducted to determine the difference in the engagement speed limit between the outer race and inner race of the one-way clutch (OWC) as rotational speed increased. As shown in Figure 10a, up to 6000 rpm, the engagement time increased proportionally with the speed difference between the inner race and outer race, while engagement remained stable. However, as shown in Figure 10b, beyond 6000 rpm, centrifugal forces destabilized the engagement, leading to further increases in engagement time. At higher rotor speeds, the speed difference at the point of engagement increases, causing higher impact forces when the rotor engages with the sun gear. This impact may lead to OWC rollover, as confirmed through computational analysis, as illustrated in Figure 10c.

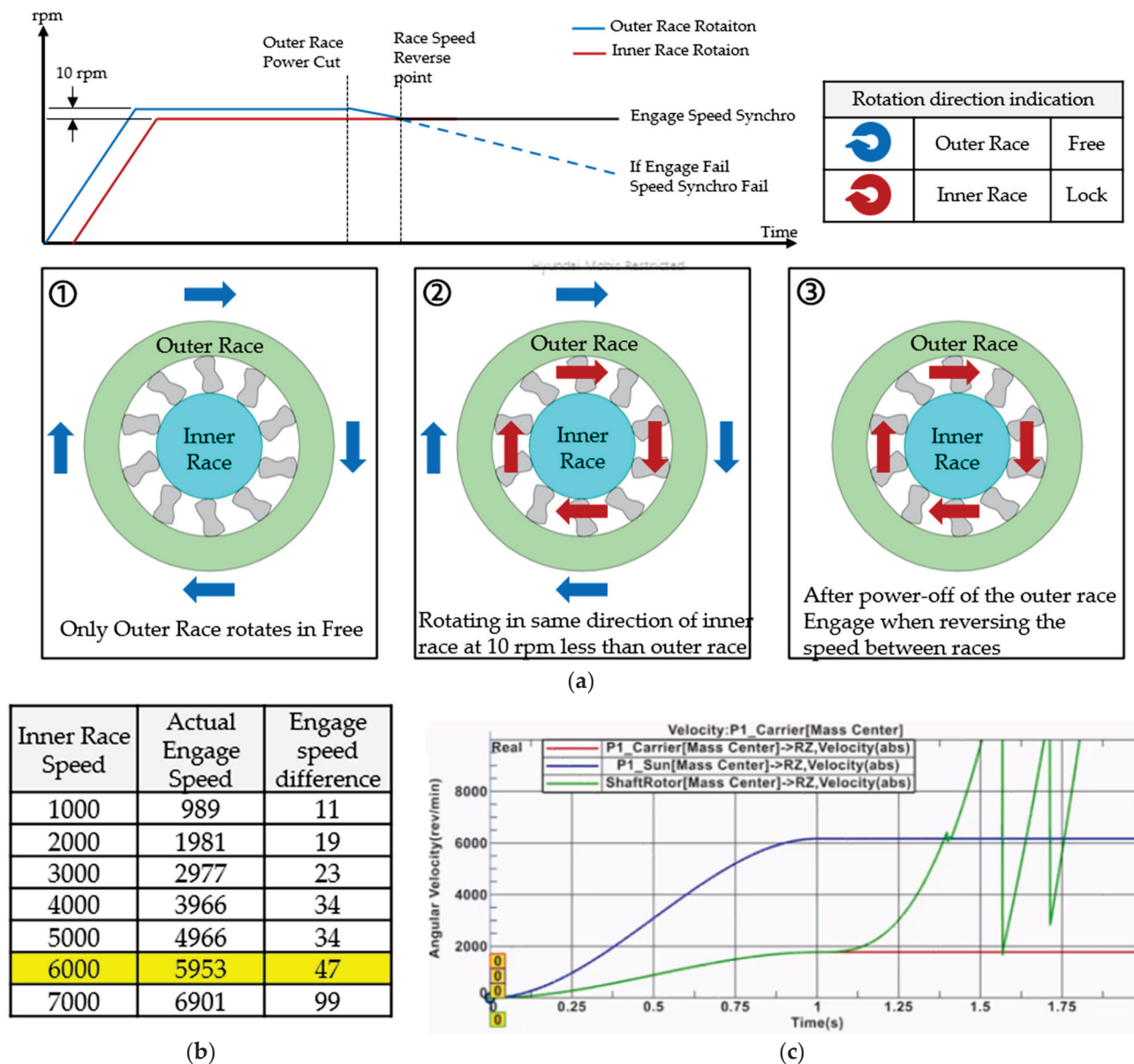


Figure 10. (a) Test of VOWC engagement limits at high rotational speeds. (b) Test results of the engagement limits. (c) Dynamic analysis of the VOWC at high speed.

4. Improvement of the VOWC

4.1. Disengage-Type OWC

Based on the multi-body dynamic analysis and experimental results, the sprag design of the OWC was modified from a disengage type to an engage type to improve its stability at high rotational speeds. In general, the engage-type OWC reduces friction losses during freewheeling by allowing centrifugal forces to disengage the sprag from the inner race. However, it is not suitable for applications requiring stable engagement at high speeds. Conversely, the disengage-type OWC maintains stable engagement at high speeds because centrifugal forces press the sprag against the inner race. However, since the sprag and race remain in continuous contact, proper lubrication of the contact surfaces is critical to ensure durability and performance. A dynamometer test was conducted using the engage-type OWC, in which the output-side speed was increased in increments of 100 rpm, and the input torque was increased in increments of 10 Nm. During testing, OWC rollover occurred, and a post-test disassembly inspection revealed that thermal stress had developed at the

contact interface between the rotor shaft and the OWC due to insufficient lubrication, as shown in Figure 11.

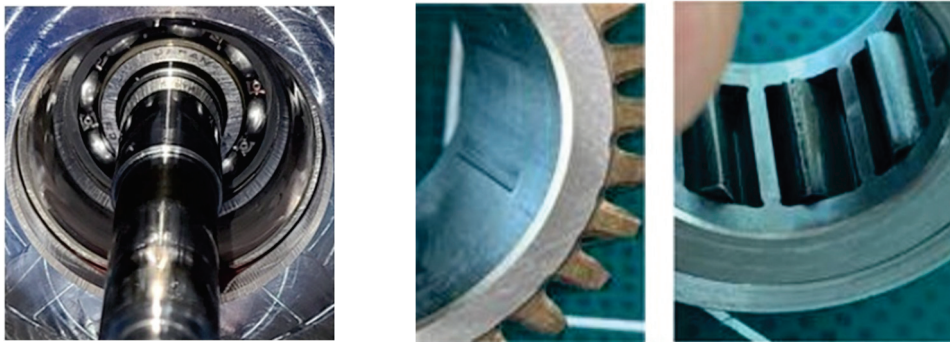


Figure 11. Thermal stress in rotor shaft and OWC Rollover.

4.2. Simulation and Visualization of Oil

The internal lubrication flow of the system is designed so that oil supplied from the oil pump is divided into two branched flow paths: one directed to the first PGS and the other to the second PGS. The oil supplied to the first PGS flows through the hollow rotor shaft, lubricating the motor, PGS bearings, and the two OWCs. However, due to the location of the oil supply holes machined into the rotor shaft, oil is first delivered to the motor and PGS support bearings, potentially leading to an insufficient oil supply to the OWCs. To assess the oil distribution to the OWCs, a fluid dynamics analysis was conducted to evaluate the oil flow rates at the first planetary reducer flow path (OUTLET1) and the second planetary reducer flow path (OUTLET 2), as shown in Figure 12a. Additionally, experimental testing revealed an unaccounted-for factor in the analysis; oil churning caused by the rotation of external gears led to air bubble formation, which in turn resulted in a reduced oil supply within the rotor shaft. This phenomenon was confirmed through experimental validation, as illustrated in Figure 12b.

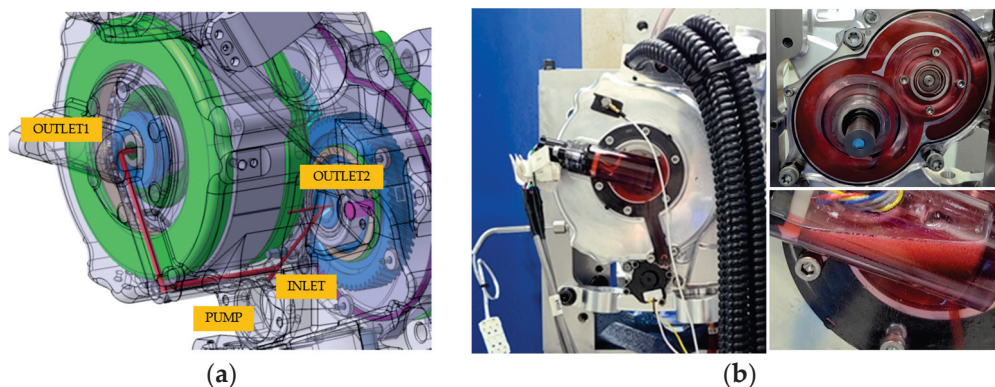


Figure 12. (a) Oil flow analysis. (b) Supplied oil visualization.

To increase the oil supply to the one-way clutch (OWC), a particle-based fluid analysis (Nextflow) was conducted to evaluate the oil flow behavior and distribution during rotor shaft rotation, as shown in Figure 13a. The particle size was set to 0.4 mm for the simulation. The analysis results indicated that as rotor speed increased, a significant amount of oil escaped through the rotor oil inlet clearance, reducing oil supply to the rotor end (Outlet 4). Beyond approximately 4 s (8000 RPM), the oil supply at Outlet 4 was nearly depleted, and after 6 s, the oil supply to the OWC (Outlet 3) was also nearly depleted. Between 0 and 6000 RPM, the oil flow rate at Outlets 1 to 3 initially increased with rotor speed. However, as inflow through the rotor inlet decreased, a critical rotational speed threshold

was reached, beyond which the oil flow at Outlets 1 to 3 also began to decrease. The oil flow distribution at each inlet is illustrated in Figure 13b. Based on the experimental and simulation results, the oil hole configuration in the rotor shaft was modified to redirect oil flow more effectively toward the rotor. As shown in Figure 13c, the oil holes were repositioned asymmetrically from both sides to a single-sided configuration to enhance oil distribution.

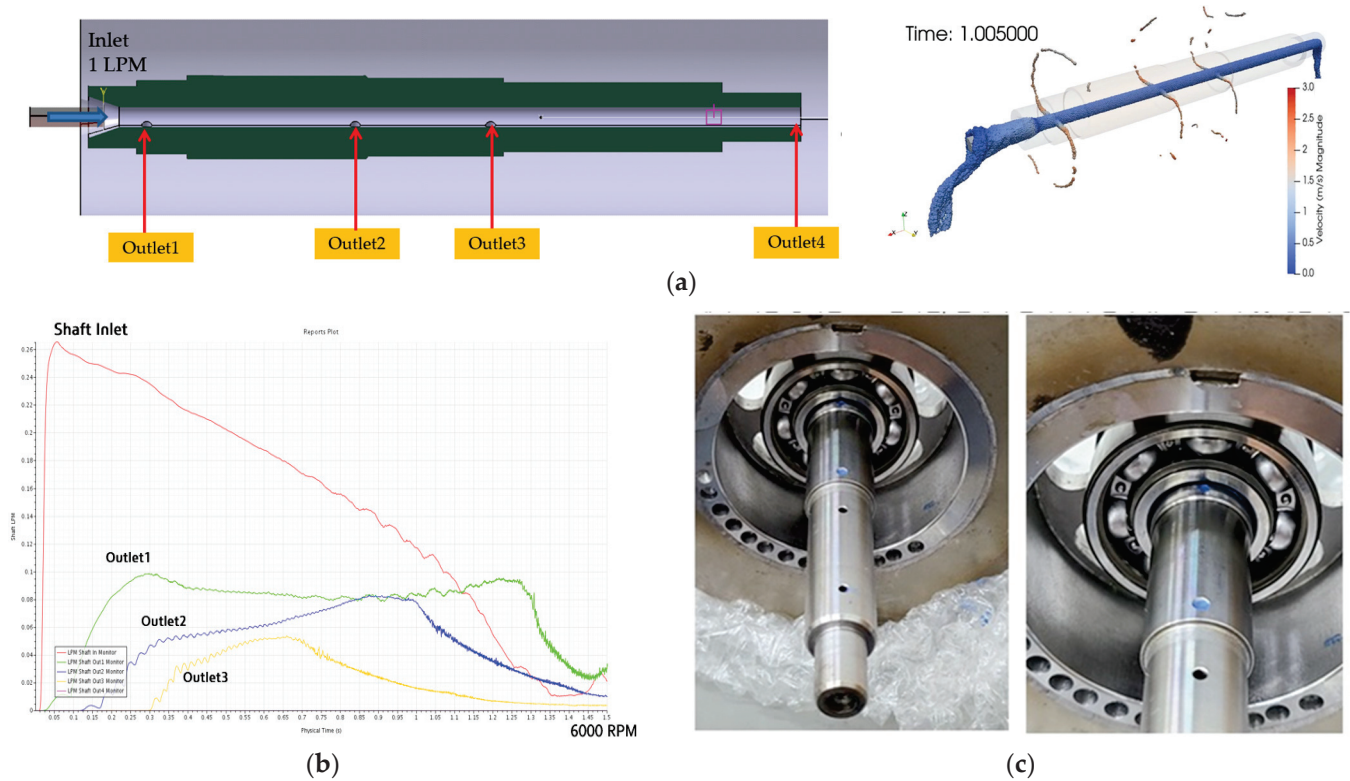
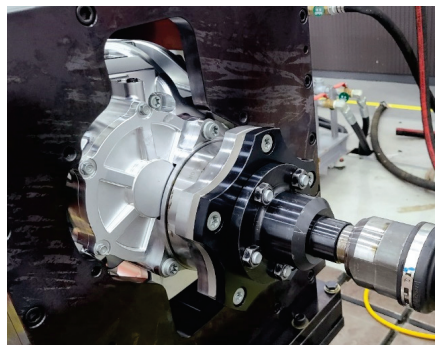


Figure 13. (a) Oil flow according to rotational speed of rotor. (b) Changes in the amount of inlet/outlet oil over time. (c) Single sided oil holes in rotor shaft.

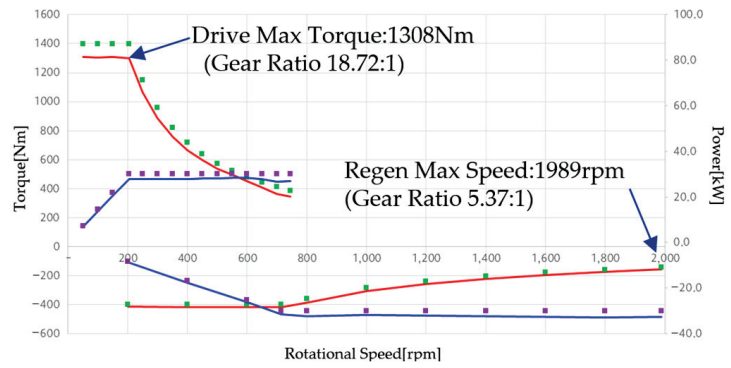
5. Results

5.1. Test of In-Wheel Assembly Performance

A prototype of the final designed variable speed-reduction in-wheel assembly was fabricated and subjected to functionality and performance testing using a dynamometer, as shown in Figure 14a. The T-N (torque–speed) characteristics were measured by applying maximum motor torque at various speeds. As illustrated in Figure 14b, the results confirmed a maximum driving torque of 1308 Nm and a maximum regenerative speed of 1989 rpm (equivalent to 270 km/h with a 19-inch wheel). The driving efficiency of the in-wheel assembly achieved an average of 81.4% with a peak efficiency of 88.1%, while the regenerative efficiency reached an average of 80% with a maximum efficiency of 85%. The efficiency map is presented in Figure 15. Furthermore, even at the maximum vehicle speed of 270 km/h, the rotor speed remained at 76% (10,681 rpm) of the motor's speed limit, demonstrating the potential for further speed increases while also reducing motor drag during freewheeling operation.



(a)



(b)

Figure 14. Performance test for variable reducer in-wheel system. (a) Variable reducer in-wheel assay PT dynamo test. (b) Wheel T-N performance.

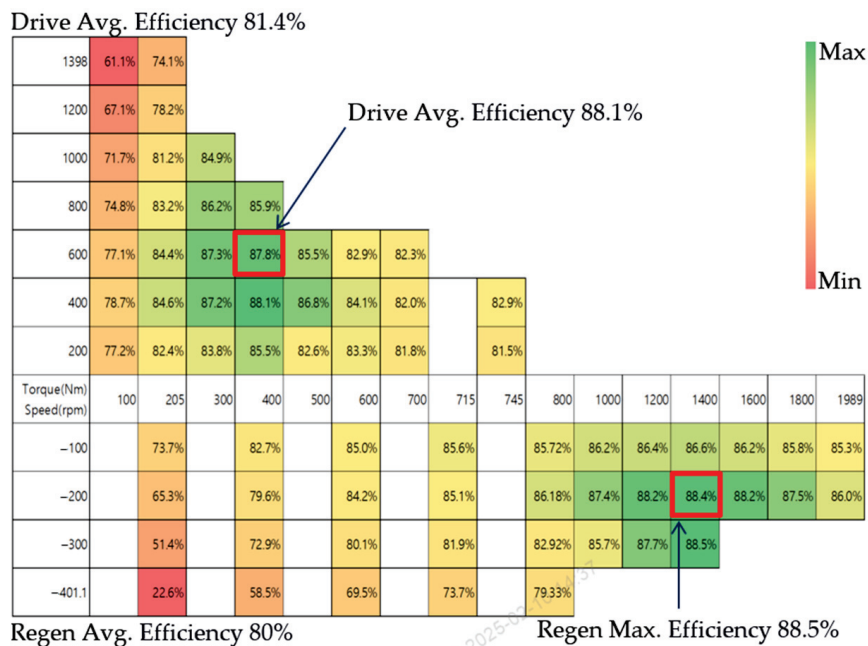


Figure 15. Efficiency for variable reducer in-wheel system.

5.2. Simulation of Vehicle Performance

To evaluate the real-world performance of the variable speed-reduction in-wheel system, a vehicle dynamics simulation (CarMaker) was conducted, as illustrated in Figure 16. The motor specifications were set to 55 kW output power and a maximum speed of 16,000 rpm, referencing Toyota's in-wheel system. The analysis compared the fixed-reduction in-wheel e-4WD and the variable speed-reduction in-wheel e-4WD under identical conditions. In the simulation, an IONIQ 5 was equipped with a direct-drive in-wheel motor (50 kW, 1500 Nm maximum torque) on the rear axle and a reduction-drive in-wheel motor on the front axle. The results showed that the variable speed-reduction in-wheel system improved longitudinal acceleration performance by 12.2% compared to the fixed-reduction system, achieving 0–100 km/h acceleration (zero to hundred) in 5.95 s, compared to 6.78 s for the fixed-reduction system.

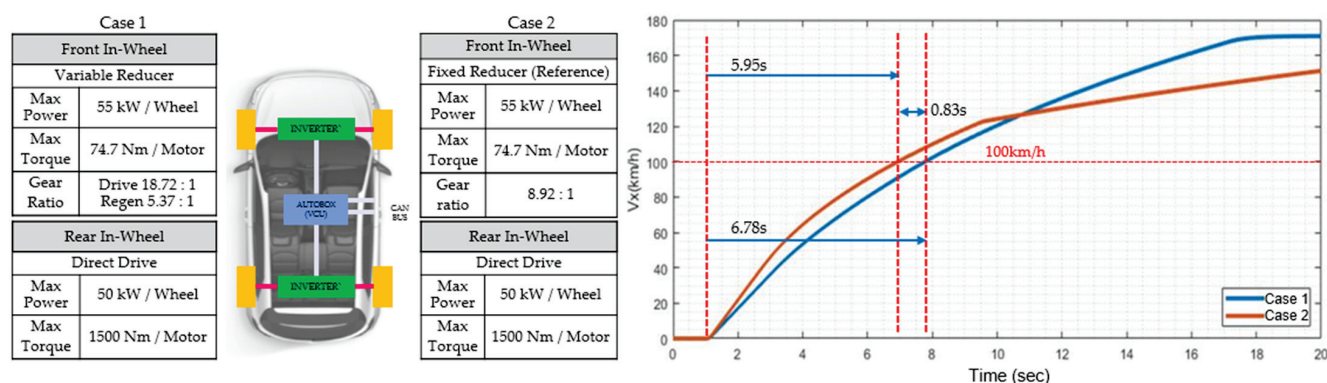


Figure 16. Longitudinal dynamic performance analysis.

6. Conclusions

This study proposed a variable speed-reduction in-wheel assembly that enables e-4WD implementation in the front axle of FR vehicles while achieving high-performance vehicle-level driving characteristics without modifying the hard points. The paper described the mechanism characteristics, analysis, experimental results, and real-world performance of the proposed system, which integrates an efficient and compact hub bearing integrated reducer, PGS, and OWC into a novel clutch solution. The proposed variable speed-reduction in-wheel assembly achieved twice the maximum torque and a 35% increase in top speed compared to previously developed in-wheel systems. Additionally, real-world performance comparisons with Toyota's in-wheel system demonstrated a 12.2% improvement in longitudinal acceleration performance.

Future research will focus on optimizing motor speed and torque control to develop an advanced control logic that ensures optimal gear-shifting performance across various driving conditions.

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Conflicts of Interest: Kyeong Ho Shin, Kyeong Jin Ko, and Jun Hwa Hwang are employees of Hyundai Mobis. The paper reflects the views of the scientists, and not the company.

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Article

Electric Long-Haul Trucks and High-Power Charging: Modelling and Analysis of the Required Infrastructure in Germany

Tobias Tietz ^{1,*}, Tu-Anh Fay ¹, Tilmann Schlenther ² and Dietmar Göhlich ¹

¹ Chair of Methods for Product Development and Mechatronics, Institute for Machine Design and System Technology, Technische Universität Berlin, 10623 Berlin, Germany; tu-anh.fay@tu-berlin.de (T.-A.F.); dietmar.goehlich@tu-berlin.de (D.G.)

² Chair of Transport Systems Planning and Transport Telematics, Institute of Land and Sea Transport Systems, Technische Universität Berlin, 10553 Berlin, Germany; t.schlenther@tu-berlin.de

* Correspondence: t.tietz@tu-berlin.de; Tel.: +49-30-3147-7928

Abstract: Heavy goods transportation is responsible for around 27% of CO₂ emissions from road transport in the EU and for 5% of total CO₂ emissions in the EU. The decarbonization of long-distance transport in particular remains a major challenge. The combination of battery electric trucks (BETs) with on-route high-power charging (HPC) offers a promising solution. Planning and setting up the required infrastructure is a critical success factor here. We propose a methodology to evaluate the charging infrastructure needed to support the large-scale introduction of heavy-duty BETs in Germany, considering different levels of electrification, taking the European driving and rest time regulations into account. Our analysis employs MATSim, an activity-based multi-agent transport simulation, to assess potential bottlenecks in the charging infrastructure and to simulate the demand-based distribution of charging stations. The MATSim simulation is combined with an extensive pre-processing of transport-related data and a suitable post-processing. This approach allows for a detailed examination of the required charging infrastructure, considering the impacts of depot charging solutions and the dynamic nature of truck movements and charging needs. The results indicate a significant need to augment HPC with substantial low power overnight charging facilities and highlight the importance of strategic infrastructure development to accommodate the growing demand for chargers for BETs. By simulating various scenarios of electrification, we demonstrate the critical role of demand-oriented infrastructure planning in reducing emissions from the road freight sector until 2030. This study contributes to the ongoing discourse on sustainable transportation, offering insights into the infrastructure requirements and planning challenges associated with the transition to battery electric heavy-duty vehicles.

Keywords: electrification; battery electric truck; charging infrastructure; heavy-duty; truck traffic simulation; MATSim

1. Introduction

In response to climate change, the European Union has set ambitious targets to achieve climate neutrality by 2055, as outlined in the European Green Deal's "Fit for 55" package [1]. Heavy-duty vehicles represent a significant challenge in this context, accounting for 6% of the EU's total CO₂ emissions and over a quarter of emissions from road transport [2]. Therefore, the European Clean Trucking Alliance with over 35 companies and organizations from across Europe is calling for zero-emission road freight [3]. However, replacing today's fleets of diesel trucks entails several challenges. First, electric trucks only recently have become

commercially available and they still need further technical improvements. Second, freight operators face several different options of electric trucks and charging technologies and a vast number of possibilities to combine these options into a system solution. All options have specific assets and drawbacks concerning technological complexity, environmental impact, capital and operational costs [4–8].

BETs, which are charged conductively, emerge as a promising alternative to traditional combustion engine trucks [9], offering a viable solution to reduce emissions from the ever-growing road freight sector [10]. However, the transition to BETs not only necessitates advancements in vehicle technology but also poses substantial planning and financial challenges in developing the requisite charging infrastructure [11,12]. The European Union has already laid down initial guidelines for the standardized expansion of a charging network as part of its “alternative fuels infrastructure” strategy [13]. To ensure effective and demand-aligned infrastructure development, research is being conducted across various projects at both European and national levels, with key initiatives including ZEFES (Europe), HoLa (Germany) and E-Charge (Sweden). In these projects, researchers and industry stakeholders collaborate to examine the efficient energy supply and strategize the deployment of conductive charging technology, utilizing the first Megawatt-charging-system (MCS) sites, by strategically determining optimal charging locations, ensuring adequate charging capabilities for BETs [14–16].

In this context, this paper proposes a methodology to evaluate the required charging infrastructure to support the increased adoption of electric vehicles in Germany, across various levels of electrification, while considering European driving and rest time regulations for drivers [17]. Additionally, this paper addresses the importance of depot charging solutions to meet these demands. We use the term “depot charging” throughout and thus summarize all charging processes (at a depot or using conventional public charging facilities) that do not take place at MCS charging points.

Different approaches can be used to support the demand and planning for BET charging infrastructure in Europe and especially in Germany. A critical distinction emerges between model-based and trip-based approaches, each offering unique insights into infrastructure demands. Model-based simulations employ theoretical frameworks to predict the necessary infrastructure, considering variables such as maximum average waiting times and charging durations. These models often rely on static assumptions about demand and do not always account for the dynamic nature of truck movements and charging needs throughout a day or over longer periods. Conversely, trip-based simulations are particularly adept at capturing the complexities of trucking logistics, including a possible variation in daily routes, the impact of mandatory rest periods on charging patterns and SoC-based recharging during the journey [11].

In a combination of a trip- and model-based simulation focusing on truck traffic in Germany, Speth et al. (2022) [18] argue for a charging infrastructure that ensures the average waiting time does not exceed 5 min, with a charging duration assumed to be 30 min. Their analysis, based on a scenario with 15% BETs and 50% public charging, suggests the need for 267 charging locations equipped with 2–8 chargers (totaling 950 chargers) spaced 50 km apart, or alternatively, 142 charging locations with 2–13 chargers (765 in total) spaced 100 km apart. They incorporate queueing theory into their model and base their data on manual traffic counts, providing insights into the operational aspects of charging infrastructure.

In Speth et al. (2023) [19], the authors model a capacity-constrained public charging infrastructure network for electric trucks in Germany. The approach from [18] has been improved in order to take limited parking capacities into account. By integrating data of available parking lots and trips based on origin-destination flows, the authors could indicate

the minimum number of charging locations for Germany to be 124 with approximately 12,000 charging points to serve 100% electric trucks with a range of 300 km.

Shoman et al. [20] provide a comprehensive analysis at the European level using the trip chain model, which includes necessary breaks for a truck fleet scenario envisaged for 2030. Their findings indicate that to support 15% of trucks as BETs, approximately 40,000 depot and 9000 Megawatt chargers would be required, suggesting a ratio of four to five times more depot charging points than MCS charging points. They estimate an average requirement per charging point of eight depot and two MCSs, utilizing charging powers ranging from 0.7 to 1.2 MW. This study lays a significant foundation in understanding the scale of infrastructure needed to accommodate depot charging demands for BETs. In Speth et al. (2022) [18], Speth et al. (2023) [19] and Shoman et al. [20], the authors apply a queuing model assuming a maximum average queuing time of 5 min, fast charging can be carried out in 30 min and 15 min of the 45 min break is for queuing, preparing for charging and leaving the charging point. Speth et al. (2023) [19] and Shoman et al. [20] consider trips; however, the real nature of truck movement and SoC-based recharging during the journey is not considered.

Menter et al. [11] adopt a trip-based simulation approach using MATSim to propose a demand-oriented charging network based on European and German fleet data for trucks. The simulation, which spans Monday through Thursday to manage computational load, considers real service areas in Germany. The findings suggest that for 1% BETs, 177 chargers at 172 charge points would suffice, whereas for a 20% adoption rate, as many as 1296 chargers at 457 charge points would be required.

Otteney et al. [21] introduce a data-driven approach to understand the charging behavior of BETs at a German Highway rest area, based on Diesel truck rest times. This study identifies a key finding: the simultaneous occupancy of multiple MCS charge points is rare, indicating a potential to optimize the number of MCS chargers. However, this analysis, focused on a single rest area, cannot fully represent the entire road network's charging needs. This limitation underscores the importance of simulating the whole charging infrastructure. Such an approach could lead to a more efficient and cost-effective planning, acknowledging that the specific findings from one rest area need to be scaled and adapted to understand and meet the wider network's requirements.

All mentioned papers in Table 1 propose a charging network and base their work on BETs that start their journey with 100% SoC, assuming all BETs can charge in their depot. To the author's knowledge, there is no assessment of the consequences of not having charging infrastructure in the depot. The aim of this paper is to propose a methodology to evaluate the required charging infrastructure to support the increased adoption of BETs in Germany, across various levels of electrification including European driving and rest time regulations, and evaluate the importance of depot charging solutions to meet these demands. Menter's work is pivotal in defining the baseline for this paper. However, the queuing algorithm needs improvement since regulation regarding breaks and working hours of drivers are not included and trucks do not always stick to their 45 min break.

The paper is organized as follows. Section 2 describes the used methodology and data. Section 3 presents our findings and in Section 4 we discuss these results. Section 5 concludes our paper and highlight future research plans.

Table 1. Literature overview infrastructure modelling.

Reference	Simulation Approach	Region	Charger Power	Share of BETs	Simulation Aim
Speth et al. (2022), [18]	Model and trip based	GER	720 kW	15%	#Charging locations and #chargers every 50 or 100 km; no exact charging location or design
Speth et al. (2023), [19]	Model and trip based	GER	720 kW	100%	#Charging locations and #chargers with maximum capacity constraints (based on real data on rest area utilization from Germany)
Shoman et al. (2023), [20]	Trip based	EUR	700 to 1200 kW	15%	Public charging requirements in 2030 (charging type, charging area capacity and energy supply); no exact charging location or design
Menter et al. (2022), [11]	Trip based	GER	720 kW	1/10/15/20%	#Charging locations and #chargers based on traffic flow and on distribution of service areas and existing infrastructure
Otteney et al. (2023), [21]	Data based	One charging location	900 kW	20%	#Chargers for one rest area based on local real time data and German wide counting stations; differentiation between MCS and CCS charging

2. Methodology

This paper contributes to understanding the planning and implementation of charging infrastructure for BETs. Building on the model of Menter et al. [11], we aim to extend the trip based MATSim analysis by not only focusing on the required charging infrastructure for different scenarios but also examining the impacts of overnight charging on MCS charger requirements. Our assumptions regarding the proportion of BETs in the future German truck fleet are grounded in the estimated sales volumes derived from cleanroom talks with various manufacturers [22]. Industry stakeholders expect a distribution of charging between depots and public infrastructure at a 50:50 ratio [22]. By contrasting these expectations with a “worst-case scenario” that excludes the possibility of overnight charging, we aim to offer a view on how overnight charging could significantly affect the frequency of charging events and the overall demand for MCS infrastructure. In this chapter we present our methodological approach to further improve the simulation at the points mentioned in the introduction.

2.1. Simulation Framework

We employ MATSim, an activity-based multi-agent transport simulation, where each vehicle is represented by one agent executing predefined plans with specific origins and destinations [23]. By leveraging the detail level, the utilization of charging infrastructure can be analyzed regarding potential bottlenecks. Our simulation model is an improvement of [11] and takes input data from Open Street Map for road mapping, rest areas and industrial zones as well as official German truck traffic statistics as shown in Figure 1. The model has undergone statistical validation based on extensive traffic counts. A detailed description of the model and the pre-processing of input data can be found in [11].

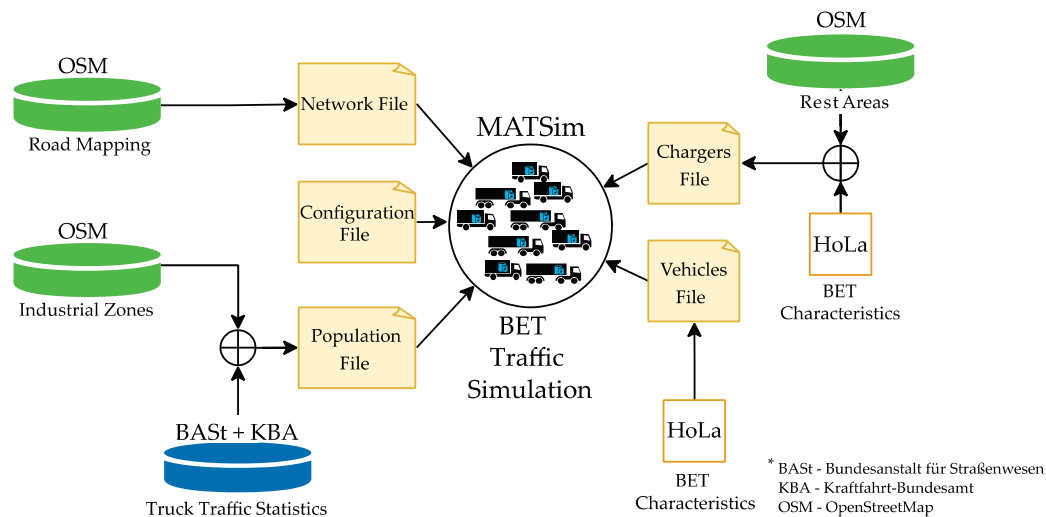


Figure 1. Overview of the simulation environment in MATSim (edited from [11]).

The framework conditions of the simulation are summarized in Table 2. Technical specifications for trucks and charging points were determined in consultation with industry partners as part of the HoLa project in Germany [15], setting a realistic framework for our analysis. As a reference we refer to the following semi-trailer BETs: Daimler eActros 600 (600 kWh) [24], Volvo FM Electric (540 kWh) [25] and Scania BEV 6 × 2 2022 (468 kWh) [26], all with a payload capacity of 22 tons. In the scenario of Menter et al. long-haul operations are categorized as journeys that span more than 300 km [11].

Table 2. Framework conditions of the simulation.

Description	Values
Simulation timeframe:	Monday to Thursday (96 h)
Simulated trips with >300 km in Germany (Mon–Thu):	~660,000
Maximum velocity:	80 km h ^{−1}
Electrification levels:	1%, 5%, 10%, 15% and 20%
BET's battery capacity:	600 kWh
BET's consumption:	1.2 kWh km ^{−1}
BET's payload:	22,000 kg
Charger specification:	720 kW (DC)
Lower SoC threshold:	20%
Max. number of potential charging sites:	588

Our demand-based approach to determine a high-power charging infrastructure design for the entire German area is based on two parameters. First, the locations of the potential charging sites and second the number of chargers per site. We assume all 588 existing rest and service stations with amenities are potential locations (upper bound). Our computer model determines which of these locations should be used and how many chargers are needed at each charging site.

2.2. Demand-Based Distribution Approach for Charging Stations

In a demand-based distribution of charging stations, it is crucial to evaluate how the number of charging points correlates with potential queues and associated waiting times for effective allocation of charging infrastructure. This assessment utilizes variable percentiles for different scenarios, where a “percentile” in statistics refers to a value below which a certain percentage of values (in this case, the number of charging processes) in a distribution falls. The 100th percentile means all BETs can charge when they arrive at a charging location. However, this results in an inefficient charging infrastructural design.

Figure 2 shows the application of the 90th percentile. Meaning, for this specific charging location the number of chargers is reduced to nine chargers, enabling 90% of all charging processes while 10% needs to wait.

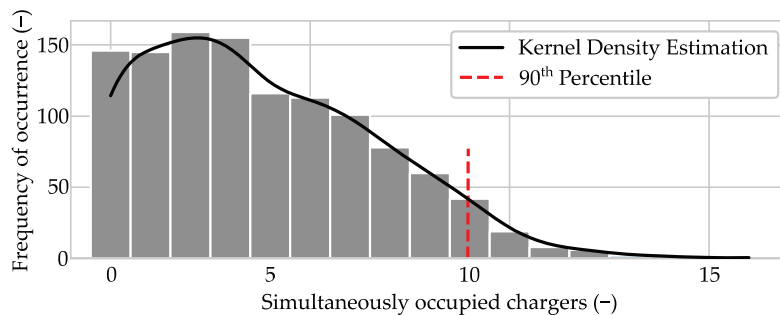


Figure 2. Application of the 90th percentile.

2.3. Data Processing

Our approach to data processing for every electrification scenario with MATSim is divided into two stages (see Figure 3). In the initial MATSim run, we send the BETs with their predefined plans and provide enough available chargers per location. This scenario yields the maximum number of simultaneously occupied charging stations, which can then be reduced to a desired percentile. To further analyze the resulting waiting times and the proportion of waiting BETs, we conduct a second simulation using the same scenario but with a demand-oriented distribution, based on the percentiles.

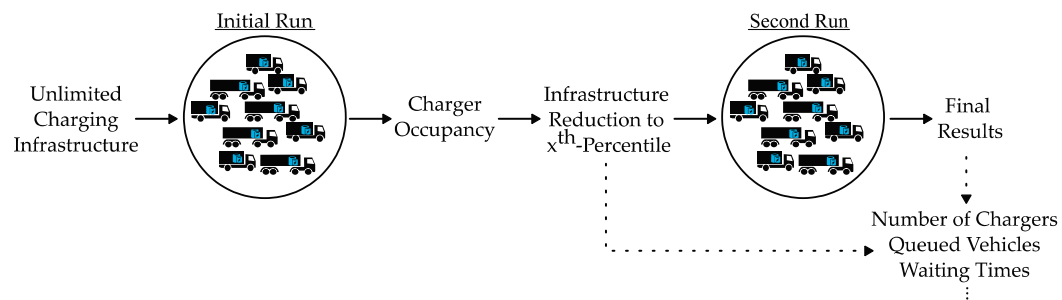


Figure 3. Overview of data processing.

2.4. Break Logic

Our model comprises a “break logic”, which takes advantage of mandatory break times in accordance with the legal framework of European driving and rest times [17] and the Working Time Directive [27].

Additionally, we force all trucks to take charging breaks upon falling below the predefined minimum SoC of 20%. Typically, a 45-min break is required after a maximum of 4.5 h of driving and according to the Working Time Directive, an employee must take a break after 6 h of work, interpreted here as a 45-min break. For truck drivers, the regulation allows a maximum of 9 h driving time followed by an 11-hour rest period. The daily schedules of the BETs emerging from this new logic are illustrated in Figure 4, indicating that the break is always 45 min long and includes recharging, regardless of whether there is a charging need or a need to interrupt driving time. The modelling of breaks up to the long 11-hour rest period is sufficient since the vehicle plans in our model do not extend beyond this timeframe.

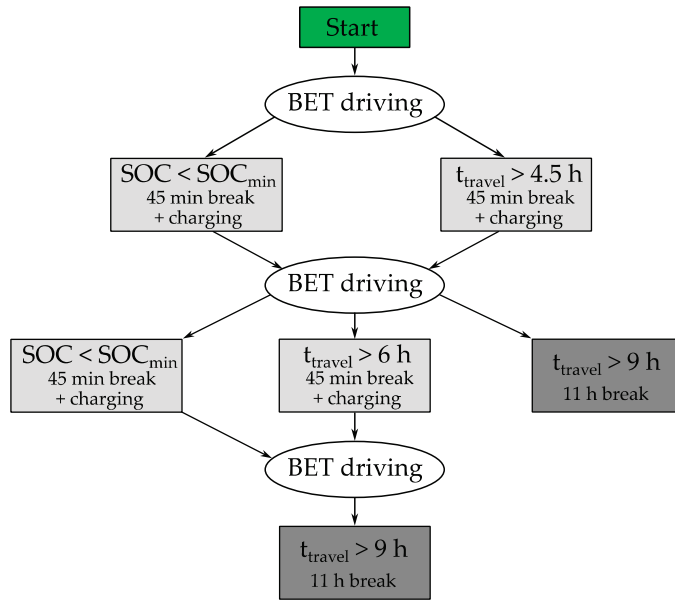


Figure 4. Overview of the break scenarios of BETs.

2.5. Enforced Charging Duration and Queueing

Applying the standard Electric Vehicles (EVs) module in MATSim [23] allows the modeling of charging activities for BET drivers including queueing and potentially waiting for a charger to become free. By standard, the BET drivers integrate the charging activities into their daily schedules as part of MATSim’s replanning step in the co-evolutionary algorithm, i.e., a priori [23]. As part of the planning procedure, the charging activity needs to be assigned a duration that covers the waiting time. However, the occupancy of the charger at the time of the BET driver’s arrival cannot be precomputed. In consequence, it is impossible to precisely account for waiting time while planning the total time spent at the charging location, a priori.

As pointed out in Section 2.4, the driver break is assumed to last exactly 45 min. This shall exclude waiting time, as the driver must not move the vehicle during the break, which is necessary for advancing the BET in the waiting queue.

Therefore, we implemented the option to enforce predefined durations for charging activities, excluding waiting time, by extending the duration one second for each second spent waiting, using MATSim’s central infrastructure for within-day replanning [28].

2.6. Expected BET Share of German Heavy-Duty Trucks

Estimating the future fleet share of BETs within the German heavy-duty truck fleet (N3 class, >12 t), this study references the 2024 Cleanroom Talks conducted by NOW GmbH [22]. During these discussions, 95% of manufacturers operating in the German market provided projections for future sales figures, segmented by drivetrain technology. Assessing the overall fleet shares through 2030 based on these projections, it is essential to estimate the annual retirement rate of N3 vehicles from the German fleet. Given the average vehicle age of approximately 7 years [29], registration data from recent years, as reported by the German Federal Motor Transport Authority [30], serves as the basis for estimating truck retirements. Furthermore, the analysis includes an extrapolation of the projected market ramp-up for BETs in subsequent years through exponential smoothing. The NOW-forecast is extended to 2033, 2035 and 2042, with fleet shares projected to reach approximately 10%, 15% and 20%, respectively (see Figure 5).

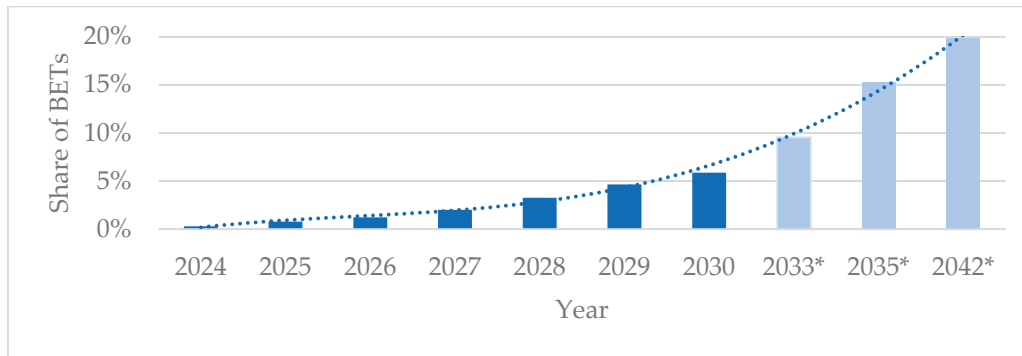


Figure 5. Estimated German heavy-duty BET fleet share (* extrapolated).

Overall, this approach represents a conservative estimate, as BETs in the N3 class are likely to be deployed primarily in short- and medium-haul applications.

2.7. State of Charge at Start of Operation

In previous simulations, it was assumed that a fleet could replenish its battery capacity before starting the trip either at a depot or using public charging infrastructure. In this paper, however, we also want to analyze what additional charging requirements arise if the fleet operations rely completely on MCS, as a “worst-case scenario”. Therefore, we need depot SoC data for a truck fleet reliant solely on MCS-charging during 45-min breaks. Lacking access to such data, we adopt an approach to generate a synthetic SoC distribution for a truck fleet. Specifically, we simulate a scenario for a Monday, limited by computational capacities, involving a 20% BET fleet starting with 100% SoC and heading to predefined destinations. The charging points are determined by previously mentioned locations, with each site having an unlimited number of charging points. At the end of the simulated day, the vehicles arrive at their destinations with their remaining capacities, which, due to the absence of depot charging infrastructure, can also be used as the fleet’s initial SoC distribution for the next day. This statistical distribution is then applied to the different shares of BET fleets we analyze in this paper. The distribution of the fleet SoC over a day is shown in Figure 6.

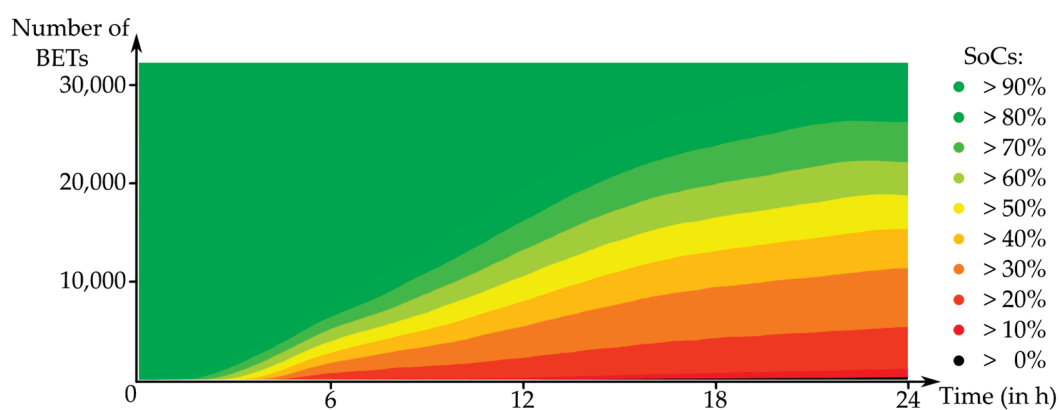


Figure 6. SoC fleet distribution over 24 h (100% start SoC).

3. Results

In the following section, we present the outcomes of our simulation analysis. In this paper, we focus on a detailed percentile-based overview for 1%, 10% and 20% share of BETs based on two scenarios, with and without depot charging.

3.1. Different Scenarios for BET Market Ramp-Up

3.1.1. The 1% BET Fleet

In this scenario, we assume that 1% of the German heavy-duty long-haul truck fleet is converted to BETs. We present findings that commence at the 92nd percentile (see Table 3), as values below this threshold are considered impracticable due to the appearance of additional waiting times exceeding 6 h. Additionally, the 100th percentile is excluded from consideration as it merely represents a statistical distribution of a synthetic fleet and a 100% supply for the real fleet cannot be guaranteed, anyhow.

Table 3. Results of different supply percentiles for a 1% BET fleet.

Supply Percentile	Number of Charging Sites	Number of Chargers	Waiting Duration (Queued Vehicles)	Share of Waiting BETs
92nd	160	163	00:45:16	35%
93rd	176	179	00:41:30	32%
94th	211	219	00:32:27	26%
95th	245	261	00:29:17	20%
96th	282	304	00:26:23	16%
97th	331	361	00:24:17	13%
98th	395	442	00:21:22	10%
99th	450	561	00:17:59	5%

For this scenario, the required number of chargers ranges from 160 to 450. Regarding waiting time, it is demonstrated that the queue waiting time for vehicles can be progressively reduced from approximately 45 min to about 18 min. Furthermore, the proportion of vehicles waiting decreases from 35% to 5% as shown in Figure 7.

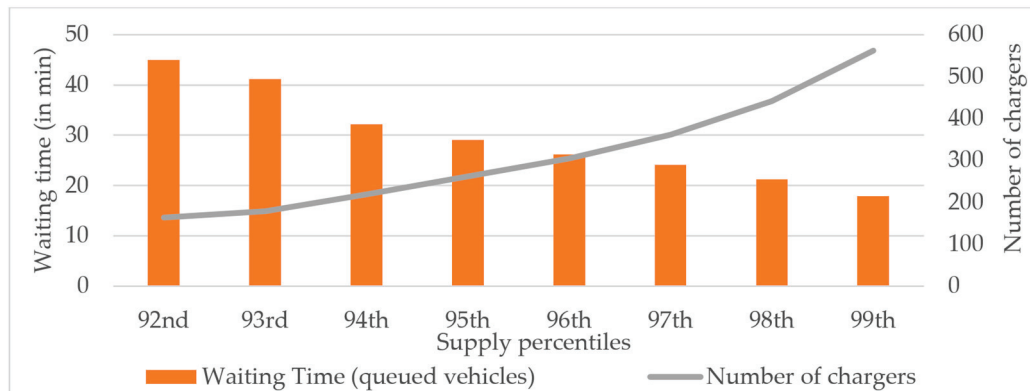


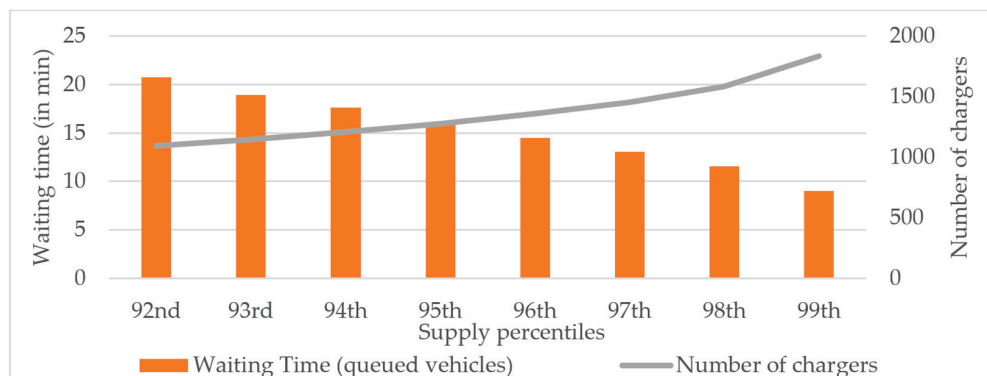
Figure 7. Waiting time over the number of chargers (1% BETs).

3.1.2. The 10% BET Fleet

In the second scenario, it is demonstrated that for lower supply reliabilities, waiting times of less than half an hour are observed. This duration can be reduced to under 10 min by expanding the number of chargers from 1092 to 1835 at the 99th percentile. Similarly, the proportion of vehicles waiting decreases from 25% to 3% (see Table 4 and Figure 8).

Table 4. Results of different supply percentiles for a 10% BET fleet.

Supply Percentile	Number of Charging Sites	Number of Chargers	Waiting Duration (Queued Vehicles)	Share of Waiting BETs
92nd	479	1092	00:21:29	25%
93rd	485	1146	00:19:39	21%
94th	490	1208	00:18:16	18%
95th	499	1274	00:16:35	15%
96th	503	1358	00:15:03	12%
97th	510	1456	00:13:31	9%
98th	515	1586	00:11:58	6%
99th	521	1835	00:09:21	3%

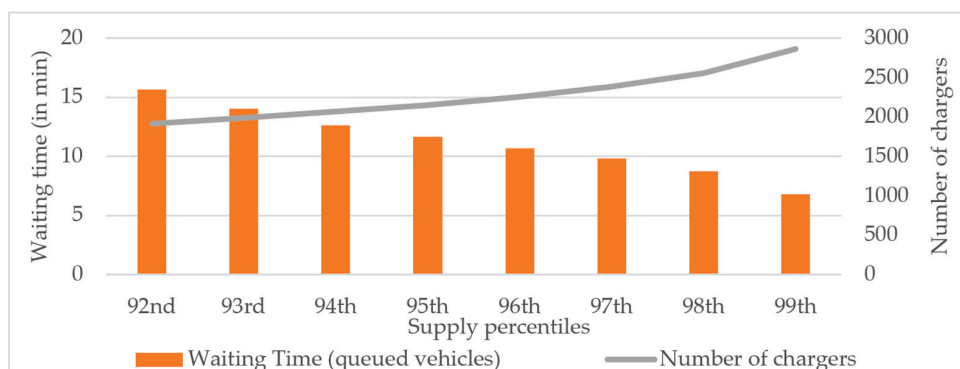
**Figure 8.** Waiting time over the number of chargers (10% BETs).

3.1.3. The 20% BET Fleet

In the third scenario, the waiting duration is again reduced, ranging from approximately 16 min to 6 min. This is achieved by increasing the number of chargers from 1911 to 2857. As a result, the share of waiting BETs declines from 22% to 3% (see Table 5 and Figure 9).

Table 5. Results of different supply percentiles for a 20% BET fleet.

Supply Percentile	Number of Charging Sites	Number of Chargers	Waiting Duration (Queued Vehicles)	Share of Waiting BETs
92nd	504	1911	00:15:45	22%
93rd	508	1984	00:14:08	19%
94th	510	2065	00:12:44	16%
95th	514	2152	00:11:46	13%
96th	519	2257	00:10:47	11%
97th	521	2386	00:09:53	8%
98th	523	2552	00:08:47	6%
99th	524	2857	00:06:50	3%

**Figure 9.** Waiting times over the number of chargers (20% BETs).

3.1.4. Necessary Infrastructure to Support Estimated Market Ramp-Up

The compilation of results for the market ramp-up from 2025 to 2042 is illustrated in Figure 10. It is observed that across all percentiles, as the fleet proportion of BETs increases, a higher number of chargers are required. However, the demand does not develop proportionally to the growing fleet. As a result, the required chargers converge. This is exemplified by the percentiles 95 and 99 over the years from 2025 to 2042, where the ratio of chargers decreases from 261 to 561 units in 2025 to 2152 and 2857 units in 2042. Despite this, it can be realized that improvements in supply from the 90th to the 95th percentile can be achieved with fewer additional chargers per expansion stage, whereas the next demonstrated step to a 99th percentile supply rate would be associated with a significantly larger increase in charger installations. In general, depending on the supply rate, between 1776 and 2857 chargers will be needed by 2042.

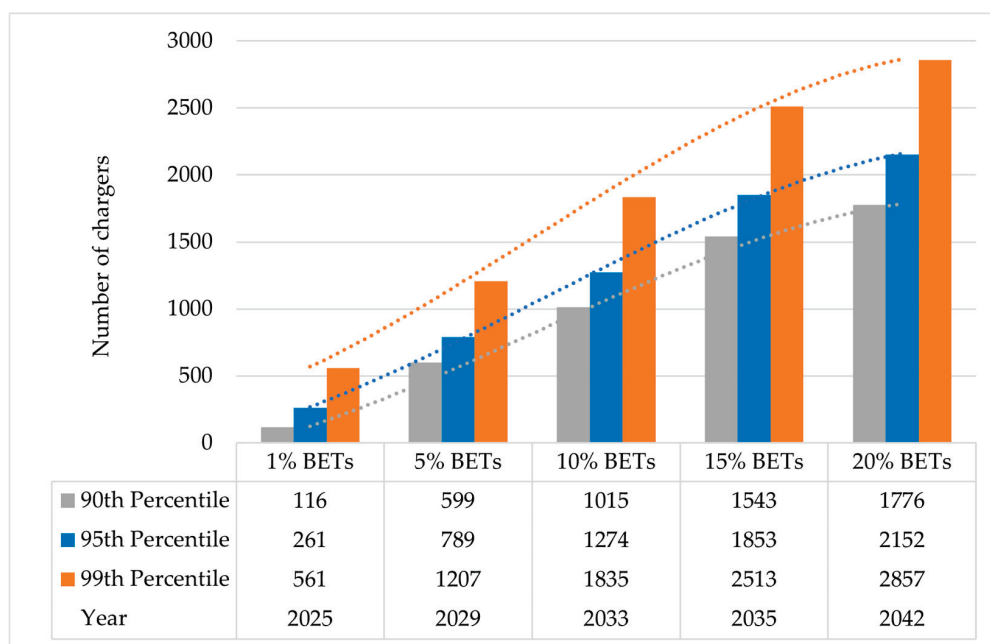


Figure 10. Necessary chargers for an assumed German market ramp-up from 2024 to 2029.

3.2. The 10% Scenario Without Depot Charging

The findings from the 10% BET fleet scenario, without depot charging, are depicted in Table 6. This analysis reveals that to meet the demand at the 90th to 95th supply percentiles, between 1471 and 1780 chargers are required. It is noteworthy that the increase in the number of charging stations is minor, moving from 503 to 513. Concurrently, there is a reduction in both the waiting time and the proportion of BETs in queue; the waiting time decreases from approximately 22 min for 26% of all BETs to 15 min, with only a 13% share of vehicles waiting in line.

Table 6. Different supply percentiles for a 10% BET fleet without depot charging.

Supply Percentile	Number of Charging Sites	Number of Chargers	Waiting Duration (Queued Vehicles)	Share of Waiting BETs
90th	503	1471	00:22:09	26%
91st	504	1534	00:20:17	23%
92nd	509	1583	00:18:50	20%
93rd	511	1642	00:17:48	18%
94th	512	1701	00:16:13	16%
95th	513	1780	00:15:00	13%

In Figure 11, the outcomes of this scenario are contrasted with those from the simulation that includes the option of depot charging. This comparison illustrates that the demand for chargers consistently differs by several hundred charging points. However, it is demonstrated that this difference just slightly diverges as the supply demand increases, resulting in a changing ratio of chargers between the two scenarios.

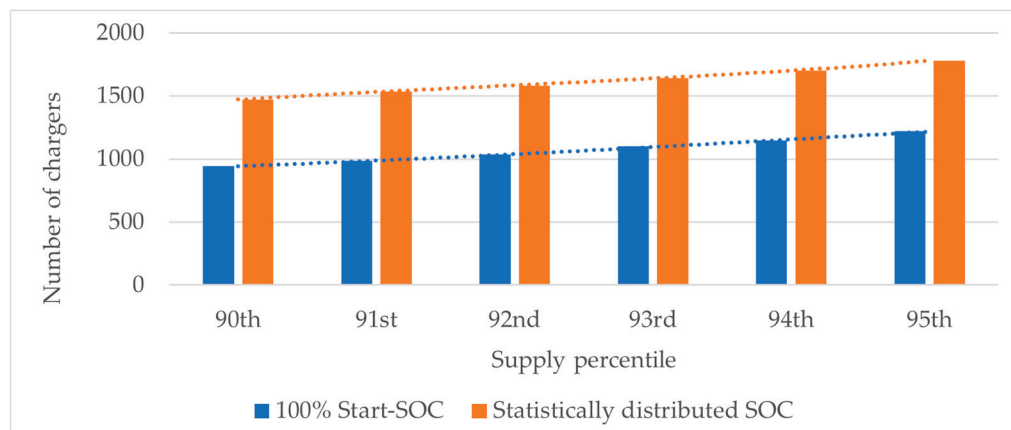


Figure 11. Charger necessity for 10% BETs with different start SoC.

Regarding the impact on the truck operations, we compare the two scenarios with a particular focus on their break behavior (see Table 7). Overall, the number of charging events increases from 46,180 to 80,800 when depot charging is not provided. Additionally, it can be demonstrated that the charging events per truck differ, moving from 0.7 in the scenario with a start SoC of 100%, to 1.2 when SoCs are statistically distributed. As a result, the average break time per truck increases from 31.5 min to 54 min.

Table 7. Comparison of breaks with and without depot charging.

Start SoC	Charging Events in Total	Charging Events per Truck	Break Time
100%	46,180	0.7	31.5 min
Statistical distribution	80,800	1.2	54 min

4. Discussion and Limitations

Our analysis reveals a larger difference in the number of required chargers between the lower and upper supply percentiles for the 1% BET scenario (1:3.4) compared to the 10% BET scenario (1:1.7), despite the calculation for the smaller scenario commencing from the 92nd percentile. This suggests that a proportionately larger initial investment in infrastructure is essential to achieve a substantial enhancement in supply security. For identical supply percentiles, charging infrastructure for a fleet of 10% BETs experiences shorter waiting times and a smaller proportion of waiting vehicles compared to 1% BETs. This is attributed to a better statistical distribution of a larger fleet across charging points. In the network expansion stages for 1% BETs, even high supply security is critically viewed for logistics companies, because if a truck ends up in a queue, despite a lower probability, waiting times exceeding 20 min are deemed too long. It is important to remember that these delays are in addition to traffic jams and other daily disruptions. Although the metrics of vehicle waiting times and the ratio of waiting vehicles to the total fleet see substantial improvements in the 10% scenario with enhanced supply security, the average required waiting time remains a point of critical concern for logistics operations.

Regarding the tolerated waiting times for trucks of 15 min [31], it is demonstrated that this benchmark cannot be met with an effective and demand orientated infrastructure

ramp-up for 1% BETs. Even at 10% BETs, a high supply percentile of more than 96th is necessary. These findings strongly suggest considering a rapid and comprehensive rollout of high-power charging infrastructure throughout Germany.

Referring to Speth et al. (2022) [18], for an electrification level of 15%, the required number of chargers ranges between 765 and 950, assuming 50% of BETs engage in public charging. When scaled up to our scenario, this translates to an estimated need for 1530 to 1900 chargers, conservatively estimated, since effectively fewer chargers would be needed due to previously described effects. Nonetheless, our results are comparable, as they fall within the 90th to 99th percentile range considered.

Incorporating insights from Shoman et al. [20], our research indicates that Germany would require approximately 8124 to 10,155 depot chargers by 2029 to meet the demands of the 95th supply percentile for a 10% BET fleet, correlating to the given 4–5 depot chargers per MCS charger.

One potential application of our findings could be the revision of the European Alternative Fuels Infrastructure Regulation (AFIR). Currently, the AFIR sets a minimum charging power requirement of 350 kW, which falls significantly short of the 720 kW assumed in our analysis. We recommend increasing these minimum requirements to account for future technological advancements and to ensure the infrastructure can support higher charging capacities and greater availability.

Our analysis highlights the critical need for depot charging in combination with HPC, demonstrating that increased charging operations, as per current plans, lead to greater downtime for logistics companies' trucks due to the requirement for additional breaks. From an infrastructure perspective, this necessitates an overall increase of 31% in MCS to accommodate the greater demand.

Some of our assumptions may be regarded as too conservative. It is conceivable that the number of charging-required breaks could be reduced in the future. First, future larger batteries will emerge, improving the range of BETs if the volumetric and gravimetric density of battery cells is increased. Second, possibly lower energy reserves (SoC_{min}) could be safely utilized as logistics companies gain experience and the charging network becomes denser. It is essential to note that traffic-related exceptions, including traffic jams and the resulting congestion in parking areas, have not been considered here.

We are well aware that the assumed energy consumption values for heavy-duty BETs do not reflect the wide range of energy consumption values reported in the literature. Furthermore, we do not take into account the influence of local topography. Potential locations for charging and parking facilities have been considered primarily based on existing infrastructure, neglecting the growing importance of installing charging stations at unmanaged rest areas, as well. Another critical aspect that has not yet been considered is the integration of trip chains, which are essential for capturing operational patterns over several days. Lastly, while the scenarios explore varying electrification rates, the overall fleet size (based on the year 2020) remains constant, disregarding the anticipated growth in the overall fleet and corresponding increases in energy demand. Future scenarios incorporating fleet expansion would likely indicate higher infrastructure requirements, underscoring the need for a more dynamic approach to scenario modelling.

5. Conclusions and Outlook

In this study, we have explored the essential infrastructure requirements for BETs in Germany, focusing on long-haul trucking in the context of the European Union's climate neutrality goals. Our trip-based analysis, relying on MATSim, underscores the critical infrastructure needs to support the market ramp-up of BETs. Through the simulation, we

examined various levels of electrification and the pivotal role of depot chargers, orienting our investigation towards demand-driven infrastructure development.

Our study showcases a detailed understanding of supply percentiles, demonstrating that enhanced infrastructure can significantly reduce waiting times and the proportion of waiting BETs, underlining the urgency of infrastructure development. Particularly, the ramp-up must occur swiftly to ensure that logistics companies and early adopters do not experience significant negative impacts, which could harm the roll-out of the technology. Another critical insight from our research is the importance of combining high-performance charging with depot charging facilities. Depot charging reduces the overall demand for daytime charging and lowers the operational downtime, underscoring the intricate interplay between charging infrastructure and logistics efficiency.

In conclusion, our research contributes to a critical perspective on the path towards achieving the EU's climate neutrality goals through the electrification of heavy-duty road transport. As we navigate the transition to a more sustainable transport sector, the insights from this study may serve as a cornerstone for policymakers, industry stakeholders and researchers, highlighting the need for intensive efforts in infrastructure planning.

For future research, we will aim to evaluate required charging power in combination with grid capacities. Additionally, we intend to address the limitations of our study by revisiting the foundational data used for fleet generation and the identification of potential charging locations. Furthermore, the evaluation and application of real data obtained from the ongoing HoLa project will offer us a unique opportunity to validate our simulations and predictions based on more accurate user behavior and system performance. Finally, we aim to simulate the operations over an entire week, providing a comprehensive view that captures the variability in usage patterns and system demands.

Author Contributions: Conceptualization, T.T.; methodology, T.T., T.-A.F. and D.G.; software, T.T. and T.S.; validation, T.T., T.-A.F. and D.G.; formal analysis, T.T.; investigation, T.T.; resources, T.T.; data curation, T.T.; writing—original draft preparation, T.T.; writing—review and editing, T.T., T.-A.F., T.S. and D.G.; visualization, T.T.; supervision, T.-A.F. and D.G.; project administration, T.T., T.-A.F. and D.G.; funding acquisition, D.G. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BET	Battery electric truck
CCS	Combined charging system
DC	Direct current
DFG	German Research Foundation
EV	Electric vehicle
HoLa	High performance charging for long-haul trucking
HPC	High-power charging
MATSim	Multi-agent transport simulation
MCS	Megawatt-charging-system
SoC	State of charge

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Article

Requirements and Test Stand Development for ERS Pantographs

Alexander Prinz ¹, Kil Young Lee ², Abhishek Gupta ¹, Dietmar Göhlich ¹ and Sangyoung Park ^{2,*}

¹ Methods for Product Development and Mechatronics, Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany; a.prinz@tu-berlin.de (A.P.); abhishek.gupta@tu-berlin.de (A.G.); dietmar.goehlich@tu-berlin.de (D.G.)

² Smart Mobility Systems, Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany; kil-young.lee@tu-berlin.de

* Correspondence: sangyoung.park@tu-berlin.de

Abstract: Electric road systems (ERSs) are a promising solution for electrifying heavy-duty freight transport by providing traction and charging power from the power lines installed along the road. Development of ERSs has been accelerated in the last decade, and several pilot projects have been successfully implemented, proving the high level of maturity that the technology has achieved. One crucial step that could be initiated before a rollout is the standardization and certification of ERS infrastructure and system components. For instance, pantographs for overhead ERSs face unique challenges, in that the power transfer should be safe and reliable in the presence of dynamic longitudinal and lateral movements of the vehicle. To tackle this problem, we outline the requirements for overhead ERSs and ERS pantograph testing. Among the key requirements are the rising and lowering times, response to lateral maneuvers, such as lane changes, and high electrical current during stillstand. We introduce our developed test stands capable of testing various aspects of an ERS pantograph. The lateral test stand was developed to test basic functionalities and simulate lateral movements. A second test stand was implemented, to test high currents and the subsequent temperature development. Furthermore, a digital test stand used for planning, design, and modeling is introduced.

Keywords: electric road systems; road freight transport; truck pantograph; standardization; testing

1. Introduction

Despite comprising a relatively small segment of the total global vehicle population in 2022, medium- and heavy-duty trucks for road freight transport contributed approximately 25% of emissions within the transportation sector worldwide [1]. Similar to passenger cars, heavy-duty commercial vehicles are undergoing a shift toward electric vehicle propulsion [2,3]. The most common technologies for the electrification of heavy-duty vehicles involve the integration of batteries or green hydrogen, encompassing battery electric vehicles (BEVs), plug-in hybrid vehicles (PHEVs), and fuel cell electric vehicles (FCEVs) [4,5]. Truck electrification through BEVs is challenging, due to the need for high-capacity batteries for long-haul routes and the necessity for adequate charging infrastructure along those routes [6,7]. On the other hand, hydrogen technology faces hurdles like high infrastructure costs and large storage tanks, particularly for long-haul freight transportation [6,8]. Potential solutions, such as battery swapping, increased battery capacity, and fast charging, have limitations including higher total cost of ownership and increased life cycle greenhouse gas emissions [6,9–11].

To improve the practical utility of the battery for freight transport, electric road systems (ERSs) enable dynamic charging directly from the electric grid, either inductively [12] or conductively [13] by rails or catenaries, thereby eliminating the need for static charging stations and vehicle idling [6]. Among the conductive ERSs, the overhead ERS, which utilizes an overhead line infrastructure, has been researched for over a decade, with advancements in pantograph variants that enable vehicles to connect and disconnect from the contact lines [14]. The transferred energy can be used directly by the electric motor or charged into the battery, depending on the propulsion concept, e.g., BEV, hybrid diesel truck, or FCEV. Multiple test tracks for the overhead ERS have been built around the world. A non-public test track was first set up by Siemens in Groß Dölln, Germany in 2011, to test and develop overhead ERS infrastructure and trucks equipped with ERS pantographs [15]. In subsequent projects, public field tests were funded in the USA [16], Sweden [17], and Germany [18–20]. More than 15 trucks are currently in operation in the public field tests in Germany.

Even with progress in technology and testing in laboratories worldwide, moving forward is difficult, due to the need for clear political decisions, global teamwork, standardization, and involvement from the automotive industry and other key players [21]. For electrification of heavy-duty trucks, the necessity for standardizing interfaces between vehicles and charging environments is crucial for interoperability and market diffusion, and this has become evident due to increasing complexity [22,23]. Standardization and legislation are accelerating the implementation of hydrogen and battery electric buses and heavy-duty trucks, though some areas still require further standardization [4]. The utilization of overhead systems in train electrification, incorporating onboard energy storage devices to extend travel range via electrical energy, is also further facilitated by the active development of standardization and legislation [24].

Regulated and standardized test stands and test protocols for new components are lacking, due to the absence of standardization and legislation for the electrification of overhead ERSs [21,25,26]. Thus, standardization and legislation need to be addressed along with concrete requirements and testing regulations, to open up the market [21,25]. In response to these concerns, this paper presents a basic groundwork for standards and regulations. Analogies are made between the current standards covering rail transport and those applicable to BEVs. Additionally, overhead ERS research projects, test stands, and test tracks were examined. Section 2 explains the system architecture of the overhead ERS. In Section 3, the current state of the art in the mentioned areas of interest and the research gaps are addressed. In Section 4, we present our established framework for extracting and defining requirements, which offers crucial input for standardization and regulation for overhead electric trucks. It also encapsulates the quantification and specification of the established requirements through the framework. Section 5 outlines the outcomes of the framework's implementation, focusing on the development of test stands for evaluating ERS pantographs. Finally, the concluding section summarizes our survey, the developed framework, and its implementation, and highlights the future scope of this work.

2. System Architecture of Overhead ERSs

The system architecture of an ERS can be divided into power supply, power transfer, and power receiving parts. A schematic of the architecture is depicted in Figure 1. For conductive ERSs utilizing overhead lines, the main system components comprise substations, overhead line infrastructure, and ERS pantographs. The substations are connected to the medium-voltage grid, and they transform the AC power to DC power at permissible levels for vehicle application (600 to 1500 V) [27]. The power is then transferred through the overhead contact lines (OCLs) to the receiving vehicle. The ERS pantograph establishes

the connection point between the overhead lines and the connecting vehicle by receiving and converting the power, so that it can be used by the drivetrain of the electric vehicle.

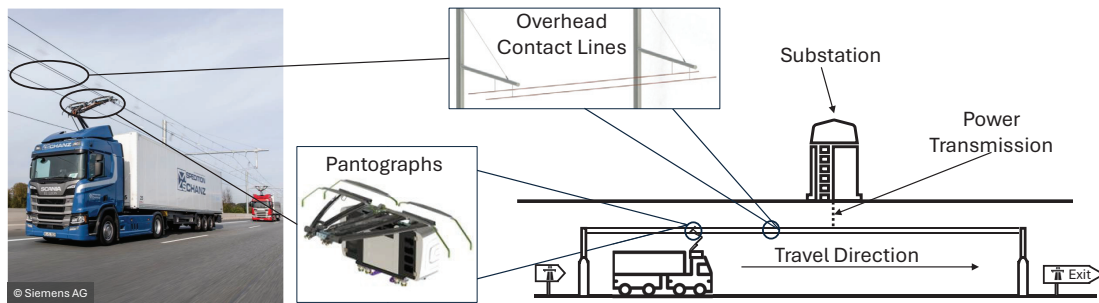


Figure 1. System architecture of an overhead electric road system (left truck picture courtesy of Siemens AG [28]).

Substations are comprised of transformers, rectifiers, surge arresters, and circuit breakers, and they can provide power up to 4 MW [27]. Substations can be placed several kilometers apart, depending on the expected traffic, or even at a distance of less than 1 km apart on highways with high-frequency use [27]. The substation supplies the electrified sections via the overhead lines. The overhead lines of the overhead ERS are two-pole, with two parallel overhead lines serving as the feeding and the return path for the current, as no return path through rails is available for trucks. Poles supporting the catenary system must be erected along the highway at distances of up to 65 m. The overhead lines used in eHighway pilot projects are of type AC150-CuMg0.5 (EN 50149) and BzII 120 mm² for the contact wire and the messenger wire, respectively [29]. While the contact wire is in direct contact with the pantograph, the messenger wire is carrying the contact wire through droppers placed every 3–4 m, to uphold a straight line of contact. The contact wire and messenger wire are tensioned with 20 kN and 10 kN, respectively [27].

The power transfer to the vehicle is made through the pantograph and a vehicle infeed circuit [29]. The pantograph of the overhead ERS faces some unique challenges compared to conventional pantographs. The ERS pantograph has to accommodate the feeding path as well as the return path, to match the two-pole overhead line structure. Also, the pantograph must be able to repeatedly connect and disconnect from the ERS at high speeds and react to lateral maneuvers such as lane changing. The vehicle infeed circuit regulates the power drawn from the ERS and is linked to the energy management system of the vehicle. Such systems can comprise batteries and motors, as well as fuel cells or internal combustion engines in cases of hybrid vehicles. To process the power drawn from the ERS, the pantograph and the vehicle infeed circuit should include fuses, polarity checks, filters, and transformers [29].

The longest installed overhead ERS is the field test ELISA [18] on highway A5 in Hessen, Germany, where a total of 17 km (12 km in one direction and 5 km in the opposite direction) are electrified. Notably, 7 km out of the 17 km were additionally installed in only one year, pointing to the scalability and rapid-rollout potential of the technology. Apart from the technological investigations, different implementation scenarios have been investigated, looking into effectiveness, cost, and environmental impact [3,30–32]. For Norway, an ERS installation on only 25% of the roads would lead to 70% traffic electrification [30]. Similar values have been proposed for Germany, where it has been suggested that about 30% of the highway (about 4000 km) be electrified by 2040, to meet climate goals [31]. A network analysis in the Netherlands found that deploying an ERS significantly reduces the need for battery-supported distances, showing that up to 80% of trips would require battery support for less than 25 km [32].

3. Survey on Standardization of Overhead ERSs and Relevant Testing Sites

3.1. Standardization of Overhead Electric Road Systems

Standardization and regulation contribute significantly to the interoperability and compatibility of the technology and, thus, facilitate deployment. Regarding ERSs, workshops and surveys on standardization have been conducted [33–35]. Furthermore, a working group of CENELEC [36], CLC/TC 9X/WG 27 [37], is looking into “Current collection systems—Technical criteria for the interaction between pantograph and overhead contact lines on electrified roads”, and a standard CLC/TS 50712 [38], “Railway applications—Current collection systems—Technical criteria for the interaction between pantograph and overhead contact lines on electrified roads”, was ratified and published in 2024. The CLC/TS 50712 describes the requirements and needs for the use of ERS pantographs in conjunction with overhead contact lines on roads in Europe.

Apart from the European standards for overhead electric road systems and their application within the European Union, refs. [39,40] mention that the eHighway solution was demonstrated in 2017 by the South Coast Air Quality Management District using three different trucks along a one-mile urban road in Carson, Los Angeles County, California, USA [41]. However, these publications do not reference any standardization for overhead electric road systems in the USA. Similarly, publications [35,42] mention the standardization initiatives in the European Union, particularly with a focus on Sweden, and highlight the gap in international standardization in other countries and their respective standardization organizations.

3.2. ERS Pantograph Testing

As outlined above, standardization efforts focus on the current collector, i.e., the pantograph, for overhead ERSs, as it is the most critical and the newest system component in the development of overhead ERS. While the ERS pantograph is similar in concept to conventional pantographs from rail transport systems, ERS pantographs differ significantly in structure and required functionality. The ERS pantograph employs an electrical two-pole structure, and the coupling and decoupling processes are much more complicated on the road, as they have to be performed while driving. Decoupling processes during lateral maneuvers, such as lane changing, are especially challenging and non-existent in rail applications. Future ERS pantographs must be tested according to the new standards, to be eligible for road operation. Common test parameters used in the rail industry are contact resistance, power factor, contact temperature, collector head wear, and dynamic behavior at different speed levels. Similar and new test procedures must be developed to fit the ERS pantograph requirements.

The interoperability of ERS pantographs has been shown in retrofitting projects [43–45], while technical feasibility has been tested during operation in field tests [15–20]. However, the field tests focused on testing the overall system rather than the specific behavior of the pantograph. A test bed for ERS pantographs has been developed by Siemens [46], which is currently used for developing and testing ERS pantographs with a focus on examining the functionality. As far as is known to the authors, there is no public test stand available for ERS pantographs, especially with the aim of independently testing standardized procedures. To conduct such independent testing and evaluation, the necessary requirements for an ERS pantograph should be examined beforehand. In this paper, we aim to present our findings from examination of rail and road standards, recommendations from the working group CLC/TC 9X/WG 27, and the defined requirements from the recently published standard CLC/TS 50712:2024 [38], to develop a secure test environment that is capable of testing an overhead ERS pantograph with regard to safety as well as functionality. The results of the

ongoing work offer a significant contribution towards certification and homologation of ERS pantographs.

4. Deriving Requirements for the ERS Pantograph Test Stand

In product development, it is essential to define a complete, unambiguous, and contradiction-free target system [47]. Various design process models have been created as a means to support designers for planning and documenting their work. Here, we followed a process model described in [48]. Although the overhead ERS is a newly developed technology, it is based on technology used in electric railways. Logically, standards and requirements do not have to be developed from scratch but can be derived from analogies between these applications. Our approach for deriving the requirements for the ERS is illustrated in Figure 2:

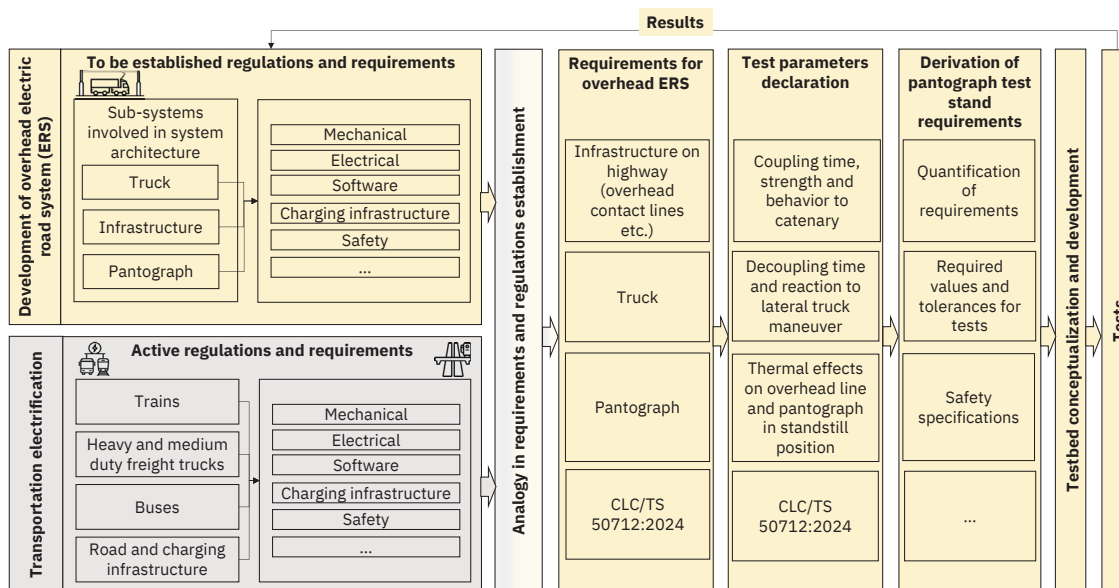


Figure 2. Approach for requirements derivation for ERS pantograph test stand.

More specifically, we aimed at deriving the requirements for an ERS pantograph test stand, such that a design capable of verifying all the requirements could be developed. To achieve this, requirements were derived from both rail and road standards, with particular emphasis on the specifications outlined in the CLC/TS 50712:2024 standard. After the critical test parameters had been determined, the requirements for the pantograph test stand were implemented.

Rail and Road Transport: In addition to the CLC/TS 50712:2024 standard, it was useful to simultaneously draw on information from existing standards to obtain a comprehensive list of requirements for the development of an ERS pantograph test stand. Since pantographs are widely used in the field of rail transport, the use of appropriate and published regulations, standards, and safety instructions as a source of information was useful and important. The ERS pantograph will be used on heavy duty vehicles on highways, so the requirements of road standards also had to be considered or checked. The requirements for the test stand needed to be derived from the requirements of the test object, i.e., the ERS pantograph. The German and European standards for ERSs, rail, and road transport describe both the physical characteristics and the safety conditions that are necessary for homologation. Test scenarios are also described in the standard. The pantograph interacts with other components of the ERS, which are in direct contact or indirectly influence its behavior. This includes the overhead contact line (OCL), the highway, the vehicle, and interactions between these components. It was necessary to determine the surrounding

components of the pantograph to be integrated, the level of detail required for integration, and the synergistic requirements that might emerge.

Derived Requirements: Special attention had to be paid to the characteristics that were different from rail pantographs. While the CLC/TS 50712:2024 standard already provided a harmonized overview of the characteristics to be complied with, others were also examined, as mentioned above. The information contained in the other standards was then compared with that of the ERS standard. If the CLC/TS 50712:2024 required something, it would be included in the scope of the test stand development. If the ERS standard did not mention something that was listed in other specific standards for rail and road transport systems, this specific requirement was still included in the test stand requirements list. A selection of the main verification scopes is listed in Table 1.

The test stand design not only had to fulfill these requirements, but it also had to have some margin to test beyond the tolerances. For this reason, the capabilities of the test stand were designed to exceed all tolerance ranges. Based on these extended requirements, a test environment could be developed that would also cover future requirement changes.

Table 1. Main test characteristics of the ERS pantograph.

Ind.	Scope	Test Characteristics and Criteria	Description and Source
R1	General decoupling	<i>Characteristics</i> • Time measurement	<i>Description</i> Time needed to lower the pantograph if the OCL ends or if an explicit instruction from the driver requires it to do so.
		<i>Criteria</i> • From <i>connected</i> to <i>cleared state</i> • From <i>cleared state</i> over failed coupling attempt back to <i>cleared state</i> ¹	<i>Source</i> • CLC/TS 50712:2024 [38] • Due to increased safety requirements, the standard requires a clearly specified time.
R2	Static contact force	<i>Characteristics</i> • Contact force measurement	<i>Description</i> The specified range of force is required to avoid excessive heating of OCL and wear of collector head and OCL.
		<i>Criteria</i> • Contact force 70–140 N	<i>Source</i> • DIN EN 50367 (VDE 0115-605): 2023-03 [49] • CLC/TS 50712:2024 [38]
R3	Decoupling due to lateral maneuvers	<i>Characteristics</i> • Condition check and monitoring • Acceleration check	<i>Description</i> When the vehicle needs to change lanes, the pantograph shall lower immediately to <i>cleared state</i> .
		<i>Criteria</i> • Lateral acceleration of pantograph of at least 0.5 m/s ²	<i>Source</i> • VKU-2007 [50] • CLC/TS 50712:2024 [38]

Table 1. Cont.

Ind.	Scope	Test Characteristics and Criteria	Description and Source
R4	Thermal behavior of OCL	<i>Characteristics</i> • Temperature measurement and monitoring • Electrical current measurement	<i>Description</i> In standstill or low-speed situations, OCL heats up, due to high current flow. Temperature should not exceed the limit within 30 min.
		<i>Criteria</i> • Max. temperature 150 °C • Contact force 70–140 N	<i>Source</i> • DIN EN 50119 (VDE 0115-601): 2021-01 [51] • DIN EN 50367 (VDE 0115-605): 2023-03 [49] • Only contact force stated in CLC/TS 50712:2024 [38]
R5	Coupling at different OCL heights	<i>Characteristics</i> • Time measurement • Condition check	<i>Description</i> A proper connection between pantograph and OCL must be established at different OCL heights.
		<i>Criteria</i> • Max. height of OCL 5.75 m • Min. height of OCL 4.5 m	<i>Source</i> • StVZO §32 [52] • RAA, Nr202;2008 [53] • CLC/TS 50712:2024 [38]
R6	Coupling at OCL with different horizontal and vertical distances to each other	<i>Characteristics</i> • Condition check • Time measurement • Contact force measurement • Positioning	<i>Description</i> The alignment of both OCLs to each other and to the road is subject to tolerances. The pantograph must be able to obtain proper contact at different OCL positions.
		<i>Criteria</i> • Contact force 70–140 N • Proper connection over entire range of motion of OCLs.	<i>Source</i> • CLC/TS 50712:2024 [38] • Both height differences and distances between OCLs are specified.

¹ When pantograph is completely folded.

5. Test Environments for ERS Pantographs

In this section, we present our test stands that are currently being developed at the Technical University of Berlin, and we describe, briefly, the implementation of the requirements. Temperature changes due to high electrical currents and the dynamic behavior of the pantograph must be investigated. To reduce complexity, in terms of safety and technical boundary conditions, it was decided to design and construct two test stands. An overview of the two test stands is presented in Figure 3.

The lateral test stand was developed to check the pantograph's behavior: for example, coupling and decoupling times. The implemented catenary sections can be positioned in both the vertical and lateral directions, as specified in the standard. The pantograph can also be moved laterally from one side to the other, to model a lane-change maneuver on a highway. The second test stand is the high-current test stand. Here, the contact between overhead line and pantograph can be investigated with respect to the temperature development due to high electrical currents. This simulates a low-speed or standstill situation of the vehicle in cases of a congestion on the ERS. In addition to both test benches, a digital test environment is being developed that is precisely designed based on the derived requirements. This digital test environment will be used to characterize the pantograph and the test benches, and will allow further virtual testing. The potential of a functional combination of the test benches was examined, including future relevant test aspects. In this way, a digital twin with a high degree of immersion and an extremely realistic laboratory test environment was created.

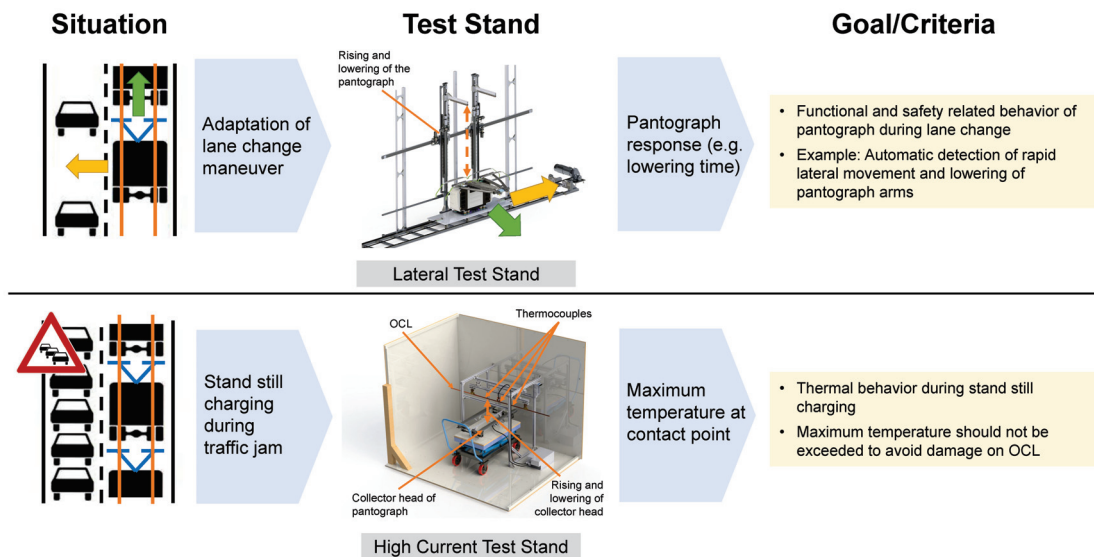


Figure 3. Overview of the two test stands being developed at the Technical University of Berlin. Above: the lateral test stand. Below: the high-current test stand.

5.1. Lateral Test Stand

The design of the lateral test stand can be divided into two parts. One is the design of the overhead contact line (OCL) module, which is laid out to replicate different OCL suspension conditions. The OCL heights listed in Table 1 Index R5 and the vertical and horizontal distance differences between the two overhead contact lines listed in Table 1 Index R6 are implemented in the form of two OCL modules. In our design (Figure 4), each OCL module can be individually moved vertically and horizontally. Additionally, spring sets are integrated to simulate OCL tension and, thus, oscillatory behavior during coupling of the pantograph. Sensors to check if the contact force is in the permissible range that is listed in Table 1 Index R2 are implemented.

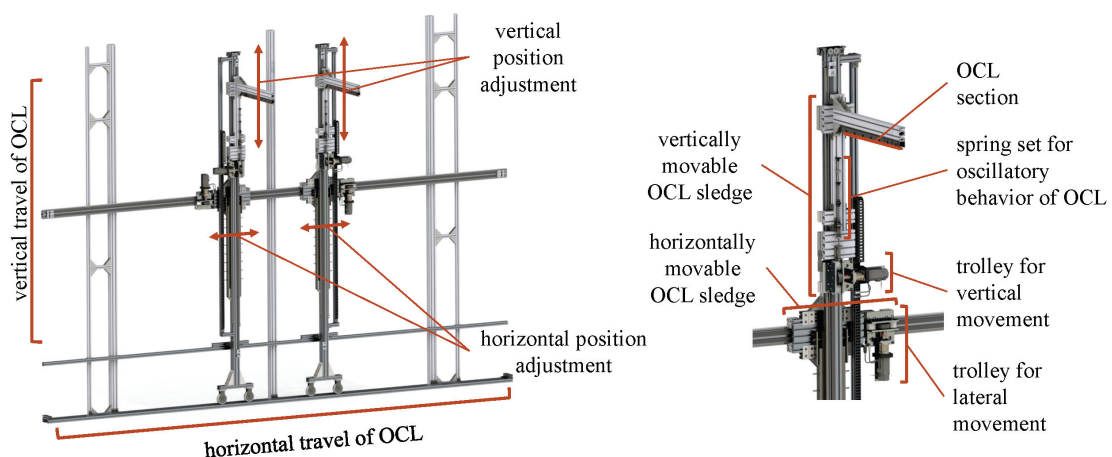


Figure 4. CAD model of the overhead line suspension system of the lateral test stand.

Figure 5 shows the two catenary modules that have already been constructed. During the design process, care was taken to ensure that both assemblies can be moved horizontally and vertically as independently as possible using their own drive elements. This configuration allows the test stand to achieve the catenary clearances defined in the CLC/TS 50712:2024 standard both in the horizontal and vertical directions. The height difference can be set to more than 1.5 m. In the test scenario, both overhead line sections could be moved in different directions relative to the pantograph position. This flexibility made

it possible to simulate operational scenarios with faulty overhead line installations. In this way, the functional safety of the system could be tested beyond the limits required by the standard.

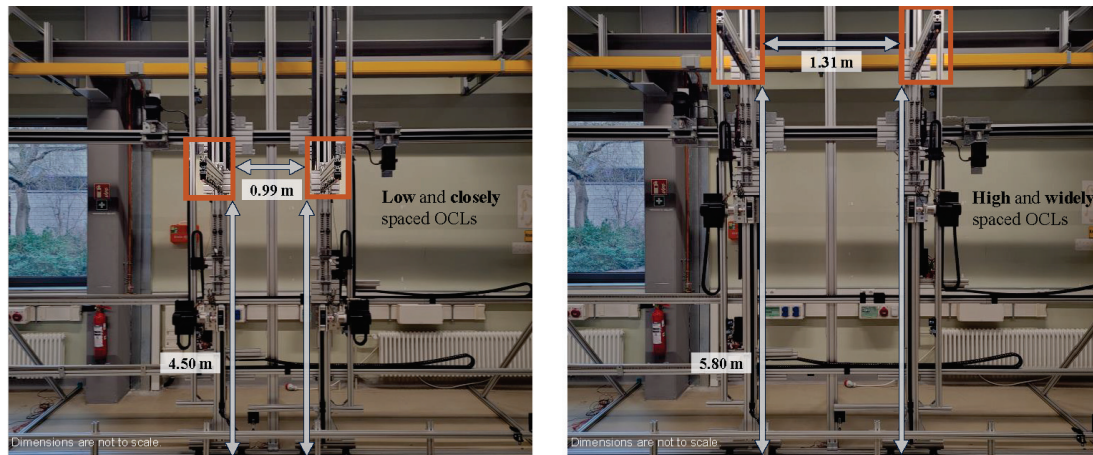


Figure 5. Constructed lateral test stand with low and closely spaced OCLs (**left**) and high and widely spaced OCLs (**right**). The denoted dimensions are the maximum and minimum distances to be tested. (Dimensions are not to scale).

The second part of the lateral test stand is designed to move the pantograph laterally with accelerations that are listed in Table 1 Index R3. The pantograph is placed on a sledge that is moved along a rail installed in the lateral direction, as illustrated in Figure 6. Using this configuration, the decoupling behavior of the pantograph as a response to the lateral maneuvers that are listed in Table 1 Index R3 can be observed. A supervised infeed circuit with a corresponding interface must be devised to measure and prove the functionality of the pantograph in response to requests sent from the operating system (the vehicle in real-world applications).

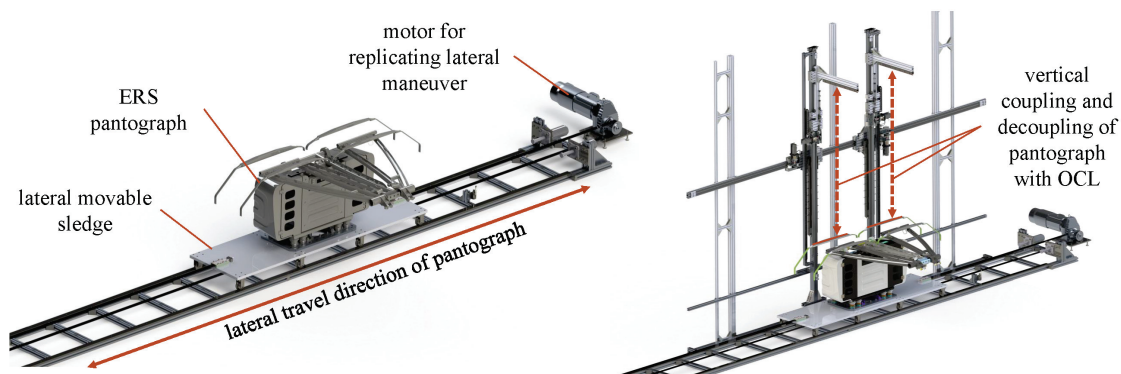


Figure 6. CAD model of lateral movement concept (**left**) and complete lateral test stand (**right**).

5.2. High-Current Test Stand

The high-current test stand illustrated in Figure 7 is designed and built to determine the maximum electric current from the overhead contact line (OCL) to the pantograph. The temperature of the OCL should not exceed the limit listed in Table 1 Index R4. A constant contact force corresponding to the permissible static contact force range listed in Table 1 Index R2 must be applied to the collector head during the test. Both optical and tactile measurement methods are used to monitor the heating process. By placing several thermocouples at suitable points on the OCL and in the ambient air, the OCL temperature is measured and recorded. To verify the thermocouple measurements, the radiant energy of the OCL is measured with a thermal imaging camera. In order to meet the data quality

requirements, the measurement methods used in this study were first tested and then verified. For this purpose, a special calibration station was developed (Figure 8), which allowed precise control of the situational boundary conditions through the targeted use of heating elements.

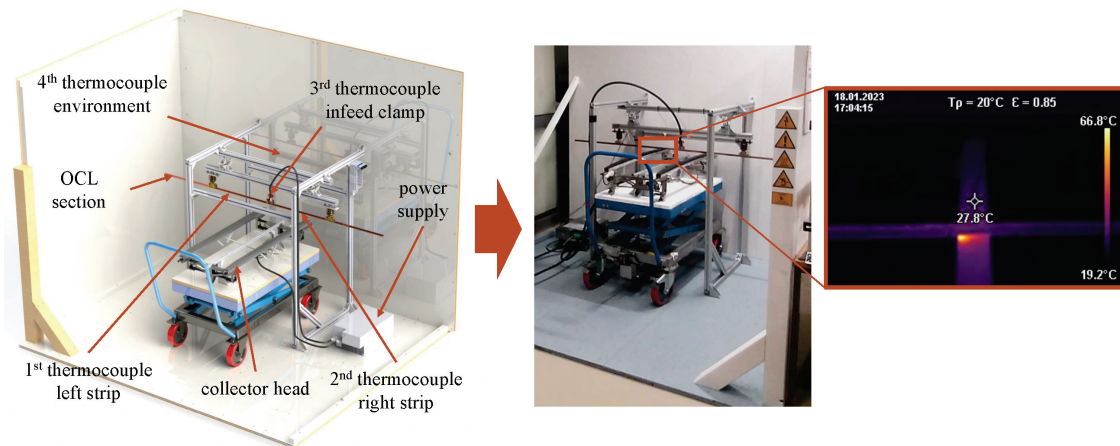


Figure 7. High-current test stand CAD model (**left**), implementation (**middle**), and temperature measurement with a thermal camera (**right**).

This arrangement made it possible to determine the sensitivity of the temperature measurement of thermocouples in relation to different measurement positions along the overhead line cross-section. In addition, the system allowed in-depth analysis of the emission values relevant to the optical measurement method, using a thermal imaging camera. This ensured high-quality data acquisition, taking into account the dependency on measurement distance, material properties of the components, and their geometric characteristics. Since the catenary wire was predominantly made of copper and had a smooth surface, measuring the surface temperature of this component in a temperature range of 100 to 200 °C was challenging, due to its inherently low emissivity. To solve this problem, a thin coating with a high emission value was applied to the overhead line. The thin coating ensured by its low thermal mass that the time delay in the temperature development remained negligible. This allowed the temperature to be measured accurately without affecting the thermal dynamics of the system. The extensive calibration of the measurement instruments achieved by this approach ensured high measurement accuracy. It also enabled redundant validation of the measured values, improving the reliability and robustness of the data acquisition process. Requirements like the minimal length of the OCL section [49], the state of wear of OCL and collector head [54], and the temperature measuring point [49] were taken into account by specific designs as a result of the methodological product development process.

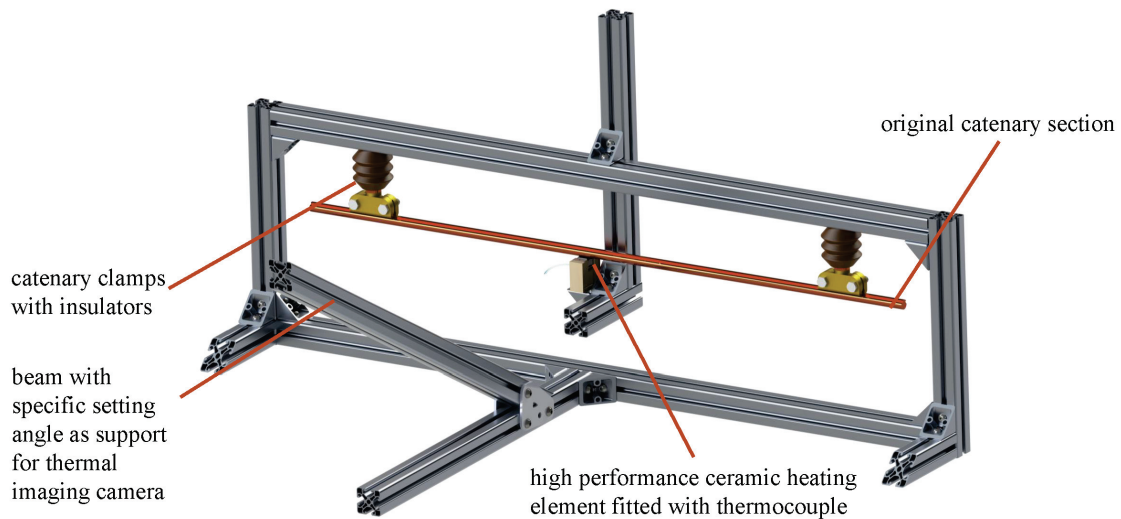


Figure 8. Test bench for calibration of optical and tactile heat meters and sensors.

5.3. Digital Test Stand

Parallel to the two test stands, a digital test environment was under development with corresponding simulations, CAD models, and an implementation in virtual reality (VR). One of the standards used to design the digital test bench was EN 50318 [55], which provides specifications for the simulation of railway pantographs. For the high-current test stand, the digital model incorporated temperature-dependent material properties, e.g., thermal and electrical conductivity as well as thermal emissivity, alongside the geometrical properties. The thermocouple sensors that were used in the high-current test stand were embedded, to reconstruct and reproduce the test results. The digital environment also had to fulfill the requirements posed by the standards. With a virtual electrical current flow, temperature-dependent material properties, and process observations from the test stand, a simulation of the heating behavior of the overhead contact line (OCL) could be carried out. To acquire accurate results, not only characteristics of the test stand itself had to be incorporated but also visual observations of the test process had to be implemented. For example, it was possible to deduce the size of the contact area from the enormous heat generation at certain points (illustrated in Figure 7). Assessing the actual contact quality between the OCL and the collector head proved to be crucial, to correctly reproduce the measurement results. The results of the digital test stand were not only qualitatively but also quantitatively comparable with those of the high-current test stand. Subsequently, different scenarios could be analyzed by taking different material and contact properties into account.

For the lateral test stand, a CAD model with movable parts is available, but kinetic properties are yet to be implemented. Simulations for the tests conducted on the lateral test stand are to be integrated in a similar manner to the development of the thermal simulation. Test stand designs were implemented in virtual reality in different configurations. This not only allowed for efficient and straightforward space planning in the workshop, but also for the evaluation of the user-friendliness of the test benches. In addition, time and cost estimations for part production improved and the transfer of technical knowledge during the presentation of different design concepts was significantly accelerated. Figure 9 shows a virtual room where assemblies, pantographs, and their kinematics are visualized at life size. As a result, better design decisions could be made and successfully implemented in a shorter period of time.

All in all, the digital test stand was used to plan the setup at the intended location before the physical implementation began. Once the test bed was up and running, test data

could be collected to create a digital twin of the test bed and the test object. This digital twin can be used to simulate extreme scenarios that cannot be tested in the real world.

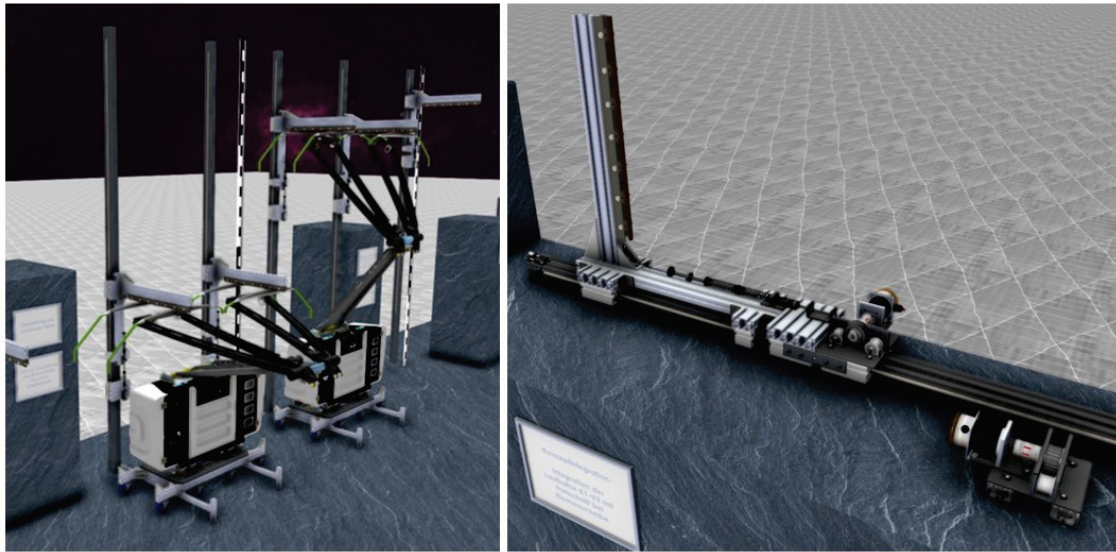


Figure 9. Different coupling states of an ERS pantograph and assembly design of a catenary test stand module.

5.4. Future Test Stand Extensions and Function Mergers

In the current project, all measures for the evaluation of the functional and safety-relevant properties of ERS pantographs were implemented by the design of two test benches. The processing of the digital information and design data of the test benches during the development allowed us to compare and complement the real test benches with their digital equivalents, in terms of form, behavior, and performance. Furthermore, the additional implementation and visualization of the test benches in virtual reality enabled the creation of an immersive digital twin. The precise definition of the requirements and the calibration of the used measurement equipment would allow the structural integration of the high-current test bench into the lateral test bench. This would enable the observation of the dynamic current conduction characteristics from the catenary to the pantograph. The modular design of the test benches allows flexible integration of additional functions. By implementing a translational movement of the catenary and the possibility of tilting the pantograph around its transverse axis, laboratory tests could be performed that reproduce the dynamic behavior of a pantograph on a truck under real operating conditions. With respect to the electrical behavior, precise measurements of the contact forces and the electrical contact resistances between catenary and pantograph could also be performed under dynamic operating conditions. This would be a unique feature, as such measurement capabilities have not been realized yet.

6. Conclusions and Outlook

6.1. Summary

The focus of this paper is on the derivation of a selection of main characteristics for ERS pantograph testing, starting from existing norms and regulations, such as the CLC/TS 50712:2024 [38]. Among other things, this standard specifies requirements for pantographs and overhead contact lines that must be understood in a European context. For the development and construction of the test stands for ERS pantographs, the requirements for the pantograph itself had to be determined first. This was done on the basis of recommenda-

tions from the CLC/TC 9X/WG 27 working group and by comparison with standards and regulations in the field of rail and road transport.

Based on these requirements, two test stands were designed. The “lateral test stand” deals with the behavior of the pantograph before, after, and during the coupling with the overhead contact lines (OCLs). It also examines the decoupling behavior resulting from regular disconnection as well as lateral maneuvers, such as lane changing on the highway.

The “high-current test stand” examines the temperature development at the contact point between pantograph and overhead line when high electrical currents flow corresponding to charging at standstill in cases of, for example, traffic congestion. The maximum temperature of the OCL should be monitored and recorded under prescribed test conditions. If the maximum temperature exceeds a material-specific value, then the set current is considered too high for practical application.

In the scope of the “digital test stand”, a simulation model was created that, in addition to optical and tactile measurement instruments of the high-current test stand, presents an additional option to validate and verify the results of the high-current tests. The simulation was configured to match the experimental results both qualitatively and quantitatively.

Some limitations of our design concepts are that neither the lateral nor the high-current test stand represent the forward movement in direction of travel of the pantograph along the overhead ERS. No vibrations and no additional frictional forces from the OCLs are introduced. Furthermore, no electrical power is currently transmitted to the pantograph via the OCLs on the lateral test stand. The supply voltage present in the field is intentionally omitted for safety reasons. The current used in the high-current test stand is only operated at a voltage of less than 10 V, which is sufficient for the thermal analysis, as only the electrical current is responsible for heating the contact point and, thus, the OCL, but it cannot replicate high-voltage phenomena like arcing. As part of the considerations, the possibility of combining the two test stands into a fully functional system is considered.

6.2. Future Scope

Despite the extensive functionality of the existing test benches, some important aspects have not yet been fully implemented. For example, the tilting of the pantograph or the movement of the catenary in the direction of travel cannot yet be realistically simulated. Similarly, the accurate measurement of electrical contact resistance and the integration of vibrations caused by uneven road surfaces have not yet been sufficiently implemented. These remaining limitations highlight the need for further development to enable more realistic test scenarios, improved measurement methods, and comprehensive risk analysis. The modular design allows the integration of all functions, including the translational movements of the catenary, the ability of the pantograph to tilt, and precise measurements of electrical contact resistances. This would provide a realistic representation of pantograph behavior on a truck and a unique test environment. The kinetic properties of the test stand could be improved so that the simulation and testing of pantograph behavior can also be tested for extreme scenarios.

It is essential to assess how environmental factors like temperature, humidity, dust, rain, and snow can be simulated on the test stand and their impact on the pantograph’s key performance indicators, ensuring relevance to real-world conditions. One crucial area for future work is conducting a comprehensive risk analysis of pantograph failures and their potential impacts on road safety. Simulating these failures on the test stand could help assess the extent of risks, including electric safety, fire accidents, traffic incidents, and hazardous objects, as outlined in [56,57]. This analysis will facilitate understanding failure scenarios and devising solutions to mitigate and test these risks effectively. The established requirements are designed to support the standardization of overhead electric

road systems and their associated test stands, particularly within the European Union. However, we advocate for broader collaboration and the expansion of standardization efforts to encompass the global community, fostering a unified approach to addressing this global challenge.

The test stands aim to provide a platform for testing future pantographs without enforcing direct modifications to trucks or charging infrastructure while enabling the identification of their environmental impact limitations through analysis methods like life cycle assessment, as demonstrated in [58]. This approach enables addressing emission reductions during the design and testing phases while also facilitating emission reductions during the utilization phase of pantograph-based trucks and infrastructure. The test stands aim to address not only ecological sustainability but also economic sustainability. As future work, it is recommended to perform a life cycle cost analysis of the test stands, to evaluate their impact on reducing costs over the life cycles of pantographs, trucks, and infrastructure, thereby assessing the overall economical impact of overhead electric road systems [59]. Similarly, conducting a total-cost-of-ownership analysis for the test stands is crucial for stakeholders, including developers and service providers of this technology [59].

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Abbreviations

The following abbreviations are used in this manuscript:

BEV	battery electric vehicle
DIN	Deutsches Institut für Normung
ERS	electric road systems
FCEV	fuel cell electric vehicle
OCL	overhead contact line
PHEV	plug-in hybrid electric vehicle
VR	virtual reality

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Article

Quantifying the Uncertainty of Electric Vehicle Charging with Probabilistic Load Forecasting

Yvenn Amara-Ouali ^{1,2,*}, Bachir Hamrouche ¹, Guillaume Principato ^{1,2,3} and Yannig Goude ^{1,2}¹ OSIRIS, EDF R&D, 91120 Palaiseau, France; bachir.hamrouche@edf.fr (B.H.)² LMO, University Paris-Saclay, 91400 Orsay, France³ CELESTE, INRIA, 91400 Orsay, France

* Correspondence: yvenn.amara-ouali@universite-paris-saclay.fr

Abstract: The transition to electric vehicles (EVs) presents challenges and opportunities for the management of electrical networks. This paper focuses on developing and evaluating probabilistic forecasting algorithms to understand and predict EV charging behaviours, crucial for optimising grid operations and ensuring a balance between electricity demand and generation. Several forecasting approaches tailored to different time horizons are proposed across diverse model classes, including direct, bottom-up, and adaptive approaches. In all approaches, the target variable can be the load curve quantiles from 0.1 to 0.9 with 0.1 increments or prediction sets with a target coverage of 80%. Direct approaches learn from past load curves using GAMLSS or QGAM methods. Bottom-up approaches predict individual charging session characteristics (arrival time, charging duration, and energy demand) with mixture models before reconstructing the load curve. Adaptive approaches correct in real-time the prediction sets issued by direct or bottom-up approaches with conformal predictions. The experiments, conducted on real-world charging session data from Palo Alto, demonstrate the effectiveness of the proposed methods with regard to different metrics, including pinball loss, empirical coverage, and RPS. Overall, the results highlight the importance of quantifying uncertainty in load forecasts and the potential of probabilistic forecasting for EV load management.

Keywords: time series; Gaussian Mixture Models; Monte-Carlo Simulation; conformal prediction; smart charging

1. Introduction

A key lever for reducing greenhouse gas emissions in the transport sector is the large-scale deployment of electrical vehicles (EVs). This has led to many governments implementing strong pro-EV policies, resulting in an increase in the number of EVs in global markets [1]. The arrival of these vehicles creates challenges in the management of the electrical network while also bringing opportunities in terms of grid flexibility. Indeed, these vehicles will become important assets for managing electricity demand whose charging can be automatically postponed when constraints are high or even used as batteries to reinject power when demand is high (vehicle-to-grid) [2]. All these operations of load optimisation are referred to as smart charging. One of the key elements of an efficient smart charging solution is a strong understanding of charging behaviours, which requires the development of efficient forecasting algorithms to predict them.

Quantifying the uncertainty in load forecasts enhances our understanding of when the grid is most likely to face constraints due to a surge in EV demand (see Section 2 for the related work). Two probabilistic outputs can be given to stakeholders to better

anticipate the EV demand: *quantile forecasts* or *prediction sets*. Quantiles provide an estimated representation of the distribution of the forecasted load curve while the prediction sets capture data in a specific range. Please note that quantiles can be directly used to produce a prediction set, but other methods introduced later in the paper can also be used to produce prediction sets with stronger theoretical guarantees (see Section 3).

In this paper, the focus is given to quantiles from 0.1 to 0.9 to have a holistic representation of the distribution while also looking at an 80% prediction set, which enables accommodation for a majority of scenarios. These two types of forecasts (quantiles and prediction sets) have to be provided at various horizons depending on industrial needs:

- Mid-term: typically spanning days to weeks ahead, they help grid operators and electricity market participants plan for infrastructure investment to meet future demand.
- Day-Ahead: critical for scheduling generation and market trading as well as managing grid constraints for EV charging, ensuring the balance between electricity demand and production, and minimising last-minute costs.
- Real-Time: offer immediate insights into electricity demand and supply balance, responses to sudden changes like spikes in EV charging demand.

As shown in Table 1, we propose different methods and classes of models depending on the horizon, taking into account the characteristics/capabilities of each model.

Table 1. Proposed approaches in this paper for each horizon and their applications.

Horizon	Model Class	Proposed Approach	Applications
Mid-Term	Direct (Section 3.2)	Generalised Additive Models (GAM, GAMLSS, QGAM) [3,4]	Infrastructure Sizing OTC Market Trading
Day-Ahead	Bottom-up (Section 3.3)	SARIMA & Gaussian Mixture Models [5]	SPOT Market Trading Smart Charging (and V2G)
Real-Time	Adaptive (Section 3.4)	Adaptive Conformal Inference (ACI) [6]	Demand/Supply balance, Smart Charging

The main contributions of this paper are: (a) an extension of the work presented in [5] to probabilistic forecasts and (b) the application of a post hoc uncertainty quantification method, namely adaptive conformal prediction, to EV charging data.

The rest of the paper is articulated as follows: Section 2 reviews the literature of work that preceded and inspired this paper. Section 3 details the direct, bottom-up, and adaptive approaches used in this paper for providing forecasted quantiles and prediction sets. Section 4 presents and discusses the results obtained on the Palo Alto charging session data [5].

2. Related Work

Forecasting charging station occupancy is a crucial problem for electricity market stakeholders when it comes to optimising their production units in line with charging demand [7]. With the development of EVs, research activities in that field have significantly increased, and many papers investigate data-driven methods, as presented in the review paper [8] and more recently in [9], where the authors highlight the superiority of performance of learning-based techniques but at the same time point out the difficulty of quantifying uncertainty in demand data. Forecasts can be used for different purposes, e.g., demand scheduling [10], trading [11], or grid management [12]. Forecasting models range from statistical models to the last generation of AI tools [9], where a major problem is the lack of data of sufficient quality for an efficient calibration of the parameters. For example, ref. [13] proposes a spatio-temporal distribution of demand with graph convolutional networks trained on a big dataset of 76,000 private EVs in Beijing. Ref. [14] uses a spatial-temporal attention transformer to model the charging demand of 321 electric buses across regions

and time in Shanghai. Ref. [15] proposes an attention-based spatio-temporal multi-graph convolutional Network fitted on two datasets of around 10 stations in Beijing and Shanghai.

The rapid development of data-driven predictive models, including complex and large-scale machine learning models, creates a need for benchmarking studies, including uncertainty quantification. This work follows the one in [5], focusing on benchmarking point estimates of day-ahead load and occupancy forecasting solutions covering eight open charging session datasets presented in the data and method review [8]. This benchmark examined two sets of methods: direct approaches that would predict the aggregate load curve for all sessions at once, and bottom-up approaches that would model individual charging sessions before aggregating them to obtain the overall load curve. The bottom-up approaches, although more complex to estimate, offer more flexibility for the deployment of smart charging solutions [16], where knowing individual arrivals and durations at the charging point is essential. We propose to extend these benchmarks to probabilistic forecasting algorithms by exploring probabilistic variations of these forecasting models. The use of probabilistic forecasts is becoming increasingly important for the efficient operation of electricity systems, as highlighted in the Global Energy Forecasting Competitions [17] and in [18].

The need for probabilistic forecasts is particularly important in the management of EVs, as the optimisation of charging loads often requires a good quantification of the uncertainty around the forecasts to manage the best- and worst-case scenarios for grid management [19] or, more generally, to maximise profit on energy markets [11]. In [20], quantile regression machine learning methods are applied to a set of charging stations in the Netherlands (the EVnetNL charging stations). The authors show the advantages of exploiting local data (load and meteorological) to forecast the global load in a hierarchical way through an ensemble methodology. Ref. [21] proposes an approach to quantify the uncertainty of parking duration forecasts in EV management. In [22], the authors compare confidence intervals derived from quantile random forest and neural networks to forecast individual charging stations in two commercial buildings. They study both the question of forecasting an aggregated load or individual charging points and conclude similarly to [5] that the aggregated EV load forecasting is an easier task.

3. Materials and Methods

Two fundamental approaches have been retained to address the probabilistic forecasting task (see Figure 1). A direct approach that provides quantile forecasts with a GAMLSS or a QGAM (see Section 3.2) model trained directly on the load curve. A bottom-up approach (see Section 3.3), which predicts individual charging session characteristics to then reconstruct the load curve. With both approaches, 9 quantile forecasts are provided from 0.1 to 0.9 with 0.1 increments as well as a mean forecast. An additional approach based on Conformal Prediction (CP) is used to build prediction sets over both quantile and mean forecasts from direct or bottom-up approaches (see Section 3.4).

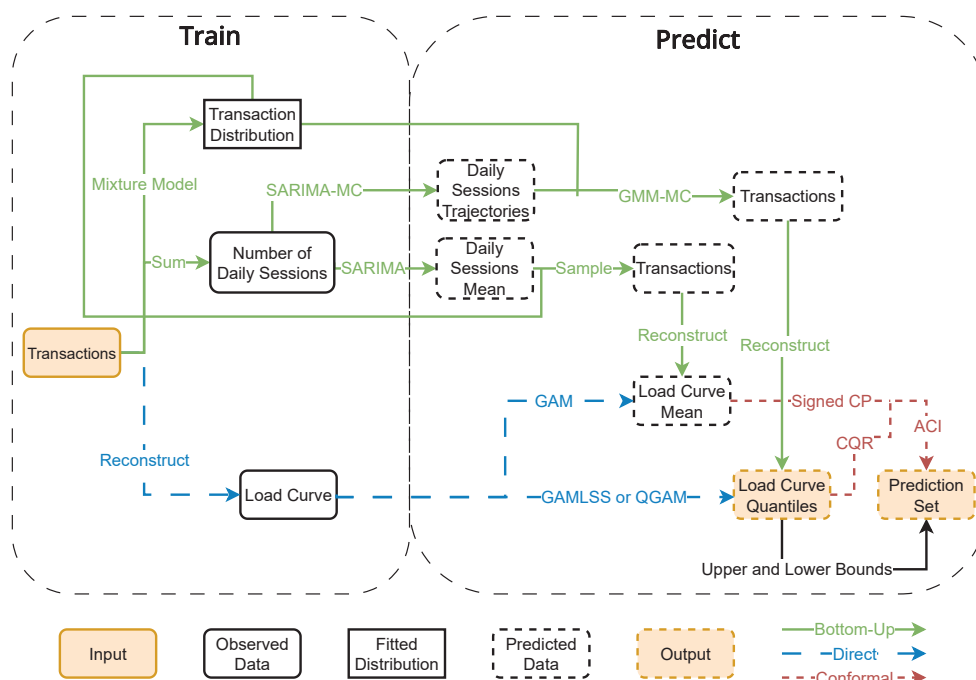


Figure 1. A summary of methods to produce quantile forecasts and/or prediction sets based on charging sessions.

3.1. Problem Statement

The load curve of an ensemble of charging stations at time $t \in \mathbb{R}^+$ can be written as a function $L(t)$. To reconstruct this load curve based on charging session data, three variables are required for each charging session i : the arrival time (a_i), the charge duration (d_i) and the energy demand (e_i). With these three variables, an elementary load curve can be reconstructed in the shape of a step function:

$$\ell_i(t) = \begin{cases} \frac{e_i}{d_i} & \text{if } t \in [a_i, a_i + d_i] \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

The overall load curve is obtained by summing all elementary load curves:

$$L(t) = \sum_{i \in \mathcal{T}} \ell_i(t) \quad (2)$$

with $\mathcal{T}$ the set of sessions observed over a given period of time. Thus, the assumption is that the electric vehicle supply equipment (EVSE) charges the EV at a constant power. It is an accurate approximation for EVSEs that are not subject to smart charging [5]. Please note that the overall load curve can also be reconstructed with a smart charging algorithm, which would yield a different formulation of Equation (1), out of the scope of this paper. In addition, to comply with the European market standard, the chosen time step for sampling the load curve is 15 min. Please note that this choice can easily be modified in the proposed implementation at this GitHub repository [23]. When necessary, switching from continuous to discrete time will be achieved with the notation L_t , $t \in \mathbb{N}$ instead of $L(t)$, $t \in \mathbb{R}^+$.

The final purpose of the following methods presented in Sections 3.2–3.4, is to provide an estimation of the predicted quantiles of L_t defined as $\widehat{L}_t^{(\tau)}$, $\tau \in \{0.1, \dots, 0.9\}$ or a prediction set $\widehat{C}_t^{(\alpha)}$ with $1-\alpha$ being the nominal coverage, set to 80% in the scope of this paper.

3.2. Direct Approach

Generalised Additive Models (GAMs) are statistical models that capture nonlinear relationships between a response variable and multiple predictors by representing them as the sum of smooth functions [3]. Let y be a continuous r.v. with conditional distribution $p(y|\mathbf{x})$, where $\mathbf{x}$ is a p -dimensional vector of covariates. Gaussian additive models assume that the conditional distribution $p(y|\mathbf{x})$ is Gaussian and such that : $y|\mathbf{x} \sim \mathcal{N}(\mu(\mathbf{x}), \sigma^2)$ with

$$\mu(\mathbf{x}) = \sum_{j=1}^m f_j(\mathbf{x}) \text{ and } \sigma^2 = \text{Var}(y|\mathbf{x}) \quad (3)$$

where f_j are linear or nonlinear smooth functions.

Generalised Additive Models for location scale and shape (GAMLSS) [24] are an extension of GAMs that enable the fine modelling of multiple parameters of a single distribution. In this study, GAMLSS are used to model both the mean and variance of the load at charging points over time, assuming the conditional distribution of the load given the covariates is Gaussian. Gaussian location-scale models assume again that $y|\mathbf{x} \sim \mathcal{N}(\mu(\mathbf{x}), \sigma^2(\mathbf{x}))$ where μ and σ are both modeled like previously as the sum of linear and nonlinear effects of the covariates.

Finally, let us also define the conditional quantiles of $p(y|\mathbf{x})$ by $\mu_\tau(\mathbf{x}) = F^{-1}(\tau|\mathbf{x})$, where $\tau \in \{0,1\}$ is the quantile level and F^{-1} is the inverse conditional cumulative distribution function (c.d.f.) of y . QGAM models each conditional quantile as the sum of linear and non linear effects like previously. In all three cases : An effect f_j is expressed as a projection

$$f_j(\mathbf{x}) = \sum_{k=1}^{m_j} \beta_{j,k} B_{j,k}(\mathbf{x}), \quad (4)$$

where $(B_{j,k})_{k=1}^{m_j}$ is a spline basis of dimension m_j and $(\beta_{j,k})_{k=1}^{m_j}$ are the corresponding coefficients estimated by a ridge regression (GAM), a maximum likelihood (GAMLSS) or by minimizing the Extended log-F (ELF) loss for each quantile level (QGAM). The ELF loss is a smooth and convex generalisation of the pinball loss (see Section 4.2 for a definition of the pinball loss). It enables the model to capture more complex data that cannot be characterised by usual statistical distributions (e.g., Gaussian). The covariates used in all three models include exogenous weather variables such as the temperature, wind speed, and relative humidity, as well as calendar variables like the time of day, which are used as a non-linear effect. The weekday and the season are used as linear effects. Finally, as an additional baseline method, a persistence model is included in the study. This simple model uses the last 9 observations of the same weekday and time of day and calculates an empirical quantile for each level.

3.3. Bottom-Up Approach

Bottom-up approaches consist of predicting characteristics of individual charging sessions occurring over time. As explained in Section 3.1, three variables are required to reconstruct the load curve of an ensemble of charging stations in an uncontrolled charging environment: (a_i, d_i, e_i) the arrival time, charge duration, and energy demand of a charging session i . These three variables can be modelled using various statistical techniques. It was shown in [25] that mixture models and, in particular, Gaussian Mixture Models (GMM) [5] are an adequate choice of methods to represent individual charging sessions (see Equation (5)).

$$p(a_i, d_i, e_i) = \sum_{k=1}^K \pi_k \mathcal{N}(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \quad (5)$$

with K the total number of components of the mixture, π_k , μ_k and Σ_k the weight, mean, and covariance of the k -th component. Assuming it is possible to predict the number of charging sessions X occurring each day with a time series model, X charging sessions from the mixture model distribution can be sampled to obtain a prediction for a particular day. In this work, SARIMA models are used as predictors for the number of daily charging sessions. A Monte-Carlo (MC) approach is used to obtain quantile forecasts $\hat{L}_t^{(\tau)}$ for quantile level $\tau \in [0, 1]$ as follows: first, $N_1 \in \mathbb{N}$ SARIMA trajectories are simulated for the given forecasting period, and for each of these N_1 SARIMA simulations, the associated number of sessions is generated N_2 times from the GMM. Therefore, $N = N_1 \times N_2$ sampled $\hat{L}_{n,t}$ of L_t are generated to then calculate empirical means and quantiles for every timestep in a given forecasting period. The index $n \in \{1, \dots, N\}$ is the simulation number.

3.4. Conformal Prediction

Conformal Prediction (CP, [26]) is a general framework for uncertainty quantification that produces a valid prediction set from a black-box forecast procedure in a finite sample under mild assumptions. Recently, CP has received increasing attention since [27] presented Split Conformal Prediction (SCP), a procedure based on data splitting. More precisely, SCP consists of splitting observations between $\mathcal{D}_{\text{train}}$, $\mathcal{D}_{\text{calib}}$ and $\mathcal{D}_{\text{test}}$, respectively, a training, a calibration, and a test set. We detail the data splitting chosen for this application in Section 4.1. The objective is then to provide a prediction set $\hat{C}_t^{(\alpha)}$ such that the probability of having L_t inside the prediction set $\hat{C}_t^{(\alpha)}$ is at least $1 - \alpha$ for $t \in \mathcal{D}_{\text{test}}$. To do so, the training set is used to learn a forecast function with a given (black-box) algorithm $\mathcal{A}$. The forecasts can either be estimates of the mean or quantiles, so $\mathcal{A}$ can be; for example, a GAM, a QGAM (see Section 3.2), or a SARIMA + GMM (see Section 3.3). Then, the calibration set is used to compute non-conformity scores. The choice of the score function is very important since it determines the usefulness of the prediction sets [28]. If $\mathcal{A}$ provides an estimate of the mean $\hat{L}_t$, we decide to use the residuals as non-conformity scores [29]:

$$\hat{s}_t = L_t - \hat{L}_t \quad (6)$$

If $\mathcal{A}$ provides estimates of the quantiles $\alpha/2$ and $1 - \alpha/2$, $\hat{L}_t^{(\alpha/2)}$ and $\hat{L}_t^{(1-\alpha/2)}$, we use Conformalised Quantile Regression (CQR, [30]), which corresponds to the non-conformity scores:

$$\hat{s}_t = \max \{ \hat{L}_t^{(\alpha/2)} - L_t, L_t - \hat{L}_t^{(1-\alpha/2)} \} \quad (7)$$

If the non-conformity scores are given by (6), then for all $t \in \mathcal{D}_{\text{test}}$, the prediction set is:

$$\hat{C}_t^{(\alpha)} := \left[\hat{L}_t + \hat{s}_{(\lfloor (\#\mathcal{D}_{\text{calib}}+1)\alpha/2 \rfloor)} ; \hat{L}_t + \hat{s}_{(\lceil (\#\mathcal{D}_{\text{calib}}+1)(1-\alpha/2) \rceil)} \right] \quad (8)$$

with $\hat{s}_{(k)}$ being the k -th order statistics of the calibration non-conformity scores and $\lfloor x \rfloor$ being the integer part of x . If the non-conformity scores are given by (7), then for all $t \in \mathcal{D}_{\text{test}}$, the prediction set is:

$$\hat{C}_t^{(\alpha)} := \left[\hat{L}_t^{(\alpha/2)} - \hat{s}_{(\lceil (\#\mathcal{D}_{\text{calib}}+1)(1-\alpha) \rceil)} ; \hat{L}_t^{(1-\alpha/2)} + \hat{s}_{(\lceil (\#\mathcal{D}_{\text{calib}}+1)(1-\alpha) \rceil)} \right] \quad (9)$$

Under the exchangeability assumption, these procedures provide valid (i.e., in terms of coverage) and efficient (i.e., in terms of sharpness) prediction sets [29,30]. However, this assumption does not hold in the context of this article since we are dealing with time series. Therefore, we use an extension of CP introduced by [6], namely Adaptive

Conformal Inference (ACI). In this variation, a surrogate adaptive α_t is used instead of using α in (8) and (9). This adaptive framework enables us to handle potential shifts in the distribution (i.e., if the behaviour of the electrical vehicles changes) and provides calibrated and efficient prediction sets for time series. For the signed non-conformity scores (6), ACI needs to be extended with an adaptive α_t for both the upper and the lower bounds of the prediction set (see details in Appendix A). This extension provides more flexibility, especially if the forecasts are biased and the main properties of ACI's prediction sets can be recovered using a symmetry argument. In [6], this surrogate quantile level α_t is defined sequentially for all $t \in \mathcal{D}_{\text{test}}$ by:

$$\alpha_{t+1} = \alpha_t + \gamma(\alpha - \text{err}_t) \quad \text{with } \text{err}_t := \begin{cases} 0 & \text{if } L_t \in \hat{C}_t^{(\alpha)} \\ 1 & \text{if } L_t \notin \hat{C}_t^{(\alpha)} \end{cases} \quad (10)$$

In this work, inspired by the latest extensions of ACI [31,32], we use an adaptive γ_t instead of a fixed γ in (10). As suggested in [32], we choose a decaying γ_t inversely proportional to the square root of the sum of the past $(\alpha - \text{err}_t)^2$. Moreover, we add a threshold so that $\gamma_t \leq 0.1$ in order to avoid instability at the beginning of the test set. This method provides theoretical guaranties (see Appendix A) both in terms of validity and in terms of efficiency for the prediction set while achieving good practical performances.

4. Results and Discussion

In the following sections, the results of the methods applied to a real-world EV charging session dataset are described and discussed. The dataset as well as the implementation of the models are available at the following GitHub repository in csv format and R code [23].

4.1. Presentation of the Dataset

Experiments were led on a dataset from the city of Palo Alto (California, USA). This dataset has been explored thoroughly in [8] and includes information on each charging session that takes place on some of the city's public chargers. Features such as the arrival time, charge duration, and energy demand for each session are available for a period of time that spans from 2011 to 2020. In this study, the focus is given to the last year of data available before the pandemic (2019).

The weekly average load curve (see Figure 2) highlights two prominent peaks - one around midday and another in the late afternoon - present on all weekdays. Notably, Fridays exhibit a more pronounced second peak, while Sundays display only a single peak. Saturdays demonstrate two peaks of similar heights, contrasting with weekdays where the midday peak significantly exceeds the afternoon peak. This dataset is openly accessible and forms part of a collection of EV charging session datasets available on this GitHub repository.

In addition to the dataset itself, exogenous variables were sourced from the `riem` R package [33], which aggregates meteorological features from weather stations worldwide. In this study, relative humidity, wind speed, and temperature from the Palo Alto weather station were used.

Given the highly non-stationary nature of the data (EV adoption and technological breakthroughs), the models are refitted every two weeks (see Figure 3). This frequent refitting allows the models to adapt to changes in the data distribution, ensuring that the predictions remain accurate and relevant. The calibration set is specifically used for the conformal predictions (see Section 3.4).

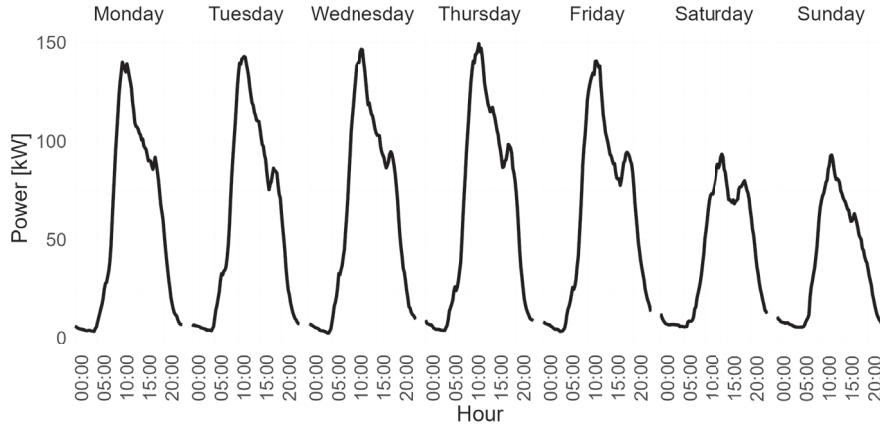


Figure 2. Average weekly load curve over the test period.

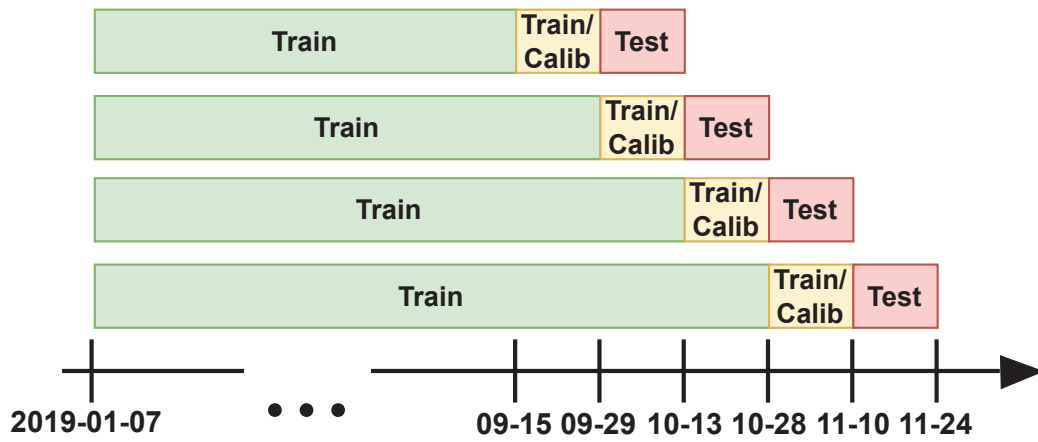


Figure 3. Data splitting for the four train, calibration, and test periods.

4.2. Quantile Forecasts

Forecasting quantiles 0.1 to 0.9 gives a complete representation of the distribution, which can be used in practice to better understand the uncertainty around the load curve forecast. Please note that in the case of the bottom-up approach, to calculate the empirical quantile and mean forecasts, 100 SARIMA trajectories with 100 GMM simulations for each of these trajectories were generated. In other words, a total of 10,000 simulated load curves were used to then calculate the quantile forecasts. In addition, one GMM is fitted per day of the week to better capture the variation in load profiles, as shown in Figure 2.

Three types of metrics have been used to evaluate quantile forecast performances. First, we consider a classical loss used in quantile regression, namely the pinball loss defined as follows:

$$Pin_{\tau} = \frac{1}{\#\mathcal{D}_{\text{test}}} \sum_{t \in \mathcal{D}_{\text{test}}} \rho_{\tau}(L_t - \hat{L}_t^{(\tau)}) \quad (11)$$

$$\rho_{\tau}(u) = \begin{cases} -(1 - \tau)u, & \text{if } u \leq 0 \\ \tau u & \text{if } u \geq 0 \end{cases} \quad (12)$$

It takes into account the desired imbalance between the true target values L_t and the predicted quantiles $\hat{L}_t^{(\tau)}$ with a degree of penalty depending on the chosen quantile level τ . Another classical metric that can be used for assessing the accuracy of quantile forecasts is the empirical coverage defined as:

$$Cov_{\tau} = \frac{1}{\#\mathcal{D}_{\text{test}}} \sum_{t \in \mathcal{D}_{\text{test}}} \mathbb{1}(L_t \leq \hat{L}_t^{(\tau)}) \quad (13)$$

Equation (13) is the empirical coverage of the predicted quantile, i.e., the proportion of observed values falling below the predicted quantile. Essentially, if $L_{\tau}^{\text{coverage}} = \tau$ the quantile forecast is said to be valid on the testing sample.

While Equations (11) and (13) evaluate the forecasts at a given quantile level, it is possible to evaluate them over all forecasted quantiles simultaneously. To do so, we define the continuous ranked probability score (CRPS) and its discrete approximation, namely the RPS:

$$\text{CRPS}(\hat{F}, L_t) = \int_{-\infty}^{+\infty} (\hat{F}(z) - \mathbb{1}_{L_t \leq z})^2 dz \quad (14)$$

where F is the predicted cumulative distribution function with $\tau_0 = 0$ and $\tau_{l+1} = 1$.

$$\text{RPS}(\{\hat{L}_t^{(\tau_1)}, \dots, \hat{L}_t^{(\tau_l)}\}, L_t) = \sum_{i \in \llbracket 1, l \rrbracket} \rho_i(L_t, \hat{L}_t^{(\tau_i)}) (\tau_{i+1} - \tau_{i-1}) \quad (15)$$

Figure 4 shows the average hourly quantile forecasts for a direct approach using QGAM and the bottom-up approach during each day of the week. It seems that both approaches capture the general shape of the observed curve in black with a peak demand in the middle of the day and another one in the late afternoon/evening for weekdays and Saturdays, and a single peak at midday on Sundays. However, the direct approach seems to better fit the finer details of the shape around the peaks, especially the second one. This is due to the fact that fitting the daily shape of the load, by time of day, is specifically expected of the QGAM or GAMLSS in the formulation of the splines optimisation problem, giving them an advantage. Tables 2 and 3 confirm these results, as the QGAM has better overall coverage, better pinball losses on all quantiles, and the best RPS.

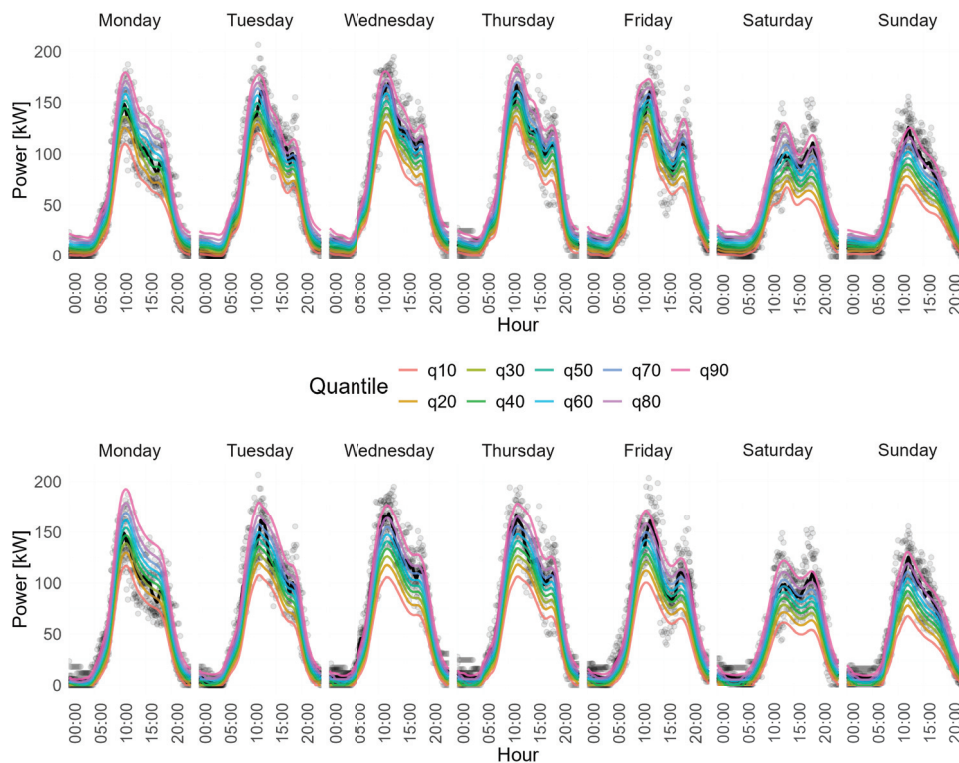


Figure 4. At the top are the QGAM averaged quantile forecasts for each quantile levels and at the bottom the same chart for the bottom-up approach. In black is the average daily load curve and the scatter plot of the daily observations over the test period. The plots are separated by day of the week.

This can be explained by the fact that QGAM minimizes the pinball loss without making any assumptions on the data distribution. On the other hand, GAMLSS assumes

that the data are Gaussian, which seems to deteriorate its performance, especially in higher quantiles. This could indicate that the real distribution of the data is slightly skewed to the right, in the higher values, compared to a Gaussian.

Finally, when analysing the performances of the bottom-up approach, it can be concluded that it is performing worse than direct approaches on most quantiles. However, this conclusion can be nuanced considering that:

- The bottom-up approach does not directly model the global load but the distribution of individual sessions. Which is, by nature, a more complex task.
- Unlike direct approaches, it does not use exogenous variables such as weather data.
- The pinball losses and empirical coverages for the 0.1 and 0.9 quantile forecasts are relatively close to their direct counterparts.

Considering all these shortcomings, the bottom-up approach giving results close to the direct approaches is promising, especially considering its key importance in smart charging applications.

Table 2. Pinball Losses (Pin_{τ}) and the empirical coverage (Cov_{τ}) for each quantile level. The best score is in bold.

Quantile	Pinball Loss				Empirical Coverage			
	Persistence	GAMLSS	QGAM	SARIMA + GMM	Persistence	GAMLSS	QGAM	SARIMA + GMM
0.1	2.64	2.64	2.56	2.77	0.16	0.11	0.11	0.10
0.2	4.25	4.31	4.24	4.59	0.23	0.20	0.20	0.15
0.3	5.38	5.44	5.40	5.88	0.29	0.28	0.30	0.20
0.4	6.08	6.11	6.12	6.67	0.36	0.37	0.41	0.27
0.5	6.48	6.41	6.44	6.96	0.43	0.46	0.51	0.35
0.6	6.38	6.33	6.32	6.82	0.51	0.54	0.59	0.43
0.7	5.89	5.82	5.74	6.22	0.60	0.62	0.69	0.54
0.8	4.99	4.81	4.67	5.08	0.69	0.71	0.79	0.66
0.9	3.51	3.13	2.96	3.19	0.78	0.81	0.89	0.80

Table 3. Average RPS metric for each model. The best score is in bold.

Models	Persistence	GAMLSS	QGAM	SARIMA + GMM
RPS	9.12	9.00	8.89	9.64

4.3. Prediction Sets

As introduced in Section 3, an important tool for uncertainty quantification is the use of prediction sets. In this Section, we consider three different approaches to produce a prediction set with nominal coverage $1 - \alpha$. The first approach is to use the quantile forecast of level $\alpha/2$ for the lower bound and of level $1 - \alpha/2$ for the upper bound of the prediction set with any given procedure that outputs quantile forecasts (for example, QGAM, GAMLSS, or SARIMA + GMM). The two other approaches are based on conformal prediction, respectively, based on mean forecasts and on quantile forecasts as described in Section 3.4. In this study, we focus on prediction sets with a nominal coverage of 80%, which means that the quantile forecasts we will use are $\hat{L}^{(10\%)}$ and $\hat{L}^{(90\%)}$. This can be justified in practice as 80% usually represents a sweet spot between over-committing resources to rare events while still accounting for a reasonable level of uncertainty [34].

Figure 5 shows an example of prediction sets forecasted during the test period. Visually, it is hard to conclude which of Quantiles SARIMA + GMM (on the left) and CQR SARIMA + GMM (on the right) is more accurate, which makes it necessary to use specific metrics.

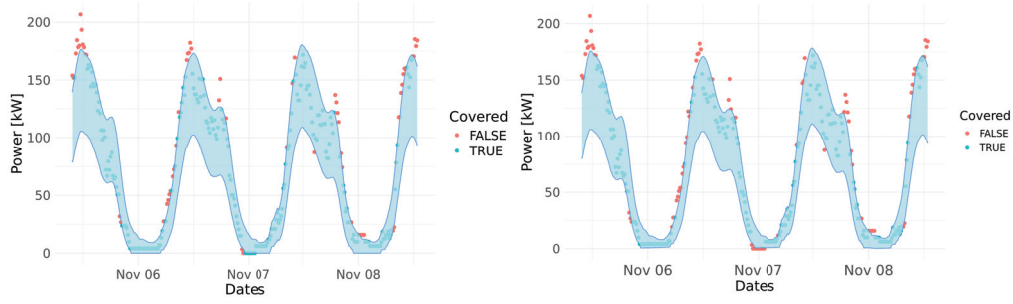


Figure 5. Coverage/Mean Width between conformal (right) and non-conformal (left) methods.

To do so, we extend the coverage metric introduced in Section 4.2 to prediction sets. Indeed, the first criteria to evaluate for a prediction set is validity, i.e., having an empirical coverage superior or equal to the target coverage $1 - \alpha$. However, this is not enough to ensure the quality of a prediction set. Indeed, one can achieve valid coverage with an infinite bound, which is completely uninformative. Therefore, to have a better understanding of the quality of a prediction set, we consider simultaneously a notion of coverage and one of efficiency by measuring its average length. More formally, denoting $\hat{C}_t^{(\alpha)-}$ the lower bound and $\hat{C}_t^{(\alpha)+}$ the upper bound of the prediction set $\hat{C}_t^{(\alpha)}$, we have:

$$Len_\alpha = \frac{1}{\#\mathcal{D}_{\text{test}}} \sum_{t \in \mathcal{D}_{\text{test}}} \left(\hat{C}_t^{(\alpha)+} - \hat{C}_t^{(\alpha)-} \right) \quad (16)$$

The prediction sets produced directly from quantile forecasts are not valid, with a lower coverage than expected (see Figure 6). In Figures 6 and 7, the empirical coverage is computed sequentially, which explains the high degree of volatility at the beginning of the test set. The lack of coverage of the quantiles-based prediction sets in Figure 6 can be explained by a shift in the distribution that the quantile forecasts we used are unable to express.

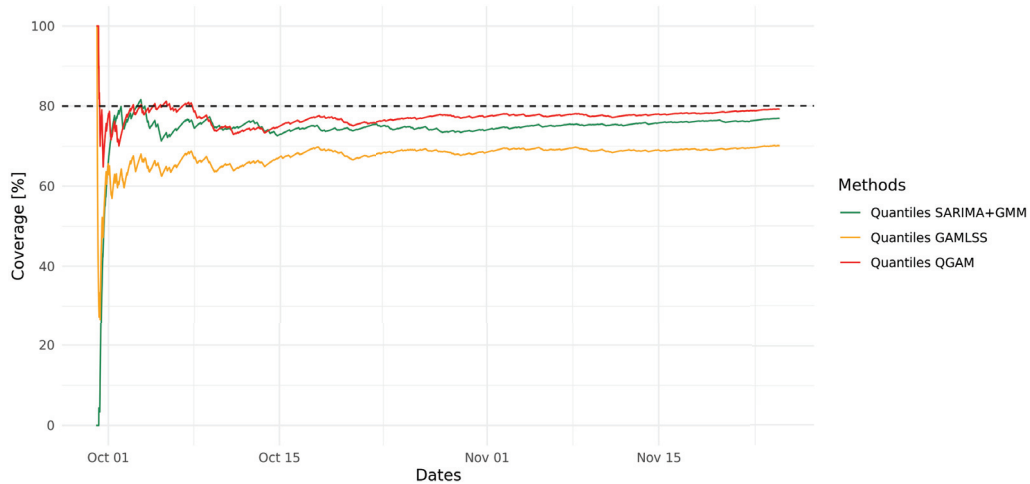


Figure 6. Empirical coverage for quantiles-based prediction sets.

Meanwhile, the conformal prediction based prediction sets are all valid, as shown in Figure 7.

We compare all the prediction sets by looking simultaneously at their coverages Cov_α and averaged lengths Len_α . Figure 8 emphasizes the trade-off between validity and efficiency since the prediction sets based on conformal prediction are valid but are less efficient than the Quantiles based prediction sets. However, Figure 8 shows that the best prediction sets appear to be Quantiles SARIMA + GMM, Quantiles QGAM and CQR

SARIMA + GMM because even if the Quantiles SARIMA + GMM and QGAM are not valid, their lack of coverage is small compared to the gain in efficiency. Among the conformal prediction based methods, the best one is based on the CQR non-conformity score which might highlight heteroscedasticity.

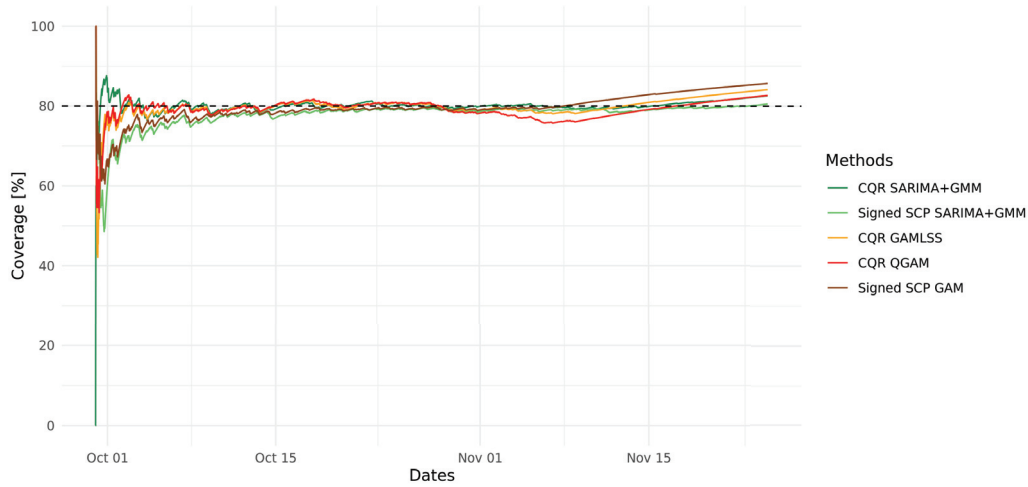


Figure 7. Empirical coverage for conformalised prediction sets.

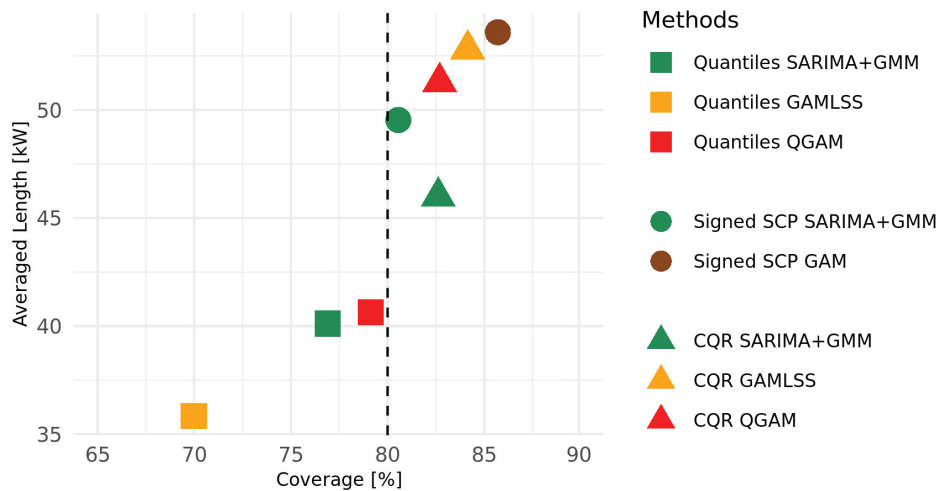


Figure 8. Coverage/Mean Width between conformal and non conformal methods.

To provide a better understanding of the improvement we obtained by using conformal prediction, we focus on two quantile forecast procedures, namely QGAM and SARIMA + GMM, along with their CQR conformalised version. In Figures 9 and 10, we see how conformal prediction improves the coverage when the quantile-based prediction sets are not large enough. Figures 9 and 10 also highlight that the prediction sets are not only valid marginally but also locally, i.e., conditionally valid with respect to a feature of interest, here the time of day. For example, a prediction set with a 100% coverage rate during the night and 70% throughout the day can be valid with respect to the 80% empirical coverage but will not be locally valid. This is very important since it is crucial to capture demand peaks for all applications detailed in Table 1.

Overall, the quantile methods produce prediction sets that capture the characteristics of the distribution but need to be recalibrated to be valid. We solved this issue online using conformal prediction, with the resulting prediction sets suffering a more or less significant loss in efficiency depending on the quantile forecasting method considered.

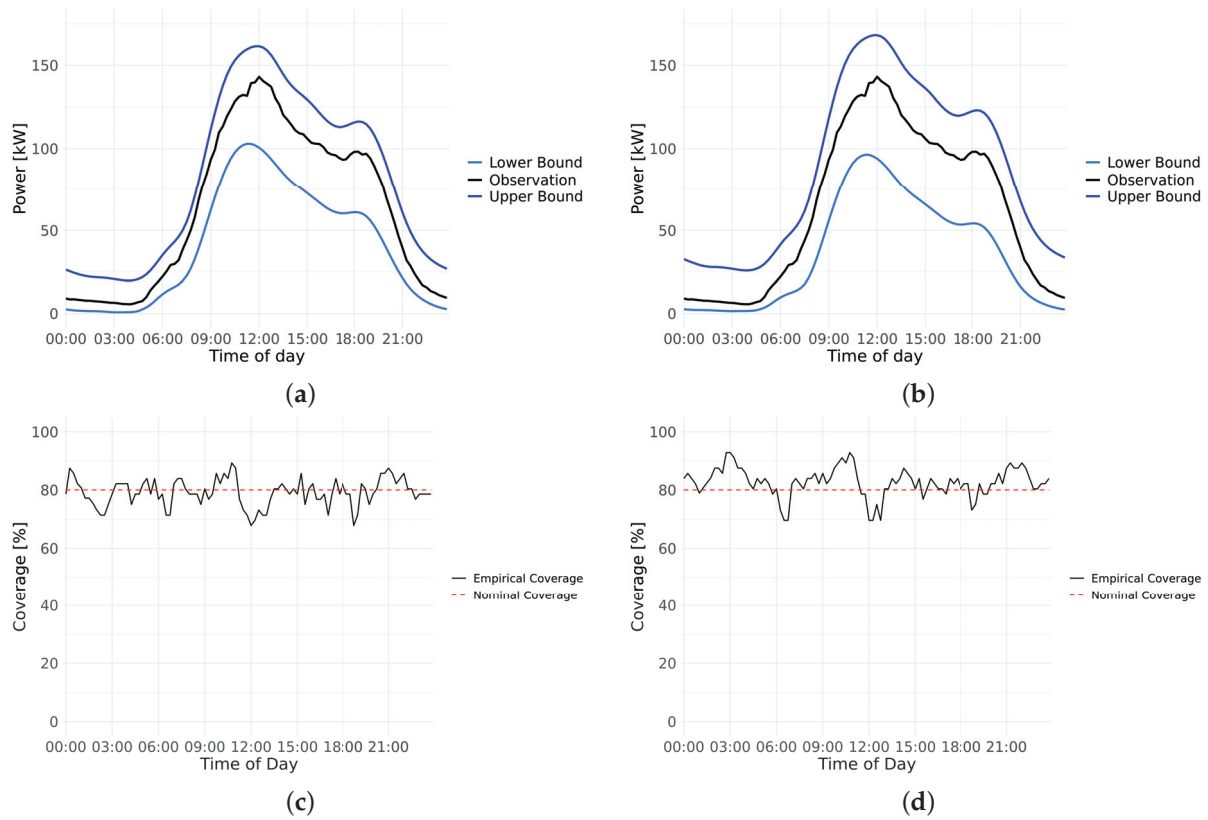


Figure 9. Daily profiles of QGAM (a) and CQR QGAM (b) and conditional coverages of QGAM (c), CQR QGAM (d).

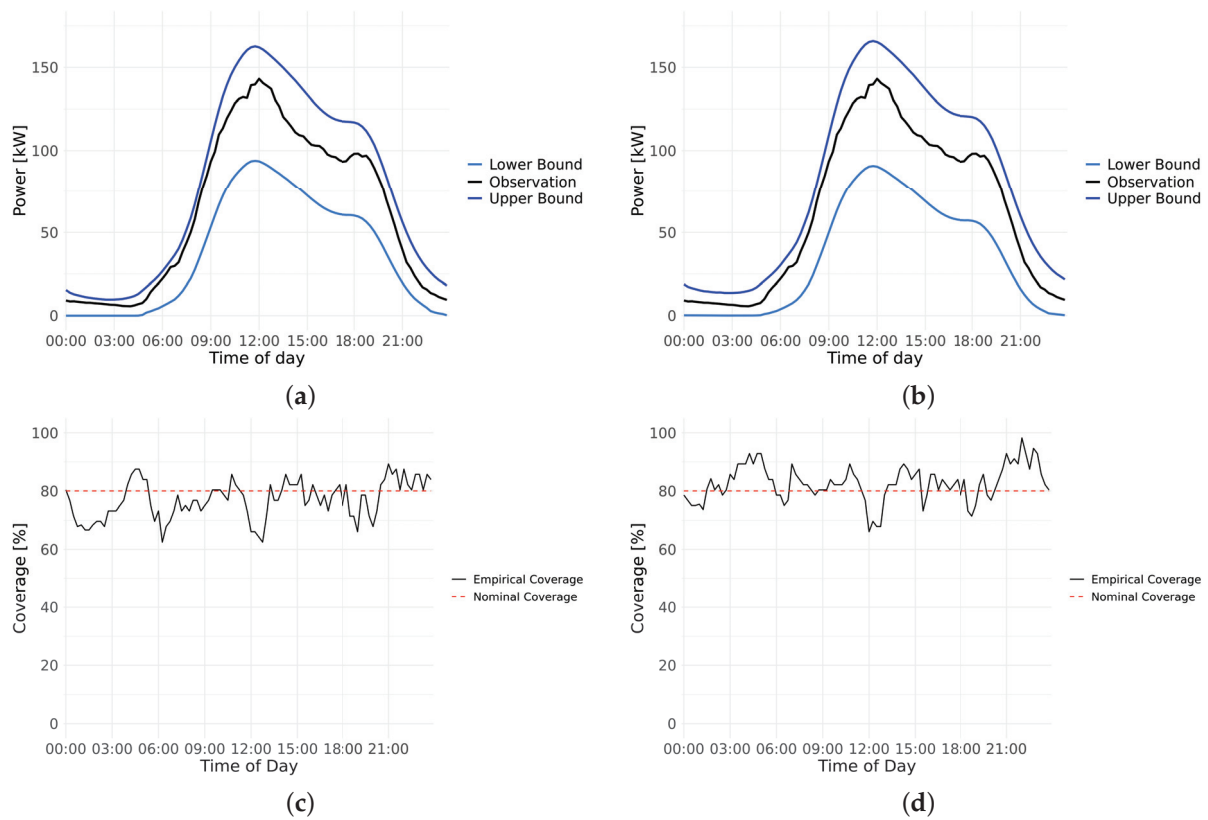


Figure 10. Daily profiles of SARIMA + GMM (a) and CQR SARIMA + GMM (b) and conditional coverages of SARIMA + GMM (c), CQR SARIMA + GMM (d).

5. Conclusions

The electrification of transport through the widespread adoption of electric vehicles (EVs) presents both challenges and opportunities in the management of electrical networks. This paper addresses the critical need for efficient forecasting algorithms to understand and anticipate EV charging behaviors, which are essential for optimising grid operations and ensuring stability. By quantifying the uncertainty in load forecasts, stakeholders can better anticipate surges in EV demand and plan accordingly. This study has evaluated probabilistic forecasting approaches at different horizons, including mid-term, day-ahead, and real-time forecasts, using various model classes tailored to each horizon's requirements. The research focused on providing forecasted quantiles and prediction sets, which offer insights into the distribution of forecasted load curves and provide a range of possible scenarios for grid management.

The experiments conducted on real-world charging session data from Palo Alto demonstrated the effectiveness of the proposed approaches. Results showed that both direct and bottom-up approaches captured the general shape of load curves, with the direct approach exhibiting better performance in capturing finer details around peak demand periods. Additionally, comparison metrics such as pinball loss and empirical coverage revealed the strengths and weaknesses of each model, with QGAMs proving to be the best quantile forecaster in terms of pinball loss. In addition, the study explored the generation of prediction sets using both direct quantile forecasts and Conformal Prediction techniques. The analysis highlighted the importance of validity and efficiency in prediction sets, with Conformal Prediction methods showing promise in correcting invalid forecasts and improving coverage. However, further research is needed to optimise the performance of prediction sets, particularly in balancing coverage and length of intervals.

Overall, the study contributes to the advancement of probabilistic forecasting algorithms for EV load management, providing valuable insights for grid operators, market participants, and policymakers in effectively integrating EVs into the electrical grid while ensuring reliability and stability. In particular, this work can help to mitigate the impact of EV charging on the grid by linking it to *smart charging* algorithms, especially robust optimisation and reinforcement learning models that can incorporate predictive inputs and thus be more realistic. Future research directions may include refining forecasting models, incorporating additional exogenous variables, and investigating advanced techniques for prediction set construction to further enhance grid management capabilities.

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Conflicts of Interest: All the authors were employed by the company EDF. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
GAM	Generalised Additive Model
GAMLSS	Generalised Additive Model for Location Scale and Shape

QGAM	Quantile Generalised Additive Model
SARIMA	Seasonal autoregressive integrated moving average
GMM	Gaussian Mixture Model
ACI	Adaptive Conformal Inference
V2G	Vehicle-to-Grid
CP	Conformal Prediction
ELF	Extended log-F
SCP	Split Conformal Prediction
MC	Monte-Carlo
CQR	Conformalised Quantile Regression
r.v.	Random Variable
c.d.f.	Cumulative Distribution Function

Appendix A. Details on Adaptive Conformal Inference

Appendix A.1. Extension of ACI for Signed Non-Conformity Scores

In Section 3.4, we introduced the signed non-conformity scores (6), which enables separate treatment of the lower and upper bounds of the prediction set. Consequently, this choice of non-conformity scores requires two adaptive quantile levels $\alpha_t^{(u)}$ and $\alpha_t^{(\ell)}$, defined recursively as:

$$\alpha_{t+1}^{(u)} = \alpha_t^{(u)} + \gamma_t \left(\frac{\alpha}{2} - \text{err}_t^{(u)} \right) \quad \text{with} \quad \text{err}_t^{(u)} := \begin{cases} 0 & \text{if } L_t \leq \hat{L}_t + \hat{s}(\lceil (\#\mathcal{D}_{\text{calib}} + 1)(1 - \alpha_t^{(u)}) \rceil) \\ 1 & \text{if } L_t > \hat{L}_t + \hat{s}(\lceil (\#\mathcal{D}_{\text{calib}} + 1)(1 - \alpha_t^{(u)}) \rceil) \end{cases}$$

and

$$\alpha_{t+1}^{(\ell)} = \alpha_t^{(\ell)} + \gamma_t \left(\frac{\alpha}{2} - \text{err}_t^{(\ell)} \right) \quad \text{with} \quad \text{err}_t^{(\ell)} := \begin{cases} 0 & \text{if } L_t \geq \hat{L}_t + \hat{s}(\lfloor (\#\mathcal{D}_{\text{calib}} + 1)\alpha_t^{(\ell)} \rfloor) \\ 1 & \text{if } L_t < \hat{L}_t + \hat{s}(\lfloor (\#\mathcal{D}_{\text{calib}} + 1)\alpha_t^{(\ell)} \rfloor) \end{cases}$$

This flexibility can be very useful if the estimate of the mean turns out to be biased because the resulting prediction set does not have to be centered on $\hat{L}_t$. Moreover, by construction of the recursive definition of $\alpha_t^{(u)}$ and $\alpha_t^{(\ell)}$, the theoretical guarantees in terms of coverage of the prediction set are the same than with the classical ACI procedures with adaptive γ_t .

Appendix A.2. Proof of Asymptotical Coverage

As stated in Section 3.4, the conformal prediction procedure used in this article based on the ACI version of CQR provides valid prediction sets in terms of asymptotic coverage, i.e., $\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \mathbb{1}_{\{L_t \notin \hat{C}_t^{(\alpha)}\}} \stackrel{a.s.}{=} \alpha$. This result can be obtained with one of the best theoretical convergence rate among the methods using an adaptive γ_t [32], namely $O\left(\frac{1}{\sqrt{T}}\right)$.

Proof. We recall, the recursive update scheme of α_t we use:

$$\alpha_{t+1} = \alpha_t + \gamma_t (\alpha - \text{err}_t) \quad \text{with} \quad \text{err}_t := \begin{cases} 0 & \text{if } L_t \in \hat{C}_t^{(\alpha)} \\ 1 & \text{if } L_t \notin \hat{C}_t^{(\alpha)} \end{cases}$$

$$\text{and } \gamma_t := \frac{\eta}{\sqrt{\sum_{s=1}^t (\alpha_s - \text{err}_s)^2}}$$

With this recursive definition, we obtained (A3) using Abel transformation:

$$(\alpha - \text{err}_t) = \frac{\alpha_{t+1} - \alpha_t}{\gamma_t} \quad (\text{A1})$$

$$\sum_{t=1}^T (\alpha - \text{err}_t) = \sum_{t=1}^T \frac{\alpha_{t+1} - \alpha_t}{\gamma_t} \quad (\text{A2})$$

$$\sum_{t=1}^T (\alpha - \text{err}_t) = \frac{\alpha_{T+1}}{\gamma_T} - \frac{\alpha_1}{\gamma_0} + \sum_{t=1}^T \alpha_t \frac{\gamma_t - \gamma_{t-1}}{\gamma_t \gamma_{t-1}} \quad (\text{A3})$$

If we use the convention that if $\alpha_t < 0$ then $\hat{s}_{(\lceil (\#D_{\text{calib}}+1)(1-\alpha_t) \rceil)} = +\infty$ and if $\alpha_t > 1$ then $\hat{s}_{(\lceil (\#D_{\text{calib}}+1)(1-\alpha_t) \rceil)} = -\infty$, we have that $\alpha_t = O(1)$, hence $\frac{\alpha_{T+1}}{\gamma_T} - \frac{\alpha_1}{\gamma_0} = O(\sqrt{T})$.

Moreover, we can also bound the other term:

$$\left| \sum_{t=1}^T \alpha_t \frac{\gamma_t - \gamma_{t-1}}{\gamma_t \gamma_{t-1}} \right| \leq \left| \sum_{t=1}^T \alpha_t \left(\frac{1}{\gamma_{t-1}} - \frac{1}{\gamma_t} \right) \right| \quad (\text{A4})$$

$$\leq \max_t (|\alpha_t|) \cdot \left| \sum_{t=1}^T \left(\frac{1}{\gamma_{t-1}} - \frac{1}{\gamma_t} \right) \right| \quad (\text{A5})$$

$$\leq \max_t (|\alpha_t|) \cdot \left| \frac{1}{\gamma_0} - \frac{1}{\gamma_T} \right| = O(\sqrt{T}) \quad (\text{A6})$$

Which concludes that $\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \mathbb{1}_{\{L_t \notin \hat{C}_t^{(\alpha)}\}} \stackrel{a.s.}{=} \alpha$. $\square$

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Article

Innovative Methodology for Generating Representative Driving Profiles for Heavy-Duty Trucks from Measured Vehicle Data

Gordon Witham *, Daniel Swierc, Anna Rozum and Lutz Eckstein

Institute for Automotive Engineering (ika), RWTH Aachen University, Steinbachstr. 7, 52074 Aachen, Germany; daniel.swierc@ika.rwth-aachen.de (D.S.); anna.rozum@ika.rwth-aachen.de (A.R.); lutz.eckstein@ika.rwth-aachen.de (L.E.)

* Correspondence: gordon.witham@ika.rwth-aachen.de

Abstract: The imperative for electrification of road transport, driven by global climate targets, underscores the need for innovative powertrain systems in heavy-duty vehicles. When developing new electric drive modules, individual operational requirements need to be considered instead of generalized usage profiles, as heavy-duty vehicles experience significantly differing loads depending on their field of operation. Real driving data, representing the demands of different application scenarios, offers great potential for digital replication of driving conditions at different stages of simulation and physical validation. Application- and vehicle-specific longitudinal requirements during operation are particularly relevant for the dimensioning of powertrain components. Road gradient and mass estimation assist in the description of these operating conditions, allowing for detailed modeling of the real load conditions. An incorporation of real driving data instead of solely relying on standardized cycles has the potential of tailoring components to the target lead users and applications. While some operating conditions can be recorded by vehicle manufacturers, these are usually not accessible by third parties. In this paper, the authors present an innovative methodology of estimating vehicle parameters for the generation of representative driving profiles for implementation into a consecutive powertrain design process. The approach combines the measurement of real driving data with state estimation. The authors show that the presented methodology enables the generation of driving profiles with less than 25% deviation from the original data set.

Keywords: electric powertrain; heavy-duty; drive cycle generation; powertrain design

1. Introduction

At nearly eight gigatonnes (Gt) of CO₂ in 2022, global mobility-related emissions represent a significant share of the 36.8 Gt total CO₂ emissions [1]. Road freight transport in particular makes up 1.8 Gt (22.5%) [2]. The electrification of commercial vehicles therefore offers promising opportunities to reduce both local and global CO₂ emissions. At the same time, it presents one of the greatest challenges for vehicle manufacturers, suppliers, and customers. Aspects such as range, charging speed, reliability, and durability are even more important in the commercial vehicle segment for economic operation than for passenger cars [3]. In order to design and optimize new electric heavy-duty vehicles to their specific requirements, new methods are required. Currently, the design of electric powertrains is mainly based on reference data and load collectives available internally to the vehicle manufacturers or standardized efficiency cycles, e.g., from the Vehicle Energy Consumption Calculation Tool (VECTO) [4], but less publicly available real driving data or derived requirements that can be shared openly. Application-specific powertrain design is

inconceivable without representative driving profiles, as heavy-duty vehicles experience a wide range of different operation conditions, influencing load profiles, efficiency, and the lifetime of the powertrain components.

The challenges of electric powertrain design for heavy-duty vehicles are the subject of numerous research endeavors. While some approaches already exist, these use either standardized driving cycles [5,6], static performance requirements [7], measured or synthetic velocity profiles [8], or state-based driving cycles [9]. However, for application-specific holistic powertrain concept design, detailed information on the usage profile of a vehicle is required. Standardized driving cycles, such as the VECTO cycles, are intended for energy demand estimations for vehicle certification [4]. They offer a basis for comparison but lack usage-individual information as well as peak operation points for powertrain design. Static performance requirements, such as maximum velocity and different gradeabilities, are important for load-dependent powertrain component design. These are known from manufacturer experience [7] or need to be derived from measured data. As dynamic driving behavior has a relevant share in real load collectives, static information is not sufficient to be representative alone. State-based driving cycle generation, as presented in [9], delivers synthetic driving profiles based on statistical evaluation of real velocity profiles. However, additional load-relevant information, such as road gradient and vehicle mass, is required for representing the driving behavior of heavy-duty trucks. Therefore, an innovative methodology of generating representative driving profiles from real driving data, incorporating road gradient and estimated vehicle mass, as initially presented in [10], is developed for integration into holistic powertrain concept design.

2. General Methodology

In order to assist the process of powertrain electrification for heavy-duty trucks, a methodology of holistic powertrain concept design has been developed at the Institute for Automotive Engineering (ika) of RWTH Aachen University [11]. The full development process is shown in Figure 1. The additions presented within this paper (Figure 1, left) focus on the integration of real driving data to derive application-specific design requirements for the subsequent powertrain design and concept evaluation (Figure 1, right).

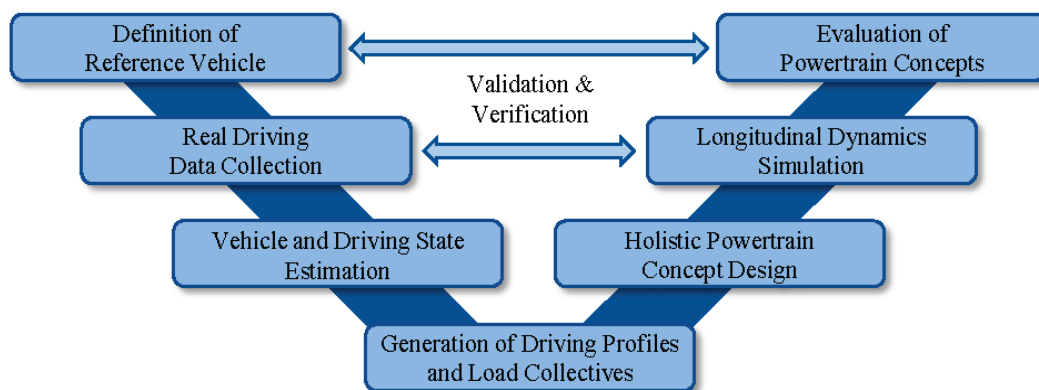


Figure 1. V-model of powertrain design methodology based on measured vehicle data [10].

Within this methodology, the first step focuses on defining a conventional reference vehicle, which is to be electrified or substituted by a requirement-appropriate vehicle with an electric powertrain. From the reference vehicle, static base and application-dependent requirements are derived, and requirements specific to the vehicle type and segment are defined. The second step in the design process consists of collecting real driving data during normal operation. From the measured real driving data, the vehicle and driving states are estimated. From here, representative driving profiles are generated for the

reference vehicle, which serve as a basis to derive load collectives for designing the electric powertrain components. With the derived requirements and load collectives, a modular holistic powertrain design process is carried out, resulting in viable powertrain concepts ready for longitudinal simulation and later prototypic assembly.

2.1. Measurement of Real Driving Data

For the measurements, a real reference vehicle and a target vehicle for the powertrain concept design are defined. The reference vehicle may be a single vehicle or part of a vehicle fleet whose operating behavior is to be recorded for a certain duration. The data logging phase depends on the diversity of the individual vehicle usage profile and is therefore not fixed. Within the data logging phase, the general operating behavior should be widely covered for the best possible design of the application-specific powertrain concepts. Since additional factors such as market and regulatory requirements are also taken into account in the later process of determining requirements and generating load spectra, incomplete coverage of the operation profile is uncritical.

The target vehicle can either be a digital twin of the reference vehicle for which an electric powertrain is to be designed or a not-yet-existing, theoretical concept. Alternatively, a different, existing, or theoretical target vehicle can be defined. In both cases, the parameters relevant for describing the longitudinal dynamic behavior are required. These are given in Table 1.

Table 1. Parameters defining the reference vehicle.

Parameter	Symbol	Unit
Vehicle curb mass	m_{veh}	kg
Aerodynamic drag coeff.	c_d	/
Frontal area	A	m ²
Rolling resistance coeff.	c_r	/
Dynamic wheel radius	r_{dyn}	m

Parameters such as the aerodynamic drag coefficient or rolling resistance coefficient are not constant under all conditions in real operation. For simplification and due to the minor influence of changes during operation compared to, for example, the variable payload mass, these parameters are assumed constant based on the reference vehicle.

The vehicle and driving behavior are measured during real operation for the subsequent powertrain concept design. Here, the assessment is reduced to longitudinal dynamic behavior, as the influences of lateral and vertical dynamics on the powertrain performance are assumed negligible. This allows the driving behavior to be approximated using the differential equation of motion from (1) and resistance forces from (2) to (4):

$$\ddot{x} = \frac{1}{(m_{veh} + m_{pl} + m_{rot})} \cdot \left[\frac{T_{wheel}}{r_{dyn}} - (F_r + F_{cl} + F_{air}) \right], \quad (1)$$

$$F_r = c_r \cdot (m_{veh} + m_{pl}) \cdot g \cdot \cos(\alpha), \quad (2)$$

$$F_{cl} = (m_{veh} + m_{pl}) \cdot g \cdot \sin(\alpha), \quad (3)$$

$$F_{air} = \frac{\rho_{air}}{2} \cdot c_d \cdot A \cdot \dot{x}^2, \quad (4)$$

which represent the relation between acceleration $\ddot{x}$, drive torque at the wheel T_{wheel} and driving resistances. Here, m_{pl} is the payload mass, m_{rot} the sum of equivalent rotational masses of the powertrain and F_r, F_{cl} , and F_{air} are rolling resistance, climbing resistance and aerodynamic drag, respectively. The resistance forces are calculated with the gravi-

tational acceleration constant g ($g = 9.81 \text{ ms}^{-2}$), road gradient α , vehicle velocity $\dot{x}$ and air density ρ_{air} , which is assumed constant at $\rho = 1.2 \text{ kgm}^{-3}$. Wind speed is neglected for simplification.

While many parameters are already defined by the reference vehicle, the following remain to be measured or estimated: vehicle velocity, vehicle acceleration, payload mass, and road gradient. To describe a truck's driving behavior adequately, using both measurement equipment for reading vehicle communication via the Controller Area Network (CAN) along with external sensors to measure environmental conditions is a suitable approach. For this, a dedicated data logger has been developed and built up at ika. A Raspberry Pi 4 forms the basis of the first prototype. It combines a USB-to-CAN interface with the sensors listed in Table 2.

Table 2. Sensor list of the developed data logger.

Sensor	Product	Data Rate (Hz)
Air pressure	STMicro LPS25HB	25
Humidity and temperature	STMicro HTS221	12.5
Inertia (x-, y-, and z-axis)	STMicro LSM9DS1	up to 1000
GPS	DFRobot UBX-G7020-KT	10

The CAN interface is connected non-invasively with the on-board diagnosis (OBD) socket as well as the fleet management system (FMS) interface to request and read communication via the OBD II and SAE J1939 protocols [12]. From CAN communication, signals such as vehicle velocity and driver requested torque are recorded.

During vehicle operation and measurement, communication requests are sent at a rate of approximately 30 Hz while sensor data is logged at the sensors' individual sample rate. Only the GPS receiver sends a position update at only 1 Hz, which is below its specified data rate. The given data rates of sensors and recorded CAN communication are sufficiently high resolution to describe the vehicle and driving status adequately.

2.2. Estimation of Vehicle and Driving States

In order to describe the vehicle and driving state adequately, vehicle velocity, vehicle acceleration, payload mass, and road gradient are required. While vehicle velocity can be measured directly, and acceleration can be derived accordingly, road gradient and payload mass have to be estimated instead.

2.2.1. Robust Road Gradient Estimation

Various approaches exist for approximating road gradient. The first considered approach matches the vehicle position history with digital elevation models, such as the Shuttle Radar Topography Mission (SRTM), as explained in [13]. Here, the absolute elevation is identified for the GPS position recording of the vehicle. The road gradient can be calculated from the determined elevation profile according to (5):

$$\tan \alpha = \frac{dh}{ds}, \quad (5)$$

where h is the determined elevation and s is the driven distance. An alternative method involves calculating elevation directly using the international elevation formula, which is given in (6):

$$h = \frac{288.15 \text{ K}}{0.0065 \frac{\text{K}}{\text{m}}} \cdot \left(1 - \left(\frac{p(h)}{1013.25 \text{ hPa}} \right)^{\frac{1}{5.255}} \right), \quad (6)$$

where $p(h)$ is the height dependent air pressure. Road gradient is also calculated according to (5). Within a third method, road gradient can be calculated from the acceleration force measured by an inertia measurement unit (IMU), using (7):

$$\alpha = \arcsin\left(\frac{a_x - \ddot{x}}{g}\right), \quad (7)$$

where a_x is the acceleration measured by the IMU with the longitudinal vehicle acceleration $\ddot{x}$ being the derivative of vehicle velocity (cf. (1)). However, it was shown in [14] that the calculated gradient based on the acceleration approach deviates strongly from reality with the measurement equipment used so far. The differences can be explained by the difficult positioning of the sensor as well as filter sensitivity. Therefore, only the estimated gradients from the map matching approach and the barometric height formula are used for now. These approaches are fused in order to obtain a robust estimation. A weighting function was chosen to combine the height and gradient profiles of both approaches, which is given in (8):

$$\alpha_{fused} = \frac{w_{\alpha,GPS} \cdot \alpha_{GPS} + w_{\alpha,baro} \cdot \alpha_{baro}}{w_{\alpha,GPS} + w_{\alpha,baro}}, \quad (8)$$

where α_{fused} is the fused gradient, $w_{\alpha,GPS}$ and α_{GPS} are the weighting factor and gradient, respectively, of the map-matching results, while $w_{\alpha,baro}$ and α_{baro} are the weighting factor and gradient, respectively, of the barometric approach. To calculate these weighting factors, potential influencing parameters were investigated. For the map matching approach, the horizontal and vertical accuracies could be identified, which provide a solid estimate of GPS quality. For the barometric approach, influences of temperature and wind were investigated, but no significant correlation could be proven. Due to the overall good quality of the barometric approach as shown in [15,16], a constant weighting factor of 0.7 is assumed for now, while the map matching approach receives a weighting factor between 0 and 1 based on a linear function of horizontal and vertical accuracy. An example of the current state of the developed road gradient fusion approach is shown in Figure 2 for a tunnel transit.

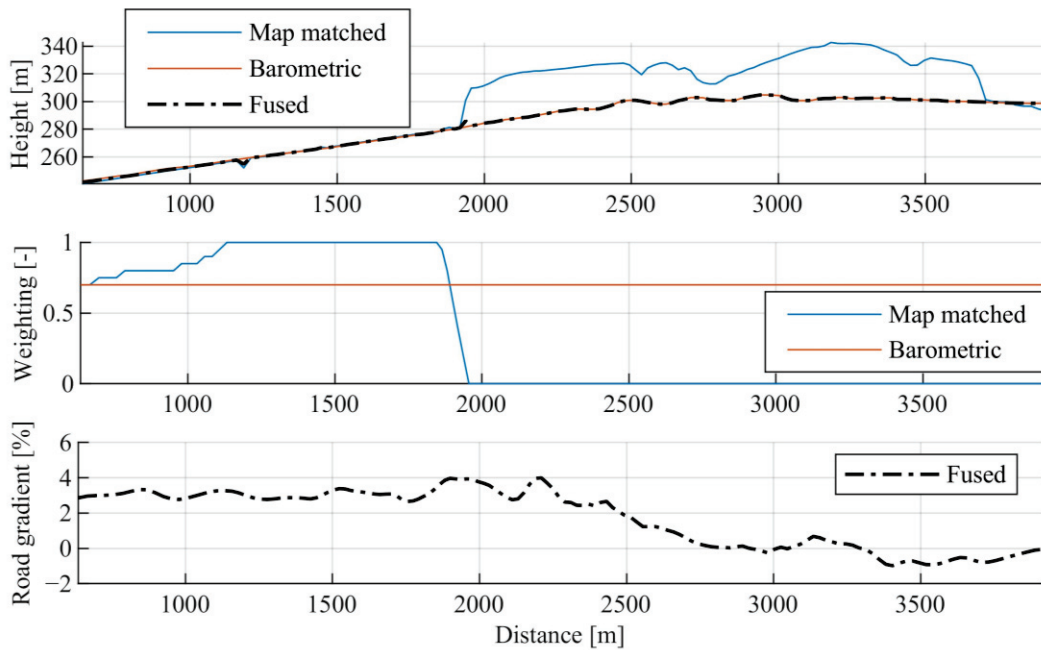


Figure 2. Example of road gradient fusion during a tunnel transit [10].

It can be seen from Figure 2 that the tunnel begins at approximately 1850 m of distance travelled, as the map matching weighting factor drops, while at the same time the height profiles diverge considerably. This behavior is attributed to the digital elevation model providing the absolute elevation of the terrain at a given GPS position, not necessarily the elevation of the road. In the case of this exemplary tunnel transit, a delta of up to 40 m exists results between the vehicle's actual elevation and the estimated elevation from GPS results. Here, the dynamic weighting of the sensor fusion function dampens or eliminates inaccurate values originating from GPS from the fused height and road gradient profiles. However, the weighting sensitivity of the map matching approach shows further optimization potential and shall be revised with more available data.

2.2.2. Payload Mass Estimation

In addition to the road gradient, payload mass is also a decisive factor of the load profile for heavy-duty trucks. While truck curb weight is defined based on the vehicle specifications, payload mass may vary during operation. This is not necessarily monitored continuously. In some vehicles, the axle load is calculated, e.g., via the air pressure of the air suspension and provided directly via the FMS interface. However, not all vehicles are equipped with an FMS interface or air suspension. Alternatively, the total mass can be approximated with a model-based estimator. Here, vehicle mass, including payload mass, is calculated based on the equation of longitudinal motion as given in (1). To solve the equation, the rolling resistance and drag coefficients are set by the reference vehicle and assumed to remain constant during operation, as well as air density. Since the total vehicle mass can be assumed to be approximately constant over a driving segment, a method for determining a scalar value based on vectors of noisy measured values is required. Several methods can be used for this purpose. The following algorithms are considered for mass estimation: Least squares (LS), Recursive Least Squares (RLS), and the Levenberg–Marquardt algorithm (LM) [16–18].

The LS approach aims at a minimization of the estimation parameter through the sum of error squares. For this purpose, the normal form of the least squares method is constructed, which is given in (9):

$$\hat{\Theta} = (H^T H)^{-1} \cdot H^T \cdot y, \quad (9)$$

where $\hat{\Theta}$ is the estimated parameter vector, H is the regression vector, and y is the measurement vector. For the estimation of mass only, the following conditions apply, as defined in (10):

$$\hat{\Theta} = m_{veh} + m_{pl}, \quad H = \ddot{x} + g \cdot \sin(\alpha) + c_r \cdot g \cdot \cos(\alpha), \quad y = \frac{T_{wheel}}{r_{dyn}} - \frac{\rho}{2} \cdot c_d \cdot A \cdot \dot{x}^2, \quad (10)$$

The RLS algorithm is an online parameter estimation method. Unlike the LS, the RLS updates its estimates recursively, as new data becomes available, making it suitable for real-time applications as well as dynamically changing behavior. The recursive form is given in (11):

$$\hat{\Theta}[k] = \hat{\Theta}[k-1] + K[k] \cdot (y[k] - H^T[k] \cdot \hat{\Theta}[k-1]), \quad (11)$$

where k is the time step, $\hat{\Theta}[k]$ is the new estimation, $\hat{\Theta}[k-1]$ is the previous estimation, $K[k]$ is the gain vector, and $y[k]$ is the new measurement data. The gain vector is calculated according to (12):

$$K[k] = P[k-1] \cdot H(k) \cdot (\lambda + H^T[k] \cdot P[k-1] \cdot H[k])^{-1}, \quad (12)$$

where $P[k-1]$ is the covariance matrix from the previous time step and λ is the forgetting factor. The forgetting factor ($0 < \lambda \leq 1$) controls how quickly previous data is forgotten. Here, $\lambda = 1$ weighs all data equally, while lower values of λ gradually discount previous data in the weighting. The covariance matrix is calculated as of (13):

$$P[k] = \frac{1}{\lambda} \left(P[k-1] - K[k] \cdot H^T[k] \cdot P[k-1] \right), \quad (13)$$

The LM algorithm extends the RLS to handle non-linear least squares problems by incorporating a damping factor and using the Jacobian matrix for gradient-based updates. The formula for the regularized covariance matrix is given in (14):

$$P_{reg}[k] = \frac{1}{\lambda} \left(P[k-1] - K[k] \cdot H^T[k] \cdot P[k-1] \right) + \mu \cdot I, \quad (14)$$

where μ is the added dampening factor and I is the identity matrix, ensuring numerical stability by preventing the covariance matrix from becoming singular.

As road gradient, the estimated and fused road gradient is used, and for simplification, the equivalent rotational mass is neglected in all approaches. Additionally, the following constraints from [19] are applied for filtering the measured data:

- Vehicle is in operation and velocity is above 5.5 m/s;
- Acceleration is above 0.1 m/s²;
- Motor torque is above 500 Nm.

These constraints filter out non-dynamic and low load driving segments from the measured data, as the algorithms require some dynamic behavior for reliable operation. In Figure 3, a comparison of the different mass estimation algorithms is displayed. Here, the mass is estimated for a simulated constant driving situation, where noise is applied to the output signals at 16 s.

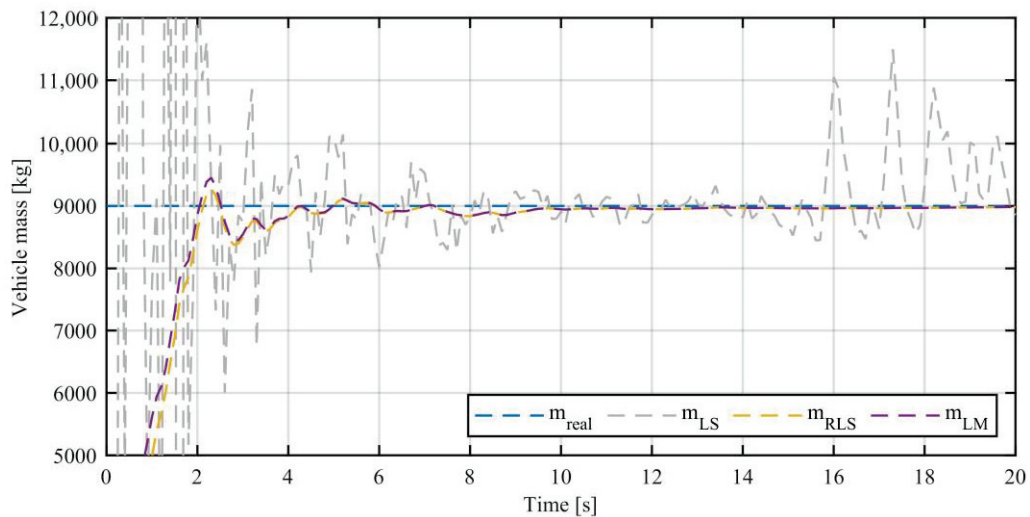


Figure 3. Comparison of mass estimation algorithms.

The comparison shows the lack of stability of the LS when the driving status changes and due to noise caused by e.g., measurement inaccuracies. It therefore does not provide a sufficient basis to be further considered as an algorithm for mass estimation. Both RLS and LM indicate close matching with the real vehicle mass. However, the LM algorithm demonstrates a marginally faster convergence to the real value than the RLS while also not being influenced by the applied noise. Therefore, the LM algorithm is chosen for the mass estimation in the following steps.

2.3. Generation of Driving Profiles and Load Collectives

According to [20], the basic principle of driving profile generation follows three steps:

1. Recording driving data during normal real-world operation,
2. Analyzing the recorded data to describe or characterize the driving conditions,
3. Develop representative driving cycles for the recorded conditions.

The first two steps are fulfilled with the measurements and the estimations of mass and road gradient distribution. Various methods exist for generating driving profiles, which can be categorized into deterministic and stochastic approaches [21]. Driving cycle generation methods, which operate deterministically, show the same results when repeated with unchanged input data. In contrast, stochastically generated cycles vary despite identical input data. However, statistical characteristics, such as the distribution of velocities and accelerations, are identical or very similar for all stochastic cycles.

A stochastic method is chosen to synthesize and consequently generalize driving profiles representing the longitudinal characteristics from the measured driving data. For this purpose, a Markov chain-Monte Carlo (MCMC) technique is utilized, which is based on the methodology presented by [22]. Using 2D Markov chains, the state and transition probabilities of $\dot{x}$, α , and m_{pl} are determined from the measured data. Therefore, each state combines a synthesized velocity, gradient, and payload mass class with a probability for the state in the next time step. To apply this 2D method in three dimensions, the gradient and payload mass classes are combined into one class, increasing its size substantially but not increasing matrix dimensions. Synthesizing velocity and gradient through 2D Markov chains takes into account their interdependencies, allowing unrealistic driving behavior, such as increasing velocity with increasing gradient or changing gradients during a standstill, to be eliminated in advance. The Monte Carlo sampling method is based on a Poisson distribution created from the measured driving data. Here, repeated random sampling allows for the generation of new samples, functioning as a random number generator. A sample is selected in each time step over a predefined length of the final driving profile. After each selection, the probability matrices are updated, which improves the resulting cycle, as the distribution characteristics asymptotically approach the original distributions if the timespan is set long enough. However, the cycle length is chosen to be relatively short for later longitudinal dynamics simulations and is far shorter than the length of the original data. Therefore, the asymptotic behavior is only utilized to a limited extent. Another issue with the high divergence of the time lengths in this stochastic method is the large scatter of the resulting cycles regarding their characteristics. For this reason, the maximum deviations from the original characteristics are limited by the following criteria:

- Deviation of mean, standard, and maximum velocity $\leq 10\%$,
- Deviation of mean, standard, minimum, and maximum gradient $\leq 15\%$,
- Deviation of mean, standard, minimum, and maximum acceleration $\leq 15\%$.

These boundary conditions limit the amount of synthesized cycles but still allow for several valid results. An evaluation function, which is given in (15), is implemented to select the result that represents the original data best from the generated cycles:

$$w_{cycle} = \frac{1}{n_{crit}} \sum_{i=1}^{n_{crit}} \frac{\sigma_i}{\sigma_{i,max}} \in [0, 1], \quad (15)$$

where n_{crit} is the number of deviation criteria, σ_i is the resulting deviation per criterion, and $\sigma_{i,max}$ is the allowed maximum deviation per criterion. The generated cycle with the lowest evaluation coefficient w_{cycle} and therefore the smallest total deviation from the measured data set is selected from the generated results.

Representing the most fitting driving profile, the selected cycle provides not only an additional source for application-specific load points but also their distribution, relevant for the derivation of load collectives for the reference vehicle. In a first step, these are calculated statically at the wheel, as the powertrain topology is unknown at this stage of development. The load collectives provide an indication of frequent operating points, to which the individual powertrain components are subsequently to be designed in terms of safety, lifetime, and efficiency.

2.4. Powertrain Concept Design and Vehicle Simulation

Based on the generated driving profiles and the reference vehicle parameters, powertrain concepts can be designed. To accomplish this task, a modular, holistic concept design methodology for electric powertrains has been developed at ika, as presented in [23,24]. This design method comprises the definition of requirements, the individual design of the components (electric machine, inverter, and transmission), and concludes with the validation of prototypes on test benches. The method is specifically designed for electric powertrain design. Its modularity allows for systematic development from scratch as well as targeted component optimization. The primary goals, similar to the metaheuristic algorithms that form the basis of the design method, are a substantial reduction in development time and costs by automatically synthesizing and evaluating powertrain concepts to determine those for further investigation early in the process.

To assess energy demands during operation, a longitudinal dynamics model of the truck is simulated. The architecture of the forward calculating model implemented in MATLAB/Simulink is shown in Figure 4.

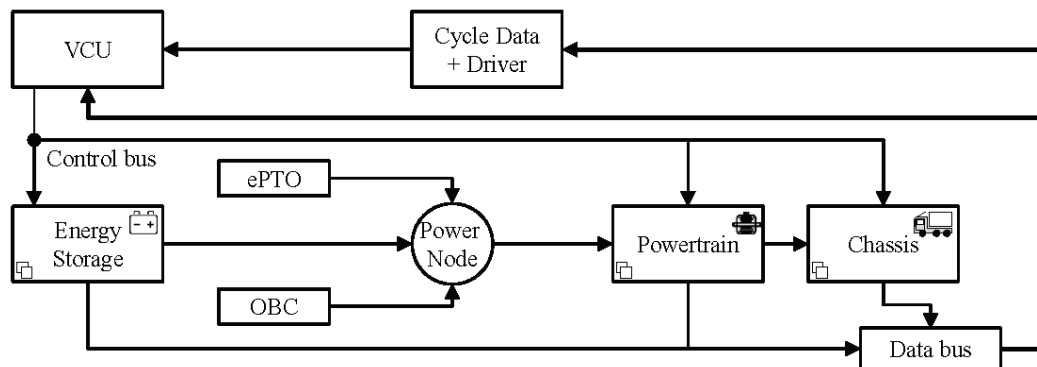


Figure 4. Architecture of longitudinal dynamics simulation model for a heavy-duty truck [10].

Contrary to simulations for passenger vehicles, cycle data for trucks are typically given as a function of distance. For this reason, an additional signal resembling the stop time for standstill is necessary. Furthermore, the driver cannot be represented by a PI controller alone to follow the demanded velocity signal. Therefore, the driver model includes distinctive states, e.g., standstill, to account for the requirements resulting from the aforementioned cycle properties. A state machine is implemented to manage the transitions in between these states. Interfaces to the HV architecture are included to connect the on-board charger (OBC) and an electric power take off (ePTO) to supply power (e.g., for a refrigerated body) or for dynamic charging (e.g., with a pantograph).

3. Results

The current state of development of the methodology presented was exemplarily demonstrated to provide conclusions on the plausibility of the processes. For this purpose, a DAF XD 450 FAN (model year 2023) was defined as the reference vehicle. The characteristic properties of the vehicle, such as aerodynamic drag and rolling resistance coefficient, were

provided by the manufacturer within the project. The vehicle was equipped with the prototypic data logger, and a short test drive was conducted, which is displayed in Figure 5.

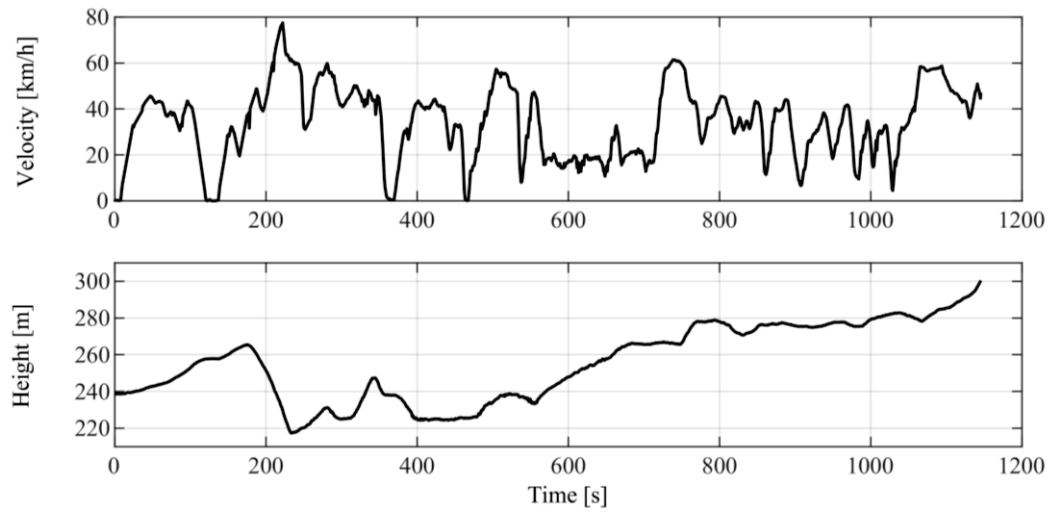


Figure 5. Measured driving profile of reference vehicle.

The minimum velocity is 0 km/h, while the maximum velocity is 76 km/h. The average velocity is 34.09 km/h, with a standard deviation of 14.18 km/h. The high standard deviation can be attributed to the dynamic velocity of the driving segment. This is an advantage for the mass estimation, as described before. The height profile shown in Figure 5 is the integration of the robust gradient estimation. For mass estimation, the LM algorithm is parametrized with a forgetting factor λ of 0.9985 and an initial mass value of 8818.8 kg, which equals the unladen mass of the truck. The comparison of estimated mass from the vehicle, the LM algorithm, as well as the real mass is displayed in Figure 6.

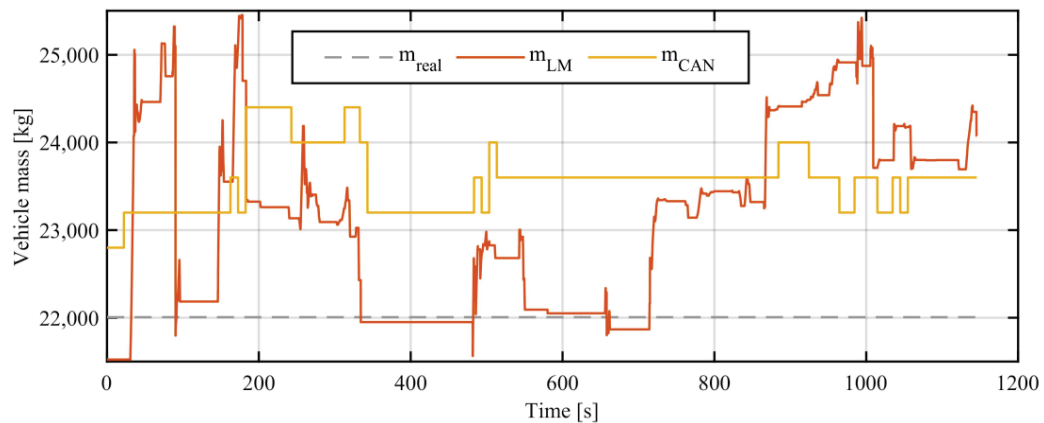


Figure 6. Mass estimated with the Levenberg–Marquardt algorithm for the test drive.

The real total vehicle mass was measured before the test drive at 22,007.4 kg. It can be observed that the algorithm is unstable until it has received sufficient usable data points for estimation. The mass is estimated close to the real measured value for several hundred seconds, but drifts off around 700 s into the data set. This behavior can be attributed to the lower dynamics and therefore lower load and torque values in the later segment of the data set, which is not beneficial for the estimation. Overall, the mass estimation using the LM algorithm shows a closer approximation to the real vehicle mass than the vehicle's own estimation read from the CAN bus. Therefore, the estimated mass is used for further cycle generation while still showing potential for further optimization.

With the given velocity, gradient, and mass profile, the cycle generation process according to chapter 2.3 is performed. Here, a workstation featuring an Intel® Core™ i9-12900 processor and 128 GB random access memory is used, and the algorithms are implemented in MATLAB. The resulting cycle is shown in Figure 7.

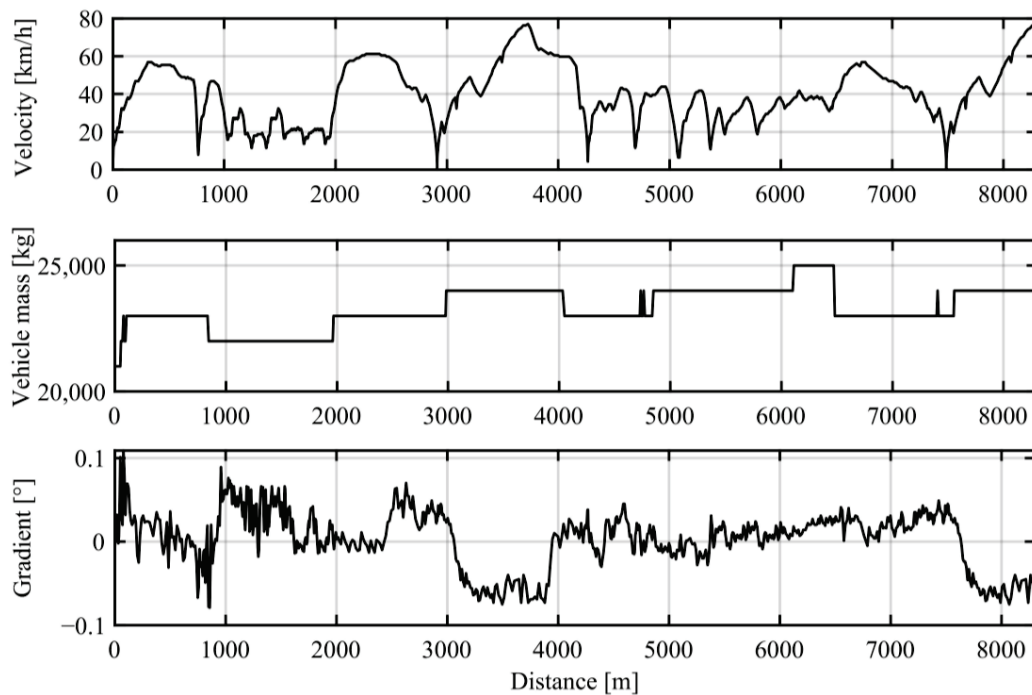


Figure 7. Velocity, vehicle mass, and gradient of the resulting generated cycle.

The generated cycle fulfills the boundary conditions set in chapter 2.3 for velocity, gradient, and acceleration. The generated mass profile deviates more significantly from the input mass profile, especially regarding the standard deviation criterion, mainly due to the high selected step size of 1000 kg. This step size was chosen due to current computational limitations, predominantly limited memory, and will be re-evaluated in the future. The generated cycle is rated with an evaluation score of 1.39 (cf. (14)), meaning that it deviates on average over all evaluation criteria at the same weighting by 39%. This again can be mainly attributed to the high deviation in mass, especially its standard deviation and minimum value evaluation. Removing the mass-related evaluation criteria from the total evaluation score results in a remaining deviation of 24.51%.

4. Discussion and Outlook

Within this paper, the authors have presented a novel approach to measured data-based generation of representative driving profiles for heavy-duty trucks, considering the velocity, gradient, and mass profiles. With a prototypic data logger, relevant vehicle, and environmental data to describe vehicle operation was measured. From the measured data, next to vehicle velocity, gradient and mass over time were individually estimated. With the dataset consisting of directly measured and estimated vehicle parameters, driving cycles are generated using 2D Markov chains. First results have proven the methodology plausible while at the same time pointing out further optimization potentials. While the estimation of road gradient from barometric data and a GPS-matched elevation model delivers reliable results, the estimation of vehicle mass using the Levenberg–Marquardt algorithm as a state estimator deviates from the real measured values. Here, further investigations within a parameter study for the filter criteria as well as the state estimator settings are required. With a closer estimation of the vehicle mass, load collectives for the powertrain components

can be derived, and powertrain concept design can be performed. Further optimization of the estimation algorithms is required to identify positive effects on the powertrain development process in terms of development time and costs.

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Article

Decarbonization of Long-Haul Heavy-Duty Truck Transport: Technologies, Life Cycle Emissions, and Costs

Anne Magdalene Syré * and Dietmar Göhlich

Methods for Product Development and Mechatronics, Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany; dietmar.goehlich@tu-berlin.de

* Correspondence: a.syre@tu-berlin.de; Tel.: +49-(0)30-314-22842

Abstract: Decarbonizing long-haul, heavy-duty transport in Europe focuses on battery-electric trucks with high-power chargers or electric road systems and fuel-cell-electric vehicles with hydrogen refueling stations. We present a comparative life cycle assessment and total cost of ownership analysis of these technologies for 20% of Germany's heavy-duty, long-haul transport alongside internal combustion engine vehicles. The results show that fuel cell vehicles with on-site hydrogen have the highest life cycle emissions (65 Mt CO₂e), followed by internal combustion engine vehicles (55 Mt CO₂e). Battery-electric vehicles using electric road systems achieve the lowest emissions (21 Mt CO₂e) and the lowest costs (EUR 45 billion). In contrast, fuel cell vehicles with on-site hydrogen have the highest costs (EUR 69 billion). Operational costs dominate total expenses, making them a compelling target for subsidies. The choice between battery and fuel cell technologies depends on the ratio of vehicles to infrastructure, transport performance, and range. Fuel cell trucks are better suited for remote areas due to their longer range, while integrating electric road systems with high-power charging could offer synergies. Recent advancements in battery and fuel cell durability further highlight the potential of both technologies in heavy-duty transport. This study provides insights for policymakers and industry stakeholders in the shift towards sustainable transport. The greenhouse gas emission savings from adopting battery-electric trucks are 54% in our high-power charging scenario and 62% in the electric road system scenario in comparison to the reference scenario with diesel trucks.

Keywords: life cycle assessment; total cost of ownership; battery-electric vehicles; fuel-cell-electric vehicles; high-power charger; electric road system; hydrogen refueling station

1. Introduction

For the decarbonization of long-haul, heavy-duty transport in Europe, the most widely discussed technology strategies are battery-electric vehicles (BEV) with large batteries and high-power chargers (HPC) and fuel-cell-electric vehicles (FCEV) with hydrogen refueling stations (HRS), supported by the European Regulation on the deployment of charging and refueling infrastructure [1]. Battery-electric trucks with electric road systems (ERS) have been tested in several countries, and some countries like The Netherlands and China are starting large investments in an overhead catenary system for trucks [2–4]. For FCEV, numerous hydrogen pathways exist. Due to the high investment costs, it seems inconceivable that all technologies will be introduced across the board in parallel.

The decision for or against the large-scale roll-out of these technologies should consider not only the system costs, but also the environmental impact. Life cycle assessments (LCA) are necessary to determine which technology is more advantageous in terms of reducing

greenhouse gas (GHG) emissions. Economic viability is best determined based on a comprehensive total cost of ownership (TCO) analysis.

No study currently offers a comprehensive assessment that integrates vehicles and their interactions into a single framework. We aim to fill this gap by evaluating the climate change potential and ownership costs associated with the adoption of BEV and FCEV for long-haul trucking. This includes all relevant vehicle components, specific powertrain configurations, and the necessary infrastructure. We analyze the interdependence between vehicle design, infrastructure, and energy provision within a defined spatial and temporal scope, establishing a reference scenario and various decarbonization scenarios (Figure 1). These scenarios depict 20% of Germany's long-haul heavy-duty fleet starting operations in 2024, representing a simplified version of reality and illustrating 'what if' scenarios. With the help of environmental and cost data from Ecoinvent and the literature, we assess these scenarios and calculate environmental impacts and ownership costs, enabling a comparison between the reference and decarbonization scenarios.

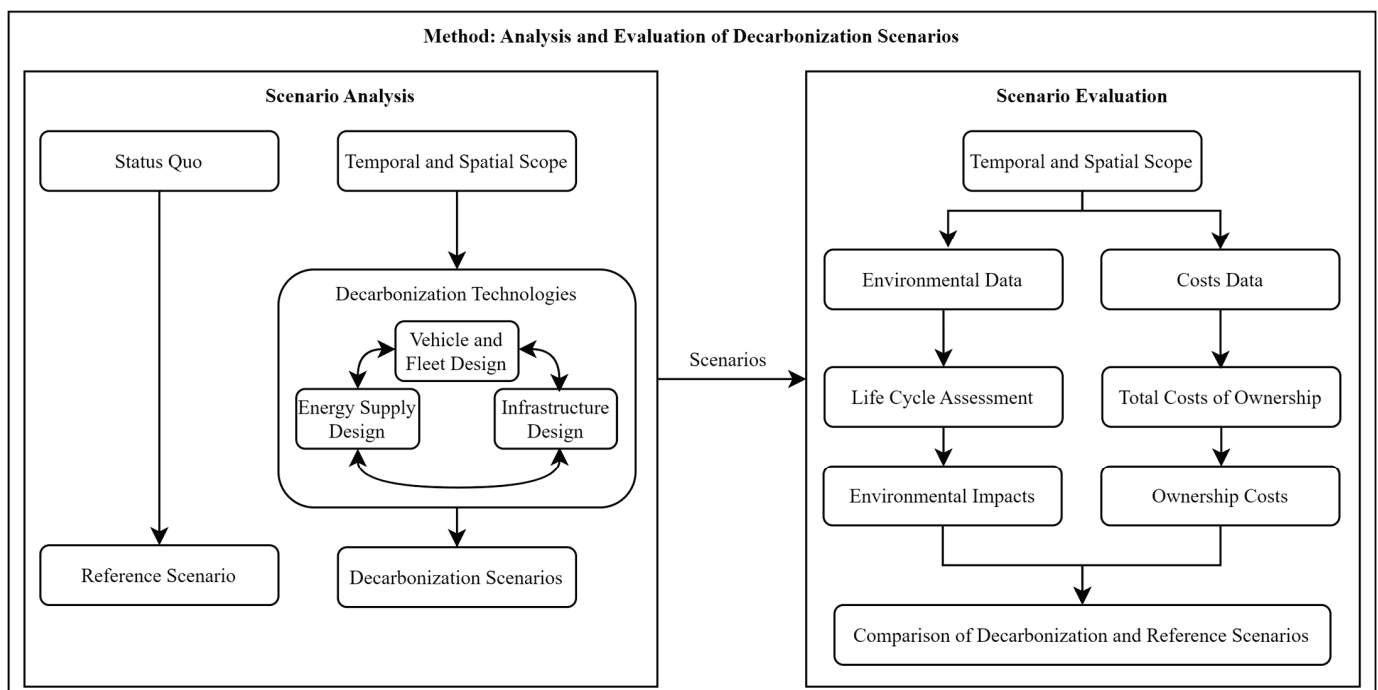


Figure 1. Method to Analyze and Evaluate Decarbonization Scenarios.

We begin by elaborating on the design of the recharging and refueling infrastructure, life cycle assessments, and total cost of ownership analyses (Section 2). Next, we introduce the technologies and scenarios under examination (Section 3). Following this, we provide a detailed explanation of our methodology, which includes a life cycle assessment and a total cost of ownership analysis for the individual components and the complete set of scenarios (Section 4). Finally, we present our results (Section 5), followed by a thorough discussion (Section 6) and conclusion (Section 7).

2. State of the Art

The state of the art encompasses the design of the recharging and refueling infrastructure, LCA of batteries, fuel cell systems, vehicles, chargers, ERS, HRS, and TCO analyses for freight vehicles.

2.1. Design of Refueling and Recharging Infrastructure

Analyzing the infrastructure design and requirements for recharging and refueling BEV and FCEV is crucial for accurately accounting for emissions. The analysis should consider the implications for the vehicle energy storage size and align with vehicle needs and transport behavior. For HPC infrastructure for BEV, Menter et al. estimated demand-oriented charging network dimensions using a microscopic traffic simulation approach [5]. Tietz et al. presented an update of the study [6]. For a 20% electrification scenario, they found that 2735 HPC (points of charge) with 720 kW charging power are sufficient to supply 20% of the German long-haul, heavy-duty BEV fleet [6]. Speth et al. developed a model based on traffic count data and on-site queueing models [7]. Shoman et al. use a trip-based model to derive charging requirements [8]. Göckeler et al. describe three expansion stages for charging infrastructure: daily, every stop, and highway [9]. Daily charging includes only overnight charging; therefore, the vehicle's daily range is restricted to its battery capacity. Every stop charging includes charging possibilities in between trips with a lower charging power; each trip is limited to the battery capacity. For highway charging, the high charging power leads to an infinite range and no restrictions through battery capacities.

For ERS infrastructure, Wietschel et al. provided a feasibility study on the potentials of catenary hybrid diesel trucks in Germany [10]. Based on their approach, Hanesch et al. and Ramshankar et al. performed an LCA for short hybrid diesel and long-haul battery-electric trucks, respectively, showing that the share of infrastructure emissions in the vehicles' life cycle depends heavily on the number of vehicles using the infrastructure and ERS share of the roads [11,12]. While Hanesch et al. assumed an ERS share of 10% [12], Ramshankar et al. assumed that from 800 km in total, 700 km was powered by the infrastructure (87.5% ERS share) [11]. Wietschel et al. stipulate a 2–3 km ERS infrastructure to support 10–30 km transportation without charging for catenary hybrid diesel trucks (6–30% ERS share) [10]. Jöhrens et al. based their study on [10] and concluded a basic ERS network of 3200 km for Germany [13]. Speth and Funke included 100 km ERS for 500 km in total [14]. Göckeler et al. assessed two expansion stages: 3800 km by 2035 or 2040 [9].

Rose models an HRS network for heavy-duty FCEV in Germany in 2050 [15]. In the study by Rose et al., the buildup of the HRS network for different electrification stages is presented [16]. For the 22% electrification scenario, they find that 70 HRS with different storage capacities are needed. In the design of the HRS, additional capacities for transit and regional transport was included [16].

2.2. Life Cycle Assessment of Long-Haul, Heavy-Duty Transport

Most LCA of BEV and FCEV deal with the manufacturing and use phase of BEV and FCEV. While LCA studies and inventories on recycling Li-ion batteries are available, LCA studies and inventories on recycling fuel cell powertrains are scarce [17]. Ecoinvent [18] is a comprehensive and widely used collection of inventory data for various materials, processes, and products encompassing a wide range of industries. Contrary, Greet [19] is a model and database provided by Argonne National Laboratory for evaluating energy and environmental impacts in the context of transportation. Most studies reviewed in this work use data from Ecoinvent or Greet. Ecoinvent offers attributional and consequential approaches, while Greet primarily focuses on attributional LCA. The attributional approach tries to answer the question of which global burdens can be attributed to a specific product [20]. In contrast, the consequential approach aims to quantify the consequences of a decision (e.g., the introduction of FCEV or BEV for the transport sector). Although both approaches can lead to different results, there are some studies that do not clearly specify their approach. Additionally, the impact assessment method varies widely. Recipe, CML,

IPPC, Eco-indicator 99, and direct life cycle inventory results are used, while not all studies specify their impact assessment method. This leads to uncertainties when analyzing, reproducing, and comparing results.

2.2.1. Batteries, Fuel Cells, and Hydrogen Tanks

In [21–23], different battery chemistries were assessed (Table S1). Lithium iron phosphate (LFP) batteries exhibit the lowest benefits or highest global warming potential (GWP) for recycling in all studies. For the production, the results of the different studies are not consistent: Mohr et al. and Ciez and Whitacre report the lowest production emissions for nickel manganese cobalt (NMC) batteries [22,23], while in [21], LFP batteries are superior. Overall, all study results show major differences, which are caused by different assumptions on the cell chemistry, cell composition (nickel, manganese, and cobalt share), pack or cell level, energy density, electricity mix for production and end of life (EoL), the background data, and model approach.

Miotti et al. [24], Evangelisti et al. [25], and Usai et al. [26] assessed fuel cell systems—consisting of the fuel cell, fuel cell auxiliaries (also referred to as the balance of the plant or BoP), and hydrogen tank (Table S2). All studies analyzed an 80 kW proton exchange membrane (PEM) fuel cell system. The difference in the results is mainly attributed to variations in the platinum content and hydrogen tank size. For evaluating the EoL of fuel cell systems, two studies conducted assessments regarding the recycling of platinum catalysts in PEM fuel cell systems [27,28]. These studies involve a comparison of two distinct hydrometallurgical recycling methods, specifically ion exchange resin and solvent extraction. Duclos et al. found that both recycling approaches yield a comparable reduction in environmental impacts, emphasizing the significance of platinum recycling. Weiszflog and Abbas present a detailed LCA of different hydrogen tanks for FCEV trucks with a capacity of 80 kg [29]. They find that the production of carbon fiber has the highest share of GHG emissions.

2.2.2. Long-Haul Trucks

Regarding the LCA of trucks, most of the reviewed studies [30–37] included the full life cycle, covering vehicle production and EoL, and a Well-to-Wheel (WTW) analysis (Table S3). Wolff et al. focused on the production phase and provided a detailed approach for a scalable inventory for heavy-duty, long-haul trucks [38]. Despite using different impact assessment methods, all studies assessed the GWP. The vehicles examined the range from light-duty (>3.5 t) to heavy-duty (<90 t), addressing both last-mile delivery and long-haul transportation. Notably, studies that exclusively assessed vehicles under 12 t were excluded from the literature review. Most studies did not present one specific outcome for GHG emissions, but rather a range of emissions based on different vehicle specifications or scenarios. These variations included the vehicle size [32,34,35,38], annual mileage [31,32,35], and payload or purpose [31,32,34,35]. Smit et al. warrant special attention as they employed a probabilistic LCA, varying multiple parameters to quantify not only a range of emissions, but also the associated uncertainties [35]. Their findings show that although internal combustion engine vehicles (ICEV) had lower emissions than BEV and FCEV in 2019, both BEV and FCEV are projected to have lower emissions in the future. FCEV, however, exhibit the highest levels of uncertainty in their results. Sacchi et al. concluded that for long-range vehicles, FCEV can exhibit lower GHG emissions per tkm, while BEV emit fewer absolute emissions [31]. However, their results using the European electricity mix for charging and hydrogen production show a lower GWP per tkm for BEV. This discrepancy primarily arises from FCEV's higher payload capacity. Contrary, Booto et al., Iyer et al., and Syré et al., who reported a single result, found that BEV exhibit a

higher reduction in the GWP compared to the FCEV [30,34,39]. Overall, the results of LCA regarding BEV and FCEV are dependent on vehicle specifics like the battery, fuel cell and hydrogen tank size, payload, consumption, upstream emissions of hydrogen and electricity, lifetime and mileage, as well as the methodological approach including the used data, system model, scope and product system, impact assessment methods, and categories.

2.2.3. Recharging and Refueling Infrastructure

Both long-haul BEV and FCEV demand infrastructure for recharging and refueling. In contrast to ICEV, these infrastructures must be built up completely. There are studies which ecologically assess plug-in charging infrastructure in detail [40–47]. Zhao et al. present inventory data on 350 kW high-power chargers and show, in the context of charging infrastructure for electric buses in Australia, that the operation emissions of the vehicles are outweighing infrastructure emissions [46]. However, the Australian grid mix is predominantly fossil-based and, therefore, the main source of emissions. All other studies assess either up to 22 kW articulate current (AC) or up to 60 kW direct current (DC) chargers. The studies differ regarding the different charger types and their power, service life, operational country, and intended vehicles. In addition, there are also methodological differences in terms of the functional unit, life cycle phases investigated, system boundaries, and impact assessment methods. In particular, the different presentations of the results make direct comparisons almost impossible (Table S4). In addition, only a few complete inventory lists are available [40,44,46,47] and often, these inventories are secondary data: the inventories in [42] are based on [40], the inventories in [47] are based on [44], and Bekel and Pauliuk—who published the most detailed inventories—took the data from [41] and scaled it with the help of data sheets. Zhang et al. include different chargers (AC and DC with 50 kW) in their LCA of electric vehicles and conclude that environmental burdens of different chargers and the vehicle-to-charger ratios should be considered in future studies [43]. They published the material composition of their chargers. However, they do not share details on the energy needed for installation or needed transportation. In summary, the variation in study methodologies, charger types, and inventory data limits the comparability of the ecological assessments of charging infrastructure, highlighting the need for more comprehensive and transparent data in future research.

Ramshankar et al. and Hanesch et al. provide inventory data for ERS and for the vehicle pantograph [11,12] (Table S5). Both underline that the superior environmental performance of BEV using ERS versus BEV with large batteries depends on the adoption rate of ERS. The ERS presented in their study consist of catenary lines and the vehicle draws its power from a pantograph mounted on the vehicle. Other systems such as ground conduction or induction are also conceivable [48], but have received little attention in Germany.

Maack, Wulf et al., Patterson et al., Burkhardt et al., and Pederzoli et al. assess HRS ecologically [49–53]; however, the focus of the studies is the generation of hydrogen [49] or the well-to-tank (WTT) emissions of hydrogen (Table S6). Despite all studies sharing the same functional unit (per kg H₂), their differing scopes make comparisons of the results challenging. Additionally, Maack evaluates air pollutants separately, whereas Wulf et al., Burkhardt et al., and Pederzoli et al. assess GHG emissions [49,50,52,53]. Maack includes the emissions from the electricity used to produce the hydrogen in her results [49]. In [50], the results are broken down by the hydrogen refueling station (including electricity for compression), the feedstock, the production, the credit, and the recycling separately. Burkhardt et al. present an HRS system directly connected to a wind power plant [53]. Maack includes only low-pressure tanks with 440 bar [49]. Wulf et al. and Burkhardt et al. include high-pressure hydrogen storage with 850 [50] and 900 bar [53]. Burkhardt et al. present the

results for the wind turbine, electrolyzer, and HRS divided into construction, operation, and decommissioning phases [53]. Patterson et al. assess the environmental impacts with the Eco-indicator assessment method [51]. Therefore, their results are in Eco-indicator points and not in g CO₂e. The assumptions regarding hydrogen production pathways and HRS design vary: In [49,53], the hydrogen is produced exclusively via electrolysis, while Wulf et al. examine various pathways, including coal and biomass gasification, steam methane reforming, transesterification, and electrolysis with both grid and renewable electricity [50]. The HRS differ in storage size, yearly and hourly capacity, lifetime, and pressure levels. While the HRS in [49,53] are exclusively designed for passenger cars, the HRS in [50,52] also serve buses. Weiszflog and Abbas perform an LCA of hydrogen storage systems for trucks and use inventories for HRS with low-pressure hydrogen storage from Maack for electricity for cooling and compressing and hydrogen boil-off losses [29,49]. They conclude that future studies should include the utilization rate of refueling infrastructure in more detail.

2.3. Total Cost of Ownership of Long-Haul, Heavy-Duty Transport

Numerous studies assess the costs of trucks [9,14,54–56]. Given the large volume of research in this area, this section primarily focuses on European and German studies from recent years that evaluate various decarbonization options for heavy-duty trucks in long-haul transportation (Table S7). Some of these studies also provide at least rough estimates for recharging and refueling infrastructure [9,14,55].

In contrast to the results from LCA (see Section 2.2), the results of TCO analyses are consistently displayed per kilometer (Table S7). This seems to enable a direct comparison of the results. However, caution is necessary, as it cannot be guaranteed that the different vehicle technologies will deliver the same transport performance (measured in ton-kilometers, tkm) on a per-kilometer basis. In addition to this ambiguity, the scope of the TCO analyses differs in various areas. Speth and Funke, Jöhrens et al., and Göckeler et al. explicitly distinguish different charging options (charging stations and electric road systems) and battery sizes for BEV [9,14,55]. Additionally, Speth and Funke assess battery swapping and Jöhrens et al. differentiate public and depot charging [14,55]. Basma and Rodriguez include the infrastructure costs implicitly in the energy costs [56]. Furthermore, the studies differ in the assessed gross vehicle weights, ownership periods or lifetimes for vehicles and infrastructures, the number of vehicles, the energy consumption, and in the cost components and their composition included in the CAPEX and OPEX calculation. Additionally, the temporal scopes of the studies differ: while Jöhrens et al. and Göckeler et al. assess the costs for the year 2030 [9,55], Basma and Rodriguez differentiate costs for the years 2023, 2030, and 2040 [56]. Noll and Speth and Funke assess current costs [14,54] and their studies were published in 2022 and 2021, respectively. Nonetheless, all studies which included an ICEV, apart from Noll et al., found that for the year 2030, BEV will have the lowest TCO per km, followed by ICEV, while FCEV do not reach TCO parity with ICEV [9,14,54–56]. For ICEV and FCEV, the largest contributors to TCO are the energy costs. In contrast, for BEV, investments in vehicles and batteries play a larger role. However, despite higher investments compared to ICEV, the low operating costs of BEV lead to overall cost advantages. Additionally, labor costs were, in all studies, the largest or second largest cost component except for the FCEV in [55]. For both BEV and FCEV, the inclusion of subsidies leads to significantly lower costs [54]. Noll et al. emphasize the superiority of targeting subsidies for OPEX parameters [54].

2.3.1. Energy Costs

The energy costs in the literature show disparities. Basma and Rodriguez and Noll et al. present current energy prices at 1.22 and 1.04 EUR/L diesel, 0.2 and 0.15 EUR/kWh electricity, and 10.3 and 7.98 EUR/kg hydrogen, respectively [54,56]. While Basma and Rodriguez analyze the EU-27 weighted average energy costs and green hydrogen with declining costs until 2040 (5.83 EUR/kg), Noll et al. assessed country-specific costs and a hydrogen mix [54,56]. Jöhrens et al. and Göckeler et al. present future energy prices for the year 2030: 1.36 and 1.20 EUR/L diesel, 0.16 and 0.18 EUR/kWh electricity, and 4.57 (import) to 9.45 (inland electrolysis) and 4.17 EUR/kg hydrogen, respectively [9,55]. The hydrogen costs show particularly large deviations in the literature examined. The price depends, among other things, on the production process, whether conventional processes such as gasification or reforming are used or rather electrolysis with (green) electricity, and whether the hydrogen is produced in Germany or imported. Jöhrens et al. distinguish between imported hydrogen and hydrogen produced by electrolysis in Germany, while Göckeler et al. create high- and low-price scenarios due to uncertainties in the future provision of hydrogen [9,55].

2.3.2. Vehicle Costs

In all studies, ICEV have the lowest investment costs, ranging from approximately EUR 70,000 to EUR 170,000. These variations are partly due to differences in the inclusion of residual values and financing costs, as well as differing time scopes. Basma and Rodriguez report an increase in costs projected for 2030 [56]. BEV costs strongly depend on the battery size. Jöhrens et al. and Göckeler et al. link battery costs to the vehicle range, estimating between 13,000 EUR/100 km and 21,450 EUR/100 km, respectively [9,55]. Noll et al. and Basma and Rodriguez present costs per kWh, ranging from 118 to 139 EUR/kWh [54,56]. Additional costs arise for BEV equipped with pantographs for ERS, though specific pantograph costs are not detailed in [9,55]. The base BEV for ERS has around EUR 16,000 higher costs for a 100 km range [55] and EUR 30,000 higher for a 200 km range [9]. The resulting costs for BEV with a 250 kWh battery and pantograph range from EUR 122,000 [55] to EUR 208,500 [14], and for a 600 kWh battery, from EUR 144,500 [55] to around EUR 250,000 [54]. In most studies, FCEV have the highest investment costs, except in [54]. Jöhrens et al. report costs of EUR 144,800, slightly higher than BEV with a large battery, while Göckeler et al. list higher FCEV costs at around EUR 254,000 [9,55]. Noll et al. provide detailed cost data for the hydrogen tank (24.75 EUR/kWh), fuel cell (250 EUR/kW), and electric motor (32.5 EUR/kW) [54].

2.3.3. Recharging and Refueling Infrastructure Costs

In the studies which distinguished charging stations and ERS, the BEV and ERS case has the lowest TCO [9,14,55]. However, Speth and Funke emphasize the high dependence of costs on the vehicle-to-infrastructure ratio for BEV and ERS [14]. Jöhrens et al. and Göckeler et al. present the highest degree of detail for the energy and infrastructure costs [9,55]. In the study by Jöhrens et al., the results are calculated for typical operational vehicle profiles, while Göckeler et al. create demand estimates for charging and refueling infrastructure with the help of market ramp-up modeling [9,55]. Both Göckeler et al. and Jöhrens et al. report on NCs with 150 kW charging power, assuming multiple vehicles per charger and calculating specific charging costs of 0.025 EUR/kWh [9] and 0.029 EUR/kWh [55]. For HPCs, Göckeler et al. specify a 1 MW charging power with costs of 0.049 EUR/kWh, while Jöhrens et al. detail a 350 kW charger with costs of 0.011 EUR/kWh [9,55]. Speth and Funke evaluate a 450 kW charger, indicating costs of 0.12 EUR/km, which translates to 0.085 EUR/kWh at 1.42 kWh/km [14]. Jöhrens et al. assume an ERS length of 3050 km,

resulting in 0.05 EUR/kWh for charging costs, while Göckeler et al. use an ERS length of 3800 km with specific costs of 0.031 EUR/kWh [9,55]. Cost estimates for ERS construction range from 1.7 to 4.1 million EUR/km in [10] and are estimated to be 2.5 million EUR/km in [57]. HRS costs range from 0.478 EUR/kg H₂ [16] to 1.485 EUR/kg H₂ [9]. While Rose presents a comprehensive TCO analysis of HRS and its components, Jöhrens et al. and Göckeler et al. assume a capex of EUR 2–3.5 million per dispenser and an OPEX at 5% of investment costs [9,15,55]. Lifetimes vary between 15 and 20 years.

2.3.4. Other Cost Components

In addition to vehicle, infrastructure, and energy costs, all studies include other cost components. These include costs for tolls, insurance, taxes, maintenance, and servicing. Jöhrens et al., Noll et al., and Basma and Rodriguez also include labor costs [54–56]. However, the grouping of these cost components differs in the studies examined, so that a direct comparison is not possible.

2.4. Synthesis of Current Research

Analyzing the design of recharging and refueling infrastructure for BEV and FCEV is essential for accurately assessing emissions and aligning vehicle energy storage needs and transport behavior. Various studies have proposed models and estimates for HPC, ERS, and HRS networks to meet electrification goals in Germany. LCA of BEV and FCEV mainly address the manufacturing and use phases, with detailed recycling data available for Li-ion batteries, but scarce data for fuel cell powertrains. The reviewed studies show inconsistencies due to varied data sources (e.g., Ecoinvent, GREET), impact assessment methods, and vehicle specifications such as the battery size and payload. Additionally, ecological assessments for recharging and refueling infrastructure differ widely, highlighting the need for more comprehensive and transparent data to enable meaningful comparisons. Recent European and German studies on TCO for trucks indicate that while ICEV have lower initial costs, BEV are projected to offer the lowest TCO by 2030 due to lower operating expenses. Infrastructure and energy costs vary significantly, with uncertainties especially high for hydrogen and difficulties in allocating infrastructure costs.

3. Technologies and Scenarios

To address these debates, our study assesses the following decarbonization technologies: BEV and FCEV. For BEV, we include two scenarios: one scenario with HPC and one with ERS. The FCEV is combined with HRS and divided into two scenarios: HRS with on-site hydrogen production and HRS with a hydrogen mix transported via trailers to the HRS. The temporal and spatial scope of our assessment is Germany from 2023 to 2050 (Table 1). The reference technology is ICEV using diesel as the energy carrier. Since the refueling infrastructure for ICEV has already been established, it is excluded from this assessment.

Table 1. Definition of Decarbonization and Reference Scenarios.

Scenario	Scenario Type	Vehicle Technology	Infrastructure	Energy Supply
A	Reference	Internal Combustion Engine Vehicle	Existing Refueling Infrastructure	Diesel
B	Decarbonization	Battery-Electric Vehicle	High-Power Charger	Grid Electricity
C	Decarbonization	Battery-Electric Vehicle	Electric Road System	Grid Electricity
D	Decarbonization	Fuel-Cell-Electric Vehicle	Hydrogen Refueling Station	Hydrogen On-Site
E	Decarbonization	Fuel-Cell-Electric Vehicle	Hydrogen Refueling Station	Hydrogen Mix

3.1. Energy Supply Design

Figure 2 presents the WTT and Well-to-Pump pathways for diesel, electricity, and hydrogen. Our scenarios depict neither complete renewable electricity nor “green” hydrogen (except for the hydrogen mix in the year 2050). Both are desirable long-term goals and will strongly support the decarbonization of the technologies in question. Nevertheless, this is currently not possible across the board in Germany. Accordingly, we consider the production paths for electricity and hydrogen as displayed in Figure 2.

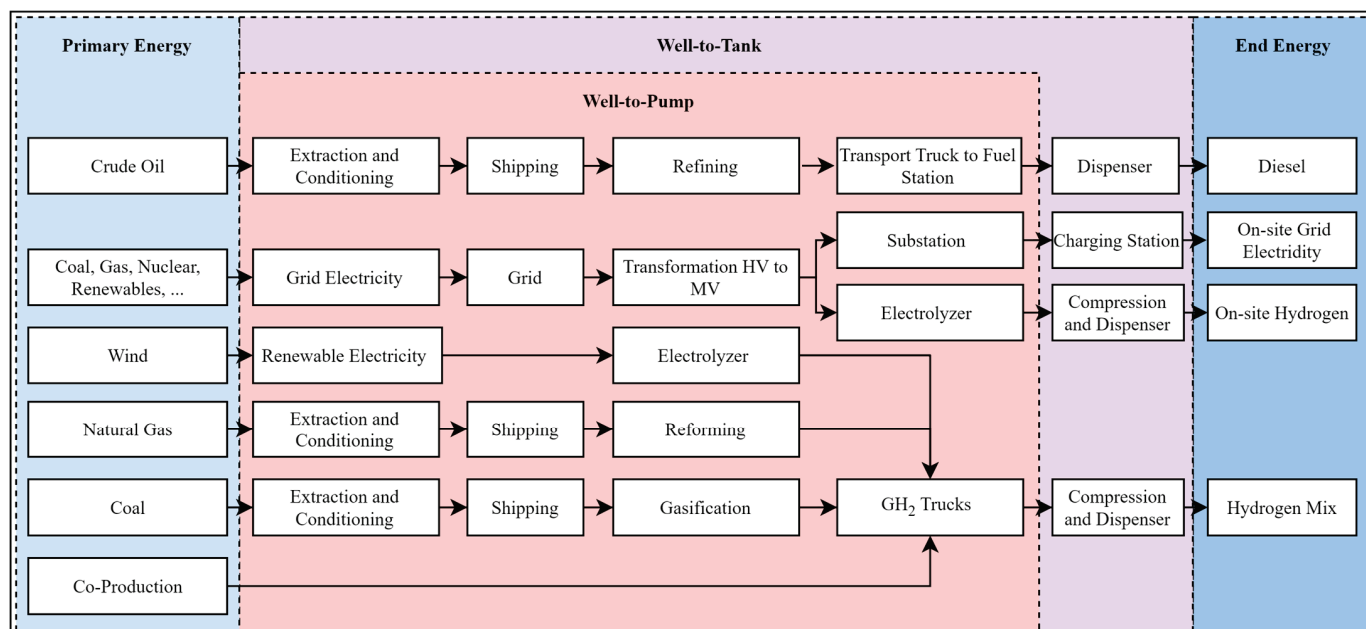


Figure 2. Well-to-Tank and Well-to-Pump Pathways. HV—High Voltage; MV—Medium Voltage; GH₂—Gaseous Hydrogen.

3.2. Vehicle Design

The long-haul, heavy-duty transport in Europe relies mainly on 40 t semi-trailer trucks [58]. In this study, we, therefore, concentrate on this type of vehicle and analyze four vehicle technologies: conventional ICEV, two BEV—one with HPC and one with ERS—and one FCEV with HRS. For all vehicles, we assume the same lifetime and yearly mileage.

We generate generic but comparable vehicle designs based on currently available technologies, as shown in Table 2. The battery size and fuel cell data were chosen based on a study by the International Energy Agency [59]. Furthermore, we considered new vehicles, which were recently presented at IAA Transportation 2024 [60]. Three vehicle types can carry the same payload of 25 metric tons (t). This can be justified because since 2019, zero-emission trucks were allowed in the EU to have 2 t extra gross weight, to compensate for the heavier powertrain, such as batteries. However, due to the large and heavy battery required for the BEV and HPC scenario, here we assume a reduced payload of 22 t. We assume an average payload utilization of 90% for all scenarios [5], incorporated in the calculation of the yearly freight mileage.

Table 2. Vehicle Parameters.

Vehicles	ICEV	BEV and HPC	BEV and ERS	FCEV and HRS
Payload (t)	25	22	25	25
Battery Size (kWh)	-	600	250	70
Consumption (L or kWh or kgH ₂ /100 km)	37.5	120	120	8

Table 2. Cont.

Vehicles	ICEV	BEV and HPC	BEV and ERS	FCEV and HRS
Lifetime (a)	10	10	10	10
Range (km)	1760	500	208	1000
Yearly Mileage (km/a)	85,927	85,927	85,927	85,927
Yearly Freight Mileage (tkm/a)	2,148,171	1,890,390	2,148,171	2,148,171
Pantograph (kg)	-	-	610	-
Fuel Cell Power (kW)	-	-	-	300
Hydrogen Tank (kgH ₂)	-	-	-	80

Following current trends, we assume LFP batteries for all vehicles, with different battery sizes for their respective application. Our BEV with ERS take advantage of catenaries and pantographs, a technology which has recently been tested in different countries [61]. The FCEV are equipped with a PEM fuel cell (300 bar) and hydrogen tanks containing 80 kg hydrogen in total as in the prototype truck Daimler GenH2 [62] and Quantron Class 8 US Truck [63].

3.3. Infrastructure Design

Tietz et al. found that for an electrification level of 20%, 2735 HPC are needed to serve the electricity demand of long-haul trucks [6]. For the BEV, we assume that 50% of the electricity used for driving is charged in depots with normal chargers (NC) and 50% is provided by HPC or ERS, as in [64]. Additionally, the number of NC is determined based on the energy required daily, assuming a charging capacity of 50 kW and a charging window of 12 h. We assign efficiency values of 97% for NC and 95% for HPC [64]. Menter et al. and Tietz et al. designed the HPC infrastructure for the complete German long-haul transport; therefore, the ERS infrastructure is designed for the total length of German freeways, which amounts to 13,200 km. Considering the wide range of the ERS share in the literature and in consultation with experts from the ELONSO research project [65], we defined the total ERS share to 50% for a 100% electrification scenario, resulting in a 10% ERS share for 20% electrification. Considering ERS in both directions for German freeways results in 2640 km ERS. For the ERS, we assign an efficiency of 98%. For the HRS infrastructure, we scale the results from [15] with the help of the total hydrogen demand of our scenario. This results in one small, one medium, four large, 16 extra-large, and 21 extra-extra-large hydrogen refueling stations with a total capacity of 0.33 million tons of hydrogen per year. For the HRS, we assume an efficiency of 95.5% [29]. The energy demand of the compressor is 3 kWh_{el}/kgH₂ [39]. To create comparable infrastructure scenarios, we assume a similar total freight mileage (Table 3) and scale the number of vehicles with their freight mileage leading to a higher vehicle number for the BEV and HPC scenario.

Table 3. Parameters for Recharging and Refueling Infrastructure (#—Number of).

Infrastructure	HPC	ERS	HRS
Total Yearly Freight Mileage (Mtkm/a)	101,814	101,814	101,814
# Vehicles	53,859	47,396	47,396
Lifetime Infrastructure (a)	12	25	20
# Normal Chargers	16,529	14,545	-
Power of Normal Charger (kW)	50	50	-
# High-Power Chargers	2735	-	-
Power of High-Power Charger (kW)	720	-	-
Electric Road System Share	-	10%	-
Electric Road System Length (km)	-	1320 km in both directions	-

Table 3. Cont.

Infrastructure	HPC	ERS	HRS
# Hydrogen Refueling Stations	-	-	43
Energy Demand Compressor at HRS (kWh/kg H ₂)	-	-	3
# Dispenser at HRS	-	-	484

4. Evaluation Methods

For the evaluation of the reference and decarbonization scenarios, we apply LCA and TCO analysis. The approaches and assumptions are explained in the following.

4.1. Life Cycle Assessment

First, we assess batteries, fuel cell systems, and hydrogen tanks in detail, followed by an analysis of 40-ton trucks equipped with different drivetrains for long-haul transportation. Subsequently, we include the infrastructure needed to support these trucks. All process modules for which we include inventories are displayed in the product system (Figure 3). We take the background data for all inventories from Ecoinvent 3.9.1 [18] using the consequential, substitution system model. We chose the consequential approach to quantify the environmental impacts of an introduction of BEV or FCEV for long-haul heavy-duty trucks. The foreground data are composed of reports and forecasts, inventories from the literature, as well as data from our research projects, and are described in detail in the following. We include the EoL processes within the production processes of the respective parts, except for the hydrogen tank and the high-pressure storage of the HRS. For both, no sufficient EoL information was available.

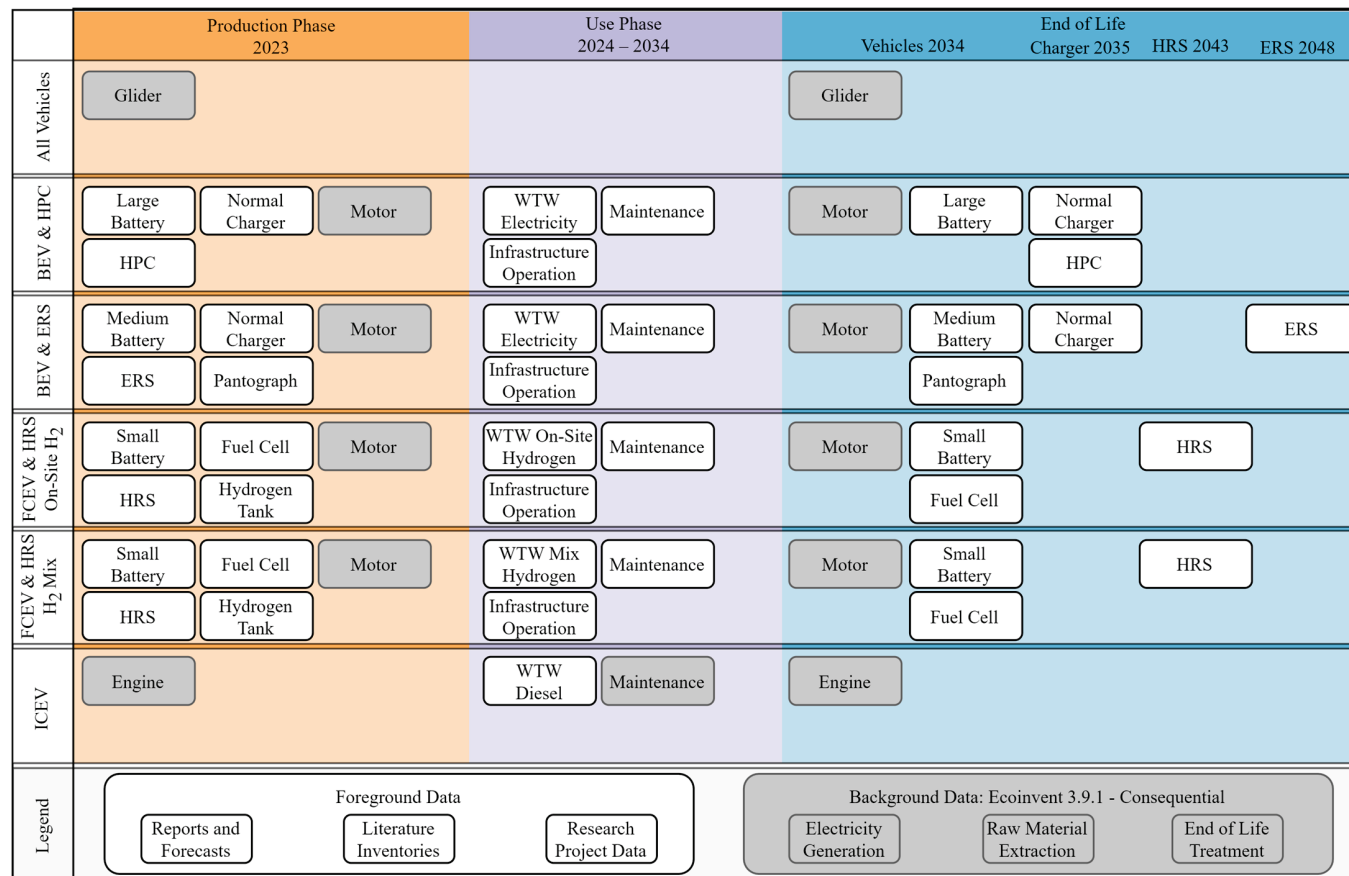


Figure 3. Scope of the Life Cycle Assessment—Product System.

4.1.1. Electricity and Hydrogen

For the assessment of grid electricity emissions, we modeled the upstream emissions of electricity (Figure 4) and hydrogen production (Figure 5) for the years 2023, 2030, and 2050 and linearized the emission factors for the years in between. All electricity demands for WTW, production, and EoL processes are served by the medium-voltage grid. Except for the battery production, which takes place in China, all production and EoL processes are in Germany. For the on-site hydrogen production with electrolyzers at the HRS, we use the German grid mix for the respective year. Within the hydrogen mix, for the hydrogen share produced by electrolysis, we exclusively use wind electricity, and we include transportation via trailers over 400 km (Figure 2).

Xu et al. describe that electrolysis from electricity can be performed with different approaches [66]. High-temperature electrolysis is commonly combined with nuclear electricity and the exhaust heat of nuclear electricity production. It can also be performed with grid electricity and heat from natural gas. However, according to Xu et al., the more promising approach for electrolysis with renewable electricity is using PEM electrolyzers [66]. The inventories are based on [67] with an electrolysis efficiency of 60% ($55 \text{ kWh}_{\text{el}}/\text{kg H}_2$). For hydrogen production as a by-product, we assume that all emissions are allocated to the main product.

In this study, the main investigation period for the WTW analysis is for the years 2024 to 2034. Additionally, we perform a sensitivity analysis in which we present the WTW analysis for the years 2035 to 2045. Due to the scope of this study, we omit an assessment of other electricity or hydrogen pathways. Their development in the coming years may slow down or accelerate depending on various influencing factors.

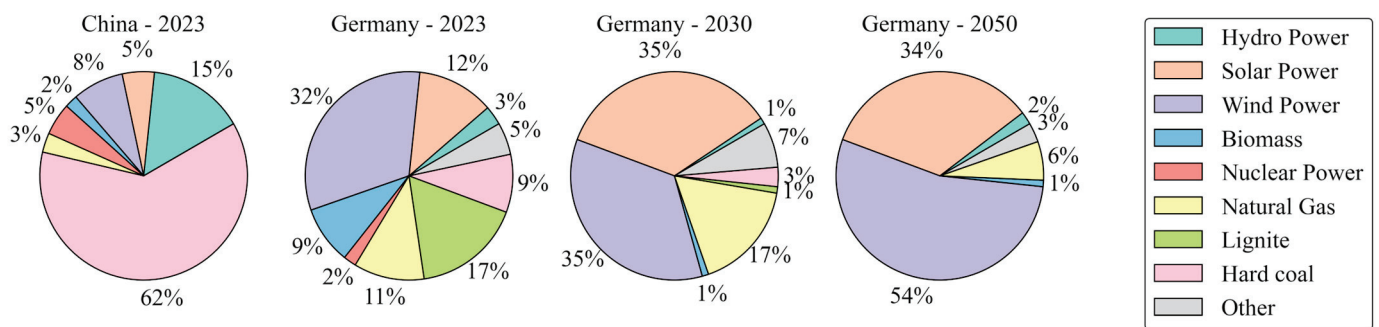


Figure 4. Grid Mix adapted from [39] based on [68,69].

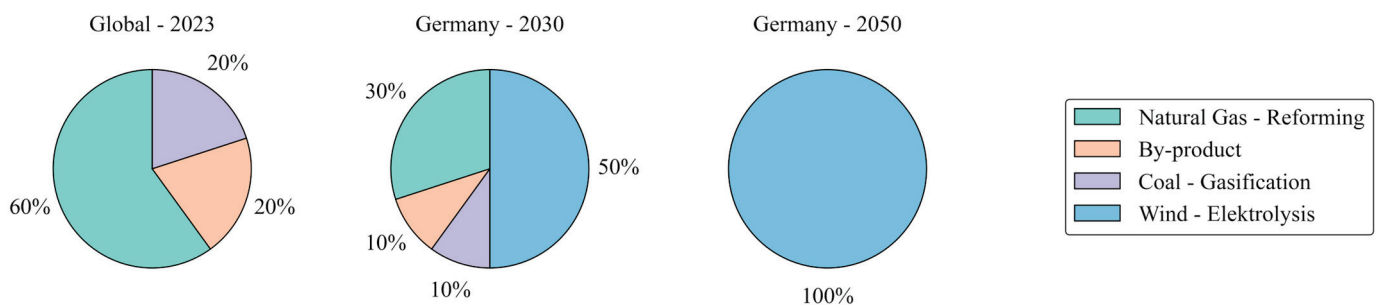


Figure 5. Hydrogen Mix adapted from [39] based on [70].

4.1.2. Batteries, Fuel Cells, and Hydrogen Tanks

We analyze LFP battery production and recycling, with an energy density of 159 Wh/kg at the cell level and 116 Wh/kg at the pack level. We assume battery production in China [39]. Therefore, we modified the Ecoinvent processes by including China's

grid mix for 2023 and transportation to Germany. For the EoL, we analyze collection, dismantling, and hydrometallurgical and pyrometallurgical recycling based on EverBatt data [71]. The fuel cell production and EoL is based on the inventories from [26]. The hydrogen tank production follows the inventories from [29]. The EoL of hydrogen tanks is excluded. Hydrogen tanks are reported to have lifetimes up to 30 years [72]. However, as explained in [39], insufficient data on the second life or recycling was available and most studies suggest only one vehicle life for the hydrogen tank use phase. LFP batteries offer up to 10,000 cycles and fuel cells can run for 25,000, as presented at the IAA Transportation 2022 [73]; therefore, we assume no exchanges during the use phase and the same lifetime as for the vehicles (10 years). Hydrogen tank production based on [26] and an assessment of NMC and NCA cell chemistries is provided in [39].

4.1.3. Vehicles

For the FCEV with HRS, we analyze different hydrogen production pathways (Section 3), and the electrolyzer is included in the WTW analysis. Therefore, the vehicle and infrastructure are the same for both cases. The pantograph inventory is based on [11]. For the vehicle body (glider) and maintenance, the original Ecoinvent processes for trucks > 32 t were modified for electric vehicles and all parts necessary for a conventional vehicle were excluded. The maintenance depends on the mileage in km. The motor is based on the electric motor provided in Ecoinvent [18].

4.1.4. Recharging and Refueling Infrastructures

For the NC, we assumed the same material composition as presented in [44]. No inventories for HPC were available; therefore, we scaled the inventories for a 350 kW charger from [46] with the help of experts from the HoLa research project [74]. All installed copper is scaled with the power of the respective chargers (scale factor copper = 2.06), the installation, user, and power unit are scaled with the dimensions of the respective parts (scale factor user unit = 1.22; scale factor power unit = 3.39), and the control unit remains equal. In contrast to [46], we include a substation for the connection to the grid.

The ERS consists of overhead cables and passive protection devices for the whole length, masts every 50 m, and substations every 2 km [10,75,76]. The inventories for cables, masts and substations were taken from [11] and the inventories for the passive protection device and installation were taken from [12]. The contact wire loss of approx. 20% over the entire service life is considered in the end-of-life process [75]. Only 80% of the contact wire produced is recycled. We do not include the loss of contact wire in the use phase. The EoL of the passive protection device is excluded as its lifetime is 60 years and no information on the EoL is available. To scale the device to the ERS lifetime, we consider 25/60 of the production emissions of the passive protection device.

We use the inventory from [53] for the HRS which includes a compressor, electrolyzer, and low- and high-pressure storage. However, Burkhardt et al.'s data on high-pressure storage lack details on the specific carbon fiber composition. Therefore, we added the respective high-pressure tanks for each station size. In our assessment, the electrolyzer is included in the hydrogen production pathways and no part of the HRS (Section 3). The installation of HRS is not included and no information was available.

The infrastructure operation for the HPC, NC, and ERS consists of the losses of the operation, described by the efficiency of the infrastructure. For the HRS, the infrastructure operation includes the electricity demand of the compressor. Electricity demands for the electrolyzer are included in the WTW of hydrogen and no part of the HRS (Section 3).

4.2. Total Costs of Ownership Analysis

Methodologically, the TCO analysis is based on the framework outlined in [55,77]. This approach incorporates a comprehensive set of cost components, including vehicle investment costs, labor costs, tolls, energy expenses, infrastructure costs, and both fixed and variable additional costs. Additionally, we divide the TCO into capital and operational costs (CAPEX and OPEX). The TCO for the scenarios is calculated by multiplying the vehicles' TCO with the number of vehicles needed in the respective scenario:

$$TCO_S = TCO_V * n_S \quad (1)$$

with TCO—Total Cost of Ownership (EUR); S—Scenario; V—Vehicle; and n_S —Number of Vehicles in the Scenario (Pcs.). The vehicles' TCO is the sum of the CAPEX and OPEX:

$$TCO_V = CAPEX_V + OPEX_V \quad (2)$$

with CAPEX—Capital Costs (EUR)—and OPEX—Operational Costs (EUR). The CAPEX consists of the vehicle price, the financing costs, and the vehicle residual value:

$$CAPEX = V_{net} + F - R \quad (3)$$

with V_{Net} —Net Vehicle Price; F—Financing costs; and R—residual value. The vehicle prices are depicted in Table 4. The prices for ICEV and BEV are based on [77] for the year 2025 with 107 EUR/kWh battery costs. For FCEV, Jöhrens et al. present vehicle prices for the year 2030 [55]. To align with the year 2025, we use the correspondingly higher prices for the FCEV. The determination of financing costs and residual values follows the procedure in [77]. The OPEX consists of additional fix and variable costs, as well as labor, energy, and toll costs. For the BEV and FCEV, we also include infrastructure costs:

$$OPEX = ((AC_{variabel} + LC + TC) * Mileage_V + AC_{fix}) * Lifetime_V + (EC + IC) * ED_{Total} \quad (4)$$

with AC—Additional Costs (fix: EUR/a; variable: EUR/km); LC—Labor Costs (EUR/km); TC—Toll Costs (EUR/km); EC—Energy Cost (EUR/L or kWh or kg H₂); IC—Infrastructure Costs (EUR/kWh or kg H₂; for ICEV = 0); and ED—Energy Demand (L or kWh or kg H₂). For the additional fix and variable, labor, energy, and toll costs, we adopt the costs from [55]. Additional fixed and variable costs include maintenance, insurance, vehicle taxes, vehicle inspection, and the cost of urea (AdBlue) and lubricants. The energy costs include the production of the energy carrier, energy taxes, and CO₂ costs. The electricity prices for direct use and electrolysis are for the draw-off at a medium voltage level. The price for the hydrogen mix is composed of 50% of the hydrogen price for electrolysis in Germany (9.45 EUR/kg H₂) and 50% of the import price (4.57 EUR/kg H₂). The infrastructure costs for the NC and the ERS are based on [55]. The costs for HPC are based on [9] and the costs for hydrogen result from the design of the HRS according to [15]. The infrastructure costs include the construction and maintenance of the infrastructure (HPC, NC, HRS, and ERS).

Table 4. Costs Parameter 2023–2034 based on [9,15,55,77].

Vehicle Infrastructure	ICEV	BEV HPC/NC	BEV ERS/NC	FCEV HRS On-Site H ₂	FCEV HRS H ₂ Mix
Net Vehicle Price (EUR)	103,000	191,100	153,650	200,000	200,000
Additional Fixed Costs (EUR/a)	18,350	18,320	18,410	18,320	18,320
Additional Variable Costs (EUR/km)	0.0406	0.0390	0.0395	0.0390	0.0390
Labor Costs (EUR/km)	0.23	0.23	0.23	0.23	0.23

Table 4. Cont.

Vehicle Infrastructure	ICEV	BEV HPC/NC	BEV ERS/NC	FCEV HRS On-Site H ₂	FCEV HRS H ₂ Mix
Toll Costs (EUR/km)	0.187	0.176	0.176	0.176	0.176
Energy Costs (EUR/L, kWh, or kg H ₂)	1.36	0.166	0.166	9.45	7.01
Infrastructure Costs (EUR/kWh or kg H ₂)	-	0.049/0.025	0.05/0.025	0.48	0.48

5. Results

The results consist of two parts. First, we present detailed findings for the GWP of the energy carriers, batteries, and the fuel cell system, followed by the vehicle GWP results based on the assumptions in Table 2, the GWP for the infrastructure, and both combined based on Table 3 and Figure 3. Next, we present the results for the TCO of vehicles and the overall scenario based on Table 4 and Figure 3. The analysis covers the periods 2024 to 2034 and 2035 to 2045. It should be noted that for the period 2035 to 2045, only the WTT pathways have been adapted.

5.1. Global Warming Potential

5.1.1. Electricity and Hydrogen

The resulting grid and hydrogen emissions are depicted in Table 5. The on-site hydrogen produced by grid electricity exhibits significantly larger emissions than the hydrogen mix, although no transportation is required and the hydrogen mix in the years 2023 and 2030 includes non-renewable hydrogen production. The results for the individual hydrogen pathways are included in the Supplementary Materials (Table S8). The GWP ranges from 1.709 kg CO₂/kg H₂ for wind electrolysis to 26.949 kg CO₂/kg H₂ for coal gasification.

Table 5. GWP of Medium-Voltage Electricity and Hydrogen Production, excluding Charger Efficiencies and Compression at Hydrogen Refueling Stations.

Process	Medium-Voltage Electricity (kg CO ₂ e/kWh)				On-Site Hydrogen (kg CO ₂ e/kg H ₂)			Hydrogen Mix (kg CO ₂ e/kg H ₂)		
Year	2023	2023	2030	2050	2023	2030	2050	2023	2030	2050
Region	CN	DE	DE	DE	DE	DE	DE	DE	DE	DE
GWP	0.733	0.487	0.251	0.094	26.830	13.813	5.184	13.097	7.250	1.787

5.1.2. Battery, Fuel Cell, and Hydrogen Tank

Figure 6a displays the GWP per kWh for the LFP battery. Aluminum (used as casing material) shows a significant impact on GWP, followed by natural gas for heating lithium iron phosphate and copper. Pyrometallurgical recycling shows more benefits in total for recycling than hydrometallurgical recycling. For both, the transport of the battery pack to the recycling facilities is the greatest contributor to recycling GWP. Hydrometallurgical recycling shows benefits for the recovery of lithium carbonate, aluminum, copper, and sulfuric acid. However, the demand for hydrogen peroxide and sodium hydroxide for hydrometallurgical recycling increases the GWP. Pyrometallurgical recycling allows no recovery of lithium carbonate or sulfuric acid, but shows benefits for the recovery of non-Fe-Co metals.

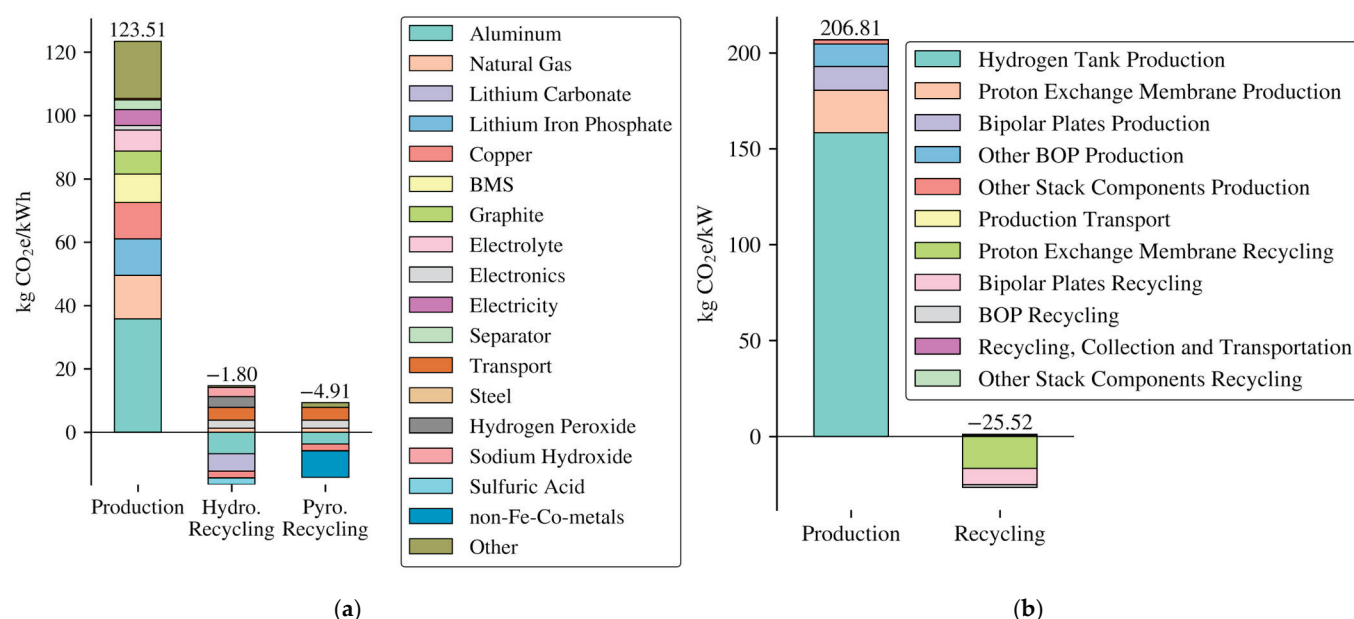


Figure 6. Global Warming Potential Production and End of Life of (a) Batteries, (b) Fuel Cell System. Hydro.—Hydrometallurgical; Pyro.—Pyrometallurgical; BOP—Balance of Plant.

Figure 6b displays the GWP per kW for a fuel cell stack and hydrogen tank. Furthermore, the tank is designed for a 300 kW fuel cell system and the auxiliaries are designed for an 80 kW fuel cell system; therefore, they are normalized by dividing them by, respectively, 300 and 80 for representation. The recycling process encompasses all fuel cell components. In production, the highest contributor to GWP is the hydrogen tank, followed by PEM production, bipolar plates, and other auxiliary components. Recycling the PEM with the catalyst reduces the GWP, followed by recycling the bipolar plates. Platinum, as a rare metal, exhibits exceptionally high GWP in the production phase, which can be mitigated through recycling. Recycling the auxiliaries lowers the GWP, while collection and transportation, along with recycling other stack components, increase the total GWP.

5.1.3. Vehicles—Production, Use Phase, and End of Life

Figure 7 displays the production and EoL GHG emissions for the vehicle components. The ICEV and BEV for ERS have lower production and EoL emissions compared to the FCEV and BEV designed for HPC. The glider for ICEV includes the engine; therefore, it shows slightly higher emission levels compared to the glider of the electric trucks. For BEV and HPC, the large battery dominates the production emissions. For FCEV, the fuel cell and hydrogen tank contribute to production emissions, and for BEV and ERS, the pantograph causes additional emissions.

Table 6 displays the vehicles' GWP per ton-kilometer (tkm) without recharging or refueling the infrastructure for the periods 2024 to 2034 and 2035 to 2045. For the period 2024 to 2034, the BEV designed for ERS exhibit the lowest GWP per tkm, while the FCEV with on-site hydrogen show by far the highest emissions per tkm. However, excluding the transport performance, the BEV and HPC vehicles exhibit the lowest lifetime emissions, closely followed by the BEV and ERS (Figure 8a,b).

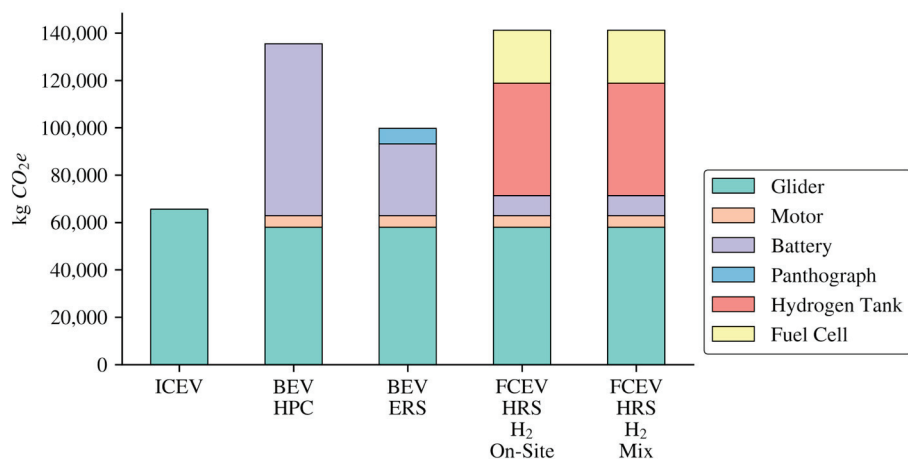


Figure 7. Global Warming Potential Production and End-of-Life Vehicles.

Table 6. Vehicle Global Warming Potential per tkm.

Vehicle	GWP (kg CO ₂ e/tkm)	
	2024–2034	2035–2045
ICEV	0.060	0.060
BEV and HPC	0.027	0.020
BEV and ERS	0.022	0.016
FCEV and On-Site H ₂	0.066	0.044
FCEV and H ₂ Mix	0.038	0.026

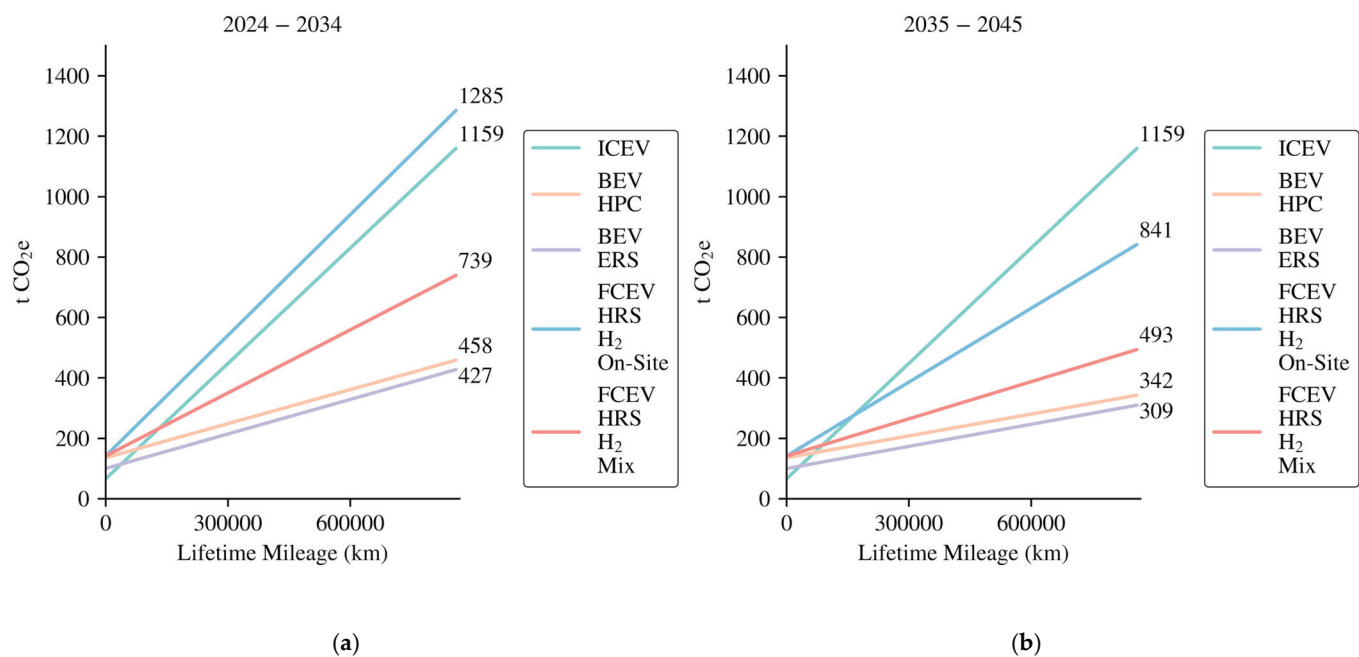


Figure 8. Global Warming Potential Vehicles over Lifetime Mileage: (a) Years 2023–2034, (b) Years 2035–2046.

The FCEV with on-site hydrogen has the highest WTW GWP, followed by the ICEV. For the period 2035 to 2045, electrified vehicles' WTW GWP decreases substantially, aligning with reductions in grid and hydrogen emissions (Table 5). As a result, all vehicles for the decarbonization scenarios have a lower GWP compared to the ICEV.

5.1.4. Recharging and Refueling Infrastructures

Figure 9a,b depict the GWP for the production, EoL, and operation of the infrastructure for the periods 2024 to 2034 and 2035 to 2045. All infrastructures are scaled with their respective lifetime to one year of operation. The HRS exhibits by far the highest production and operation emissions. The production emissions are dominated by the production of the compressor and storage units, while operation emissions stem from the energy demand of the compressor. The ERS shows the second-highest production emissions, primarily caused due to passive protection and masts. This is followed by the NC, with 5.6 t CO₂e per charger. Although the HPC has a higher GWP per item (16.7 t CO₂e per charger, including the substation) compared to the NC, its total contribution to infrastructure emissions is lower, caused by the high number of NC needed to charge the vehicles in the depot. For all infrastructures, the operation emissions decrease substantially for the period 2035 to 2045, aligning with reductions in grid emissions (Table 5). As the HPC has a lower efficiency compared to the ERS, the savings for the infrastructure operation are higher. This, combined with lower production emissions, results in lower yearly emissions for the HPC infrastructure in the period 2035 to 2045 compared to the ERS.

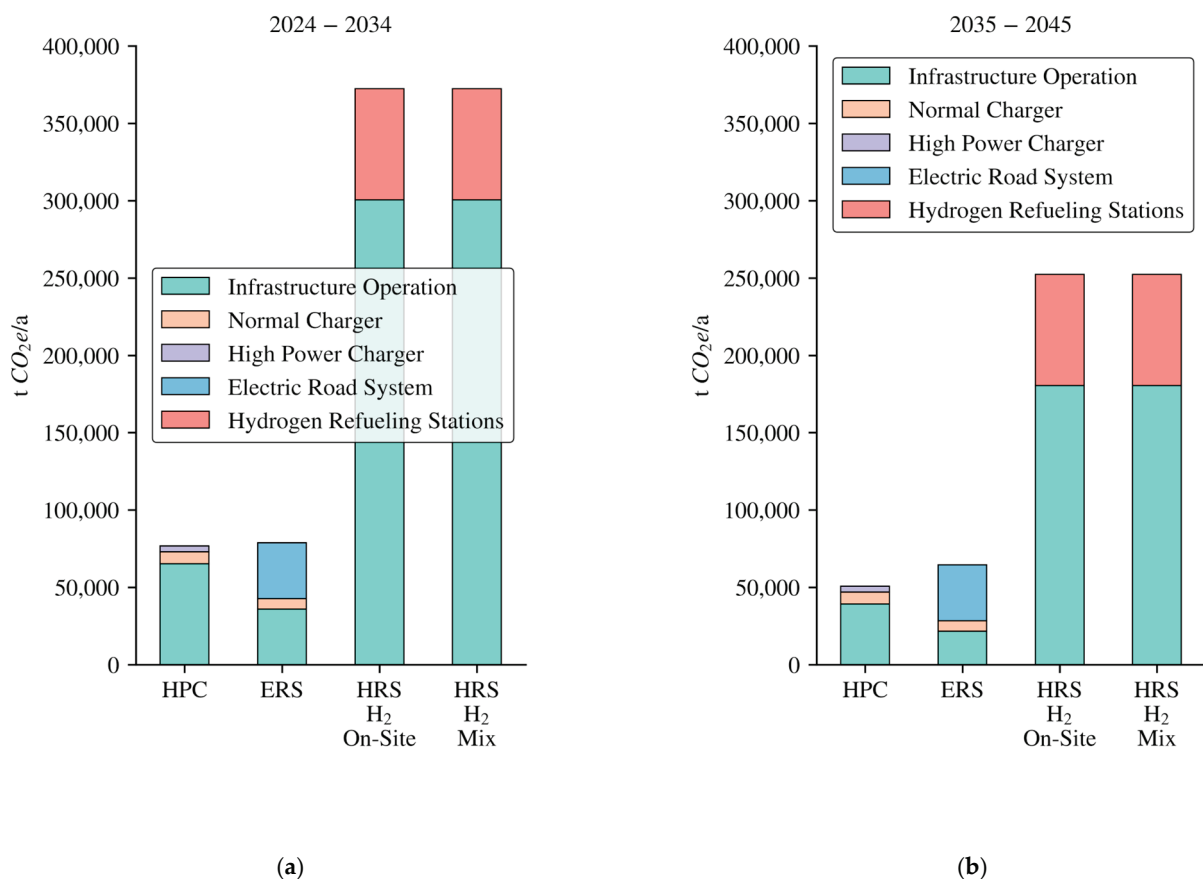


Figure 9. Global Warming Potential Infrastructure: (a) Years 2023–2034, (b) Years 2035–2046.

5.1.5. Reference and Decarbonization Scenarios

Figure 10a,b display the GWP for the 20% fleet scenario including vehicles and infrastructure, as described in Table 3. Due to the higher vehicle demand for the BEV and HPC case, the BEV and ERS case has the lowest GWP. The FCEV and HRS with the on-site hydrogen scenario exhibit the highest GWP. For the period 2035 to 2045, all decarbonization scenarios have lower emissions than the reference scenario. For both assessed time periods, the WTW is the highest contributor to life cycle emissions for all scenarios.

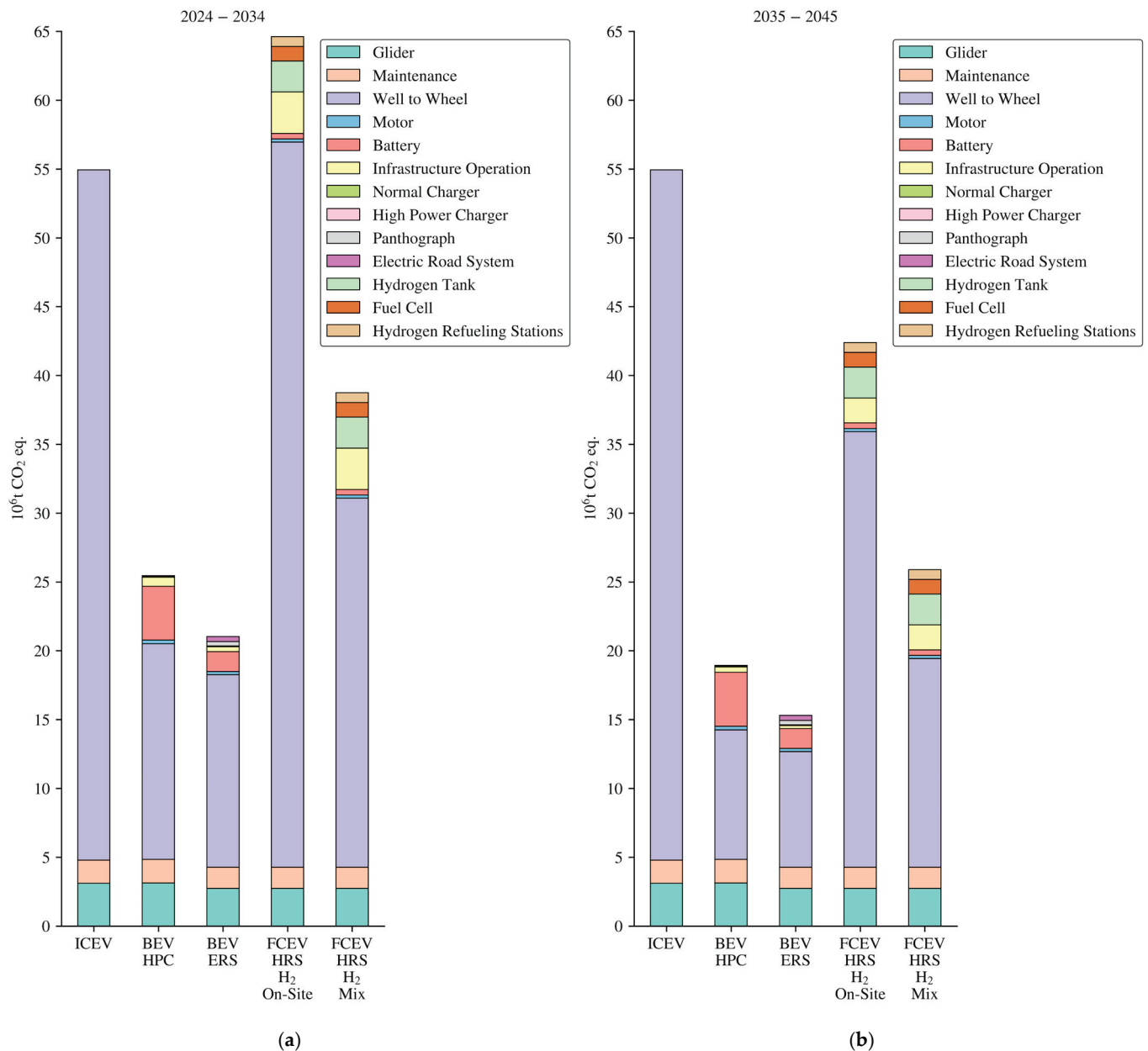


Figure 10. Global Warming Potential of 20% Fleet Scenario: (a) Years 2023–2034, (b) Years 2035–2046.

In comparison to the WTW, the share of infrastructure emissions in the scenario results are small. However, for the HRS, the contribution of the infrastructure (production and operation) is comparable to the fuel cell and glider production. The HPC and ERS infrastructure have a minor impact.

5.2. Total Costs Analysis

Figure 11a presents the TCO of the vehicles per km and Figure 11b displays the TCO of the 20% fleet scenarios in billions of EUR. Regarding the costs of the individual vehicles, the costs for the BEV and HPC are nearly identical to those of the BEV and ERS. However, the costs for FCEV and HRS with on-site hydrogen or a hydrogen mix differ substantially due to the varying costs of hydrogen. For all vehicles, the investment costs are below 20% of the TCO. For ICEV and FCEV, the energy costs dominate; for BEV investment, energy, labor, toll, and additional fix costs have similarly high shares in TCO. When considering the entire scenario, the costs for BEV, HPC, BEV, and ERS are significantly more divergent.

This disparity arises from the higher number of vehicles needed for the BEV and HPC case to achieve the same transport performance.

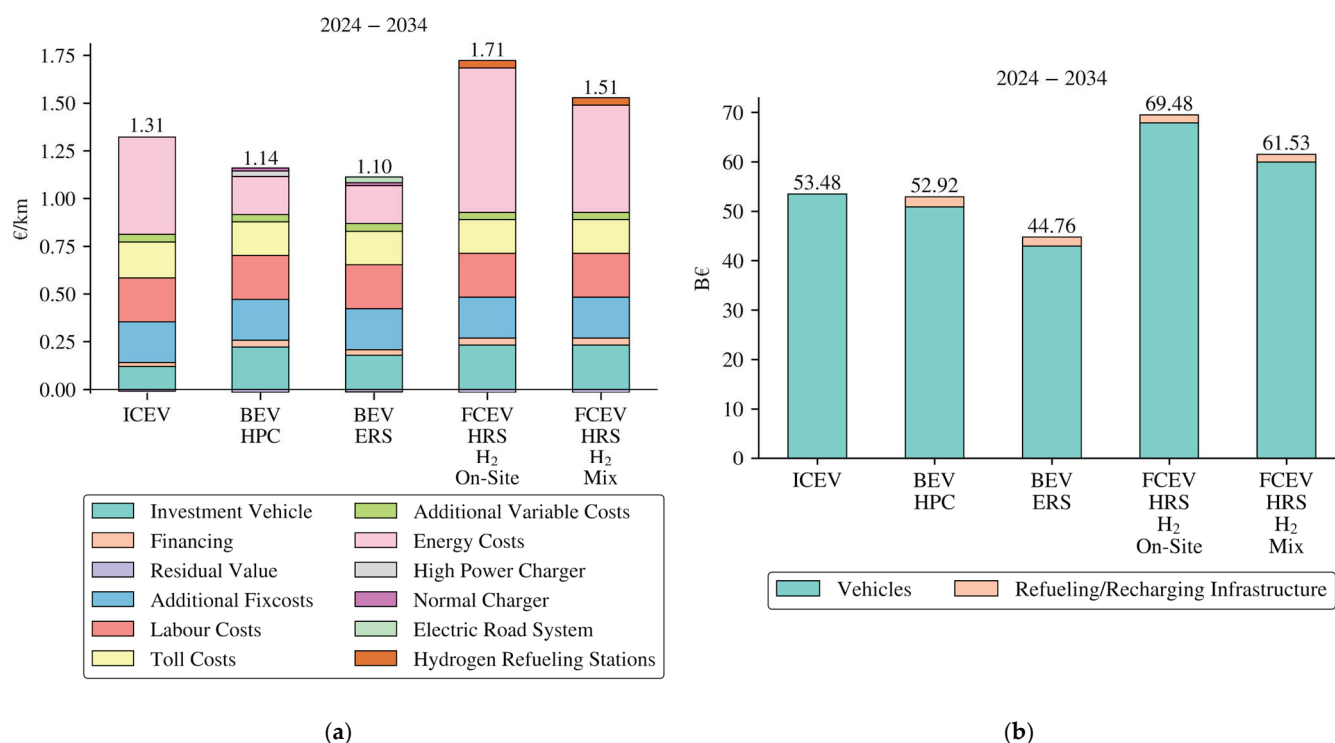


Figure 11. Total Cost of Ownership (a) per Vehicle in EUR per km, (b) 20% Fleet Scenario in billion EUR.

Based on our analysis, we found comparable overall costs for the infrastructure of the 20% fleet scenarios: For the BEV and HPC scenario, the costs are divided into EUR 1.36 billion for HPC and EUR 0.69 billion for NC. For the BEV and ERS scenario, the costs are EUR 1.22 billion for ERS and EUR 0.61 billion for NC. The HRS costs are EUR 1.60 billion for the FCEV and HRS scenario.

6. Discussion and Limitations

In this study, we provide a comparative life cycle assessment and total cost of ownership analysis of heavy-duty, long-haul trucks with BEV and FCEV drivetrains and their recharging or refueling infrastructure. Our in-depth analysis shows that fuel cell vehicles with on-site hydrogen generation have the highest life cycle emissions (65 Mt CO₂e), followed by internal combustion engine vehicles (55 Mt CO₂e). Battery-electric vehicles using electric road systems achieve the lowest emissions (21 Mt CO₂e) and the lowest ownership costs (EUR 45 billion). In contrast, fuel cell vehicles with on-site hydrogen have the highest costs (EUR 69 billion). Operational costs dominate total ownership expenses, making them a compelling target for subsidy programs. The choice between battery and fuel cell technologies depends on the ratio of vehicles to infrastructure, transport performance, and range. Fuel cell trucks are better suited for remote areas due to their longer range, while integrating electric road systems with high-power charging could offer synergies and mitigate limitations.

As in any future forecast, our results are based on simplifications and assumptions, which we want to critically discuss in the following. Where applicable, we compare our results with other relevant studies.

6.1. Technology Choice and Scenario Definition

We analyzed four different decarbonization scenarios, which differ in vehicle and infrastructure design and the provision of the respective energy carriers (Section 3). Our study assumes that 20% of the German fleet will be converted to one of these technology options. The vehicles and infrastructure have been designed to ensure that the current conditions for freight logistics are not significantly impacted. Based on our literature review and current market developments, we identified LFP Li-ion batteries and PEM fuel cells with hydrogen tanks for gaseous hydrogen as the most promising. However, there is still significant development potential in both battery and fuel cell technologies. Both performance and cost parameters could change drastically with solid-state batteries for BEV and liquid or cryo-cooled hydrogen or hydrogen combustion for FCEV, just to give some examples.

In our analysis, the infrastructure was designed to match the number of vehicles and their energy requirements for one, and only one, particular technology. This ignores the very likely simultaneous occurrence of different technologies. In addition, the use of the infrastructure by regional and transit freight traffic has not been considered, which could in turn reduce the allocated emissions and costs. Those changes would also influence the infrastructure design and should be regularly reviewed and, if necessary, integrated into the corresponding analyses.

All technologies assessed in this study are at least at the prototype stage, with technical feasibility and scalability demonstrated through multiple studies (e.g., [10,59,78]). Current technologies pursued by the truck industry, such as low-temperature PEM fuel cells and LFP batteries, are considered the most promising for long-haul applications and align with the global focus on decarbonization. Furthermore, the solutions analyzed in this paper are being implemented in various pilot and demonstration projects worldwide, reinforcing their relevance for real-world applications. While dimensions such as safety, reliability, and social acceptance are critical, they were outside the primary scope of this study. These aspects warrant further research to ensure the sustainable deployment of these technologies.

6.2. Life Cycle Assessment

We separated the discussion of the life cycle assessment into five parts, starting with the WTT analysis, followed by the discussion on the battery, fuel cell, and hydrogen tank. Thereafter, we discuss the LCA of vehicles, then the LCA of the infrastructure, and close this subsection with the overall scenario LCA.

6.2.1. Electricity and Hydrogen

For the WTT analysis of electricity, we used today's (2023) grid mix in Germany and China. The forecasts for 2030 and 2050 assume an ongoing and successful conversion to renewables with a strong emphasis on wind power. To what extent these forecasts materialize depends on political and economic developments that cannot be discussed here. Not only the overall share of renewables, but also the distribution of wind, solar, and other sources is an important factor. Therefore, the methods can be transferred to other regions, but not the specific results.

Additionally, it would be conceivable that both depots and public charging infrastructure are not (only) supplied by the electricity mix, but that renewable energies are expanded on-site for direct use. This could reduce WTT emissions accordingly.

Hydrogen generated through electricity derived from fossil energy carriers without carbon capture causes high GHG emissions. We assumed producing hydrogen with PEM electrolysis with the efficiency of 60% [67]. Despite the need for transport with

hydrogen trailers, our assessment shows that a hydrogen mix including hydrogen from fossil energy carriers can have lower emissions than hydrogen produced by electrolysis on-site (Table 5). Even for the year 2050, hydrogen from wind energy with additional trailer transport has lower emissions than hydrogen from on-site electrolysis due to the higher emissions of photovoltaic electricity production. Integrating fluctuating renewable energy sources like wind and solar with hydrogen production via electrolysis can enhance the efficiency of energy utilization [79]. Key challenges include determining the optimal electrolyzer operation hours and aligning hydrogen production with periods of a renewable energy surplus. Burkhard et al. show that by increasing the electrolyzer full-load hours, the resulting GHG emissions per kg hydrogen decrease [53]. In Germany, the available excess energy is unlikely to meet the future hydrogen demand, emphasizing the need for a diversified approach to hydrogen production [80]. While coupling renewable energy with hydrogen production holds promise, further research is required to address these challenges and optimize integration. One recent study reviews the current challenges in the decarbonization of the energy sector in detail [81]. It should be noted that we used an average transport of 400 km per kg of hydrogen. Depending on the distance of the HRS from hydrogen production and the different renewable electricity sources for on-site electrolysis, different results may occur. A third option, which is commonly discussed, is transportation via pipes. The construction of the German hydrogen core network is scheduled for completion in 2032; however, connections are primarily planned for industrial centers, power plants, storage facilities, generation plants, and import corridors [82]. Whether and how HRS can be connected are still to be decided at this stage. Emphasizing these uncertainties, the European Court of Auditors recently addressed the production and import plans by the European Union in [83]. They doubted meeting the targets for 2030 and have called for a reality check.

6.2.2. Battery, Fuel Cell, and Hydrogen Tank

The LFP battery has a considerable GWP during the production phase. However, other cell chemistries (NMC or NCA) have higher production emissions, mainly driven by cobalt sulfate and nickel sulfate production [39]. It is important to note that, unlike other chemistries where recycling can lead to a significant GWP reduction [39], recycling only marginally decreased the overall GWP for LFP batteries. The results for the recycling of LFP batteries show higher benefits for pyrometallurgical recycling than for hydrometallurgical recycling. However, NMC or NCA batteries typically reveal higher benefits for hydrometallurgical recycling [39]. This is caused by the recovery of lithium carbonate and the higher recovery of nickel compared to pyrometallurgical recycling.

Our results for the production phase of fuel cells and hydrogen tanks are in good agreement with [26,29]. However, our study utilizes an updated Ecoinvent database and incorporates more recent electricity mixes compared to the data in [26]. Weiszflog and Abbas assumed the production in Sweden, which has a greener electricity mix and, therefore, lower GWP. The PEM fuel cells in our decarbonization scenarios reach around 12,300 operating hours. Regarding the most recent developments, up to 25,000 operating hours were presented by Daimler and Volvo at the IAA Transportation 2022 [73]. Nonetheless, other studies show much lower operating hours (between 4100–6400 h) for fuel cells used in passenger cars or light-duty vehicles with significantly lower mileage [84]. One recent study explored the “fuel cell health” estimation and durability predictions in detail [85]. We assessed a tank for gaseous hydrogen. Weiszflog and Abbas additionally analyzed tanks for liquid and cryo-compressed hydrogen, which have lower GHG emissions. They also assessed the EoL of hydrogen tanks and revealed large benefits for pyrolysis and chemical and fluidized bed recycling. However, mechanical recycling, which downcycles

carbon fiber, shows only small benefits. In contrast to [39], the share of the hydrogen tank regarding the GWP for the complete fuel cell system is higher. In [39], the fuel cell and hydrogen tank under study have a power of 80 kW and a capacity of 5 of kg hydrogen. In terms of the stored mass of hydrogen, however, the results are very similar (593 kg CO₂e/kg of hydrogen in our analysis and 622 kg CO₂e/kg of hydrogen in [39]).

Concerning the EoL of the fuel cell system, recycling technology exhibits significant potential, particularly for the catalyst. The recycling processes for fuel cell auxiliaries and stack components, excluding the catalyst, were simplified due to insufficient data, omitting electricity, heat, and transportation emissions, which would elevate the overall GWP. Additionally, the analyzed fuel cell catalyst recycling approach does not represent industrial-scale recycling, potentially impacting the results, as some steps could be optimized more efficiently at an industrial scale.

6.2.3. Vehicles

Our results for the GWP of the vehicles per tkm are lower compared to [31], in their case, with the European electricity mix, and to [37] (Table 6); however, this can be easily explained. Sacchi et al. and Tahir et al. include road construction and road wear emissions [31,37]. Additionally, Sacchi et al. consider a lower transport performance with a payload factor of 36% [31]. Regarding the absolute emissions (Figure 8a), our results deviate from the results in [33,36]. Lyu et al. consider smaller vehicles with only around 20% of the lifetime mileage specified in our study [33]. Therefore, their ICEV and BEV have lower lifetime emissions. Mandouri et al. have higher resulting lifetime emissions than our study; however, this is attributable to the higher lifetime mileage and lifetime [36]. The results by Booto et al. also show a lower GWP for the BEV [30]. The authors conducted a study in Norway with the respective electricity and hydrogen production; therefore, the WTW emissions are not comparable. Additionally, the product system of FCEV in [30] does not include the small but necessary battery.

We assumed the same consumption for the BEV for ERS and HPC, given the reduced payload of the HPC vehicle in combination with a payload factor of 90%. Trucks operating in short-haul transport often reveal lower payload factors and this could lead to lower consumption values for the ERS vehicle in comparison to the HPC vehicle with the larger battery. Furthermore, the overall efficiency of FCEV is inferior to BEV. Consequently, FCEV would only demonstrate a lower GWP for WTW compared to their BEV counterparts in regions where the grid mix is more carbon-intensive than the hydrogen mix.

6.2.4. Recharging and Refueling Infrastructure

Only a few studies present the absolute emissions per charger [40,41,46]; these range between 4.6 and 8.1 t CO₂e for a 50 or 60 kW charger (Table S4). The NC in our assessment exhibits a comparable result (5.6 t CO₂e per charger). The HPC in Zhao et al. shows only 8.2 t CO₂e per charger, which is only half of the results for the HPC presented in our study with 16.7 t CO₂e per charger [46]. However, the HPC assessed here has a higher charging power (720 kW) and we included substations for the grid connection. Nonetheless, inventory data for HPC are scarce, which underlines the need for further research in this area. However, moderate increases or decreases in the production and EoL emissions of the HPC would have only a minor impact on the scenario results for BEV and HPC, as this scenario is primarily dominated by the WTW, battery, and vehicle production emissions. In line with the vehicle use phase emissions being the significant contributor, the operation emissions of the chargers also play a larger role in the overall results. For chargers, these emissions arise from electricity losses during charging and are determined by the efficiency of the chargers. The efficiency of conductive charging varies between 85% in [43] to 98%

in [46]. Given this wide range, further research and clarification are necessary to refine efficiency estimates for broader assessments. For the evaluation of specific charging stations, direct measurements or charger-specific data would be preferable.

The results for the ERS are comparable to those presented in [12]. Ramshankar et al. exclude the passive protection device from their study and have, therefore, lower infrastructure emissions [11]. Hanesch et al. note that the amount of material used for the passive protection device remains a topic of debate and may be oversized. The ERS exhibits a substantially higher production GWP compared to the HPC infrastructure, making it more sensitive to the number of vehicles using the infrastructure, as described in [11]. Operating a few trucks with HPC may be easier than managing the same number with ERS; the potential for long-distance transport primarily arises from a comprehensive expansion of the infrastructure.

The main drivers for the GWP of the HRS are the operation and the production of the compressor and storage unit. Currently, various hydrogen tank designs are being discussed, including hydrogen stored at 300–400 bar, 700 bar, and liquid or cryo-compressed hydrogen. The state in which hydrogen is transported in the vehicle not only affects the vehicle tank, but also influences the design of the HRS, including the compressors, storage, dispensers, and their energy requirements. In particular, the electricity demand of the compressor significantly contributes to the emissions and varies in the reviewed studies between 3.0 and 9.4 kWh/kg H₂ (Table S6). The interaction of these components also has a corresponding impact on vehicle emissions and decarbonization scenarios, as shown also in [29]. We specified that HRS must be able to provide hydrogen at 700 bar at least at one dispenser, in accordance with current European directives [1].

6.2.5. Reference and Decarbonization Scenario

Due to the higher payload of the BEV and ERS vehicles, fewer vehicles are needed than for the BEV and HPC scenario. In contrast to the results over the lifetime (Figure 8), the difference in the total GWP has become more pronounced (Figure 10). For both BEV scenarios, the infrastructure emissions play only a minor role in the overall emissions. In contrast, the emissions from the HRS have a larger contribution aligning with the reviewed studies (Table S6).

The literature indicates that LCA results for vehicles and their infrastructure are highly sensitive to the underlying assumptions, methodological choices, and the study's objectives and scope (Section 2). While the present study focused on the interactions of the electrified vehicles and their infrastructure in long-haul freight transport and its impact on emissions and costs, incorporating an uncertainty analysis would extend beyond its intended scope. Therefore, we recommend that future research assess the uncertainty of existing LCA results, potentially through a probabilistic LCA, as demonstrated in [35].

6.3. Total Cost of Ownership

The recent literature indicates considerable variation in the magnitude of TCO results for vehicles and their infrastructure (Table S7). However, consistent with the findings of this study, BEV generally exhibit the lowest costs, followed by ICEV and FCEV [9,14,55,56]. Notably, for Germany, one of the least recent studies found slightly lower costs for ICEV compared to BEV [54]. However, the lower cost of ICEV in [54] is mainly caused by the low diesel costs in their analysis (1.037 EUR/L diesel), which seem unrealistic regarding current diesel prices. From an economic standpoint, the electrification of long-haul transport is clearly advantageous. In contrast, the FCEV scenarios show higher costs. Aligned with the results of the LCA, the lower number of vehicles required for the BEV and ERS scenario,

compared to the BEV and HPC scenario, incur lower overall costs, despite the higher costs for the ERS compared to the HPC.

It is important to note that cost calculations are highly sensitive to the spatial context, as regional differences in policies and price structures have a significant impact. Therefore, for other regions or markets, region-specific cost calculations are necessary to accurately reflect local conditions and provide relevant insights. Regarding the temporal scope, disruptive events such as the COVID-19 pandemic, the war in Ukraine, or the blockage of the Suez Canal in 2021 can significantly impact the costs of raw materials and energy sources, as well as influence international trade. Consequently, predictions regarding future price structures should be approached with caution. The conditions underlying future scenarios must be continually assessed, and results should be adjusted as necessary. To evaluate the reliability of projections, tools like uncertainty analysis can be incorporated, as shown in [86].

In the following, we discuss energy, vehicle, and infrastructure costs, other cost components, and lastly, temporal and spatial limitations.

6.3.1. Energy Costs

This study specifies energy costs according to [55], but recent trends show that diesel prices might be underestimated as they have already reached around 1.6 EUR/L (1.45 EUR/L excluding VAT). This would lead to higher TCO for the reference scenario. Similarly, hydrogen costs may be underestimated, with current prices at HRS around 17 EUR/kg H₂ (14.65 EUR/kg H₂ excluding VAT). The electricity prices used correspond to current industry rates. These low prices are attainable only under specific conditions and should be viewed cautiously.

6.3.2. Vehicle Costs

The vehicle investment costs demonstrate substantial variability in the reviewed literature (Section 2.3.2). The continuous monitoring of price trends is essential, as changes should be promptly reflected in updated TCO analyses. At the same time, the share of investment costs for the vehicles in the TCO is comparable to the costs of labor, tolls, and additional fixed costs. The impact of vehicle investments is, therefore, limited. Energy costs dominate for ICEV and FCEV.

6.3.3. Recharging and Refueling Infrastructure Costs

We display the infrastructure costs for the whole scenario and, in contrast to the detailed LCA of the individual infrastructures, we omit a detailed TCO and use infrastructure costs based on [9,15,55]. For the HRS, the costs are low compared to their 22% scenario in [16]; however, comparing the demand and delivery, their 2030 design is oversized and designed for additional vehicles from regional and transit transport. Therefore, we used their cost assumptions for the individual components of the HRS design and calculated the infrastructure costs for our decarbonization scenario. We chose this approach in line with the design of the BEV and HPC decarbonization scenario, resulting in a fleet-specific infrastructure design.

Through this approach, the resulting recharging and refueling infrastructure costs (Figure 11b) translate to approximately EUR 543 k per HPC, EUR 45 k per NC, 2.5 million EUR/km ERS, and EUR 3.3 million per hydrogen dispenser at HRS. The costs for the HPC are comparable to [9], but higher compared to the costs presented in [55]. However, Jöhrens et al. included a 350 kW charger [55] and in this study, 720 kW chargers are analyzed. For the costs of the NC, our results are lower than in [9,55]. However, in contrast to their 150 kW chargers, we included 50 kW chargers for depot charging. The reviewed literature (Section 2.3.3) shows a wide range of ERS costs per kilometer. Our result of 2.5 million

EUR/km falls within the mid-range of these values. A major uncertainty in both the HPC and ERS scenarios is the cost of the necessary grid expansion, which is highly dependent on regional conditions.

For the HRS costs, our results with 6.5 million EUR/dispenser are in the same range as specified in [9]. However, Göckeler et al. specify a range for the CAPEX from 2–3.5 million EUR/dispenser and Rose et al. define different expansion stages for which the ratio of deliverable and delivered hydrogen changes, resulting in different specific infrastructure costs [9,16]. Those different approaches and assumptions lead to price ranges from 0.48 EUR/kg H₂ [16] to 1.49 EUR/kg H₂ [9]. The allocation of infrastructure costs highly depends on the infrastructure design and the total delivered energy (or number of supplied vehicles). The expansion of infrastructure should be aligned with fleet electrification wherever feasible.

6.3.4. Other Cost Components

While most studies included labor costs [54–56], Göckeler et al. omit including labor costs [9]. In our study, labor costs are higher for the BEV and HPC scenario due to the need for more vehicles; therefore, the scenario has a higher total mileage. Additional labor costs resulting from different operational demands during recharging and refueling, and potential impacts on driver break times, were not included. Practical insights from industry operations should be incorporated in future TCO analyses.

Current analyses include toll costs, but zero-emission vehicles are presently exempt from them, which lowers their overall costs. However, this exemption is set to end in December 2025, potentially altering future TCO comparisons. According to current plans, zero-emission vehicles will pay a 75% reduced toll rate for infrastructure costs—plus the toll rates for air and noise pollution—from 2026 [87].

7. Conclusions and Outlook

This study presents a comparative life cycle assessment and total cost of ownership analysis of long-haul internal combustion engine, battery-electric, and fuel-cell-electric trucks, including infrastructure considerations. The analysis encompasses lithium-ion batteries, fuel cells, hydrogen tanks, grid electricity, on-site hydrogen, a hydrogen mix, electric road systems, hydrogen refueling stations, high-power chargers, and normal chargers.

The results indicate that fuel-cell-electric trucks with hydrogen refueling stations and on-site hydrogen exhibit the highest life cycle emissions, followed by internal combustion engine trucks. Notably, both fuel-cell-electric truck scenarios incur higher costs than internal combustion engine trucks. However, fuel-cell-electric trucks powered by a hydrogen mix demonstrate lower emissions than their internal combustion engine counterparts, while battery-electric trucks reveal the lowest emissions and costs overall. Among battery-electric trucks, those utilizing the electric road system display the lowest life cycle emissions and costs. Nevertheless, the electric road system has higher production emissions compared to high-power chargers. Due to the necessity for additional normal chargers and the energy demands of infrastructure operation, both scenarios yield comparable infrastructure emissions.

Hydrogen refueling stations generate the highest emissions during both the setup and operation. All infrastructure types entail additional expenses, and the resulting global warming potential per vehicle or per ton-kilometer is heavily influenced by the vehicle-to-infrastructure ratio and infrastructure design. Fuel-cell-electric vehicles offer a greater range than battery-electric vehicles and can often operate without additional refueling infrastructure during stopovers, making them suitable for remote, less frequented routes.

Electric road systems could be integrated with high-power charging to mitigate the higher infrastructure burden while leveraging potential synergies between both technologies.

Future research should explicitly provide integrated considerations of the different technologies and corresponding simulations. This could involve studies that combine various decarbonization technologies within a single simulation framework, particularly for mixed fleets. These studies should assess the fleet size and composition as well as infrastructure requirements to better understand the interdependence between different technologies and infrastructures. In addition, the use of the infrastructure by regional and transit freight traffic and smaller vehicles is also conceivable and could, in turn, reduce the allocated emissions and costs. Those changes would also influence the infrastructure design and should be regularly reviewed and, if necessary, integrated into the corresponding analyses.

The findings of this study may guide policymakers when developing regulations and incentives. The comparative analysis of life cycle emissions and the total cost of ownership can guide investments in infrastructure, such as electric road systems and hydrogen refueling stations, to ensure that they meet sustainability goals while providing economic feasibility for operators. Given that operational costs constitute a significantly larger portion of total ownership expenses, subsidy programs would be more effective if directed towards offsetting these costs rather than solely focusing on vehicle investment subsidies. The necessity for ongoing research, particularly regarding the infrastructure demand and technology integration, highlights the need for collaborative efforts among researchers, industry players, and policymakers to establish coherent frameworks and strategies for the decarbonization of the transport sector. Additionally, research focusing on the realistic implementation of these technologies, including operational interdependencies that may not be fully captured in simulations, is crucial. Social impacts should also be considered through the Social Life Cycle Assessment to better understand the broader implications of decarbonization strategies on society.

The precise prediction of the infrastructure demand remains an area of ongoing research. Future assessments should aim for a common simulation platform and coherent scenarios to enable mixed-scenario analyses combined with sensitivity analyses. This would facilitate a comprehensive assessment of uncertainties and could incorporate probabilistic LCA or Monte Carlo simulations. With the ongoing decarbonization of electricity generation, the GWP associated with battery production is likely to decline in the future. State-of-the-art hydrogen tanks for 350–700 bar applications require carbon fiber, which has high production emissions. In contrast, liquid or cryo-compressed hydrogen tanks offer lower production emissions but involve cooling requirements and hydrogen boil-off losses. Future assessments should carefully consider the trade-offs between reduced production emissions and increased use-phase emissions, particularly in drivetrain and hydrogen refueling station designs. Furthermore, predictions and forecasts should not only depict future grid and hydrogen mixes, but also address the additional grid capacity needed to accommodate these technologies, transport routes for hydrogen, and the associated infrastructure costs. This will help to ensure a more complete understanding of the future demands and challenges of the transport sector's decarbonization.

Additionally, future analyses should incorporate emerging technologies such as solid-state batteries, hydrogen combustion, liquid or cryo-cooled hydrogen, and synthetic fuels. While these technologies are not yet market-ready, forecasts and predictions can be utilized to explore how and when they might complement existing lithium-ion batteries and fuel cells. Furthermore, it is essential to investigate the challenges associated with their implementation and assess whether new interdependencies might emerge. Such interdependencies could influence the current ramp-up of refueling and recharging infrastructure, grid expansion, electricity production, and related developments. Our method

enables the evaluation and comparison of different decarbonization scenarios, including system interdependence regarding costs and emissions. We focus on long-haul, heavy-duty transport in Germany, but the methods presented here, can be applied to other regions and other transport segments (e.g., motorized individual transport).

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/wevj16020076/s1>, Table S1: Literature Overview Batteries; Table S2: Literature Overview Fuel Cell and Hydrogen Tank; Table S3: Literature Life Cycle Assessment Trucks; Table S4: Literature Life Cycle Assessment Charger; Table S5: Literature Life Cycle Assessment Electric Road System; Table S6: Literature Life Cycle Assessment Hydrogen Refueling Station; Table S7: Literature Total Cost of Ownership Trucks; Table S8: GWP of Hydrogen Pathways.

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Article

Exploring Thermal Runaway: Role of Battery Chemistry and Testing Methodology

Sébastien Sallard ^{1,*}, Oliver Nolte ², Lorenz von Roemer ², Brahim Soltani ¹, Alexander Fandakov ², Karsten Mueller ², Maria Kalogirou ² and Marc Sens ²

¹ IAV France S.A.S., 4 Rue Georges Guynemer, 78280 Guyancourt, France; brahim.soltani@iav.de

² IAV GmbH, Carnotstrasse 1, 10587 Berlin, Germany; oliver.nolte@iav.de (O.N.); lorenz.von.roemer@iav.de (L.v.R.); alexander.fandakov@iav.de (A.F.); karsten.mueller@iav.de (K.M.); maria.kalogirou@iav.de (M.K.); marc.sens@iav.de (M.S.)

* Correspondence: sebastien.sallard@iav.de

Abstract: One of the major concerns for battery electric vehicles (BEVs) is the occurrence of thermal runaway (TR), usually of a single cell, and its propagation to adjacent cells in a battery pack. To guarantee sufficient safety for the vehicle occupants, the TR mechanisms must be known and predictable. In this work, we compare thermal runaway scenarios using different initiation protocols (heat–wait–seek, constant heating, nail penetration) and battery chemistries (nickel manganese cobalt oxide, NMC; lithium iron phosphate, LFP; and sodium-ion batteries, SIB) with the cells in a fully charged state. Our goal is to specifically trigger a variety of different possible TR scenarios (internal failure, external hotspot, mechanical damage) with different types of chemistries to obtain reliable data that are subsequently employed for modeling and prediction of the phenomenon. The safety of the tested cells depending on their chemistry can be summarized as LFP > SIB >> NMC. The data of the TR experiments were used as the basis for high-fidelity modeling and predicting of TR phenomena in 3D. The models simulated reaction rates, represented by the typically employed Arrhenius approach. The effects of the investigated TR triggering methods and cell chemistries were represented with sufficient accuracy, enabling the application of the models for the simulation of thermal propagation in battery packs.

Keywords: thermal runaway; simulation; battery cells; LFP; NMC; sodium-ion; BEV; battery chemistry; Arrhenius approach

1. Introduction

In the past decade, BEVs have emerged as challengers to vehicles relying on conventional internal combustion engines (ICEs). In 2022, BEV sales represented more than 10% of all car sales worldwide [1]. The increasing share of BEVs is, however, also leading to an increase in safety-related incidents with these vehicles that can be traced back to their batteries, which is concomitant with an increasing public awareness of BEV safety issues. Even though an accident-related BEV fire may not originate from the battery pack, the biggest safety concern is the occurrence of a thermal event, starting with the thermal runaway of a single cell and its propagation within the battery pack.

The safety of the vehicle occupants is paramount for the vehicle and battery manufacturers. The international regulation E/ECE/Rev.2/Add.99/Rev.3 stipulates a warning signal 5 min before the occurrence of a hazardous situation inside the passenger compartment [2]. In this context, it should be noted that a considerable extension of the time from the advance warning and the hazardous situation for passengers is currently under

consideration. However, based on today's state of the art, the prevention and the warning of a cell thermal runaway and its propagation is facing several challenges.

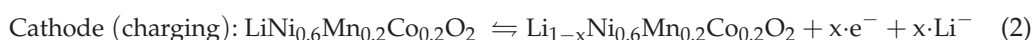
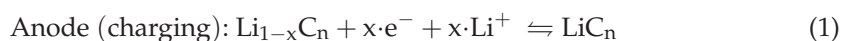
The TR behavior of batteries is highly complex and involves multiple factors, for example, the cell chemistry and format, the cell integration approach in the battery module or pack, the thermal management system layout as well as the implemented active safety measures such as thermal sensing and emergency cooling system operation mode, and finally, the battery management system (BMS). This yields a highly complex system strongly affecting the already complex phenomenon of cell TR in multiple ways.

Battery technology is continuously evolving, with improved LIB chemistries (Ni-rich, LMFP, ...) as well as post-lithium-ion and post-lithium chemistries that are completely new in the field of automotive applications (e.g., solid-state, sodium-ion, respectively). This necessitates an equal evolution of safety-related knowledge for these battery materials.

The goal of this contribution is hence to establish the solid experimental basis needed for modeling—and crucially predicting—thermal runaways for different battery materials and chemistries.

The principle of an electrochemical alkali-metal ion battery cell can be summarized as such: The cell is composed of a positive electrode (typically designated as cathode), a negative electrode (typically designated as anode), and a dielectric separator between them, filled with an ion-conducting electrolyte. The electrodes are connected electrically via a load or source (electrical circuit). During cell discharge, the reduced graphite LiC_6 present in the charged anode is oxidized, and the alkali metal ions are removed from the anode host lattice. At the same time, the generated electrons are collected by the anode current collector so that they can reach the cathode via the electrical circuit where the electrons are able to reduce transition metal cations in the cathode host lattice.

To keep the overall charge balance, the alkali cations generated at the anode/electrolyte interface are transported through the separator, eventually reaching the cathode surface to be incorporated into the reduced cathode host material lattice. During charging, inverse reactions occur. These processes and the underlying electrochemical reactions can be summarized into global reactions, for example, for a typical Li-ion cell:



Among the various electrode materials used in automotive LIB cells, the most common ones are layered oxides, such as NMC (nickel manganese cobalt oxide) or NCA (nickel cobalt aluminum oxide), followed by LFP (lithium iron phosphate) as cathode materials and graphite as anode material. Layered oxide materials are usually considered to offer the best energy density while the LFP is cheaper, more stable, safer, and cobalt-free (i.e., limited socio-ecological footprint). However, LFP cells typically suffer from lower energy density, especially on a volumetric basis (Wh/L).

The battery industry is now increasingly facing concerns regarding the need for sustainable battery technologies. Among the different "post-lithium" battery technologies, sodium-ion batteries (SIBs) can be reasonably considered to be among the most promising. This technology has a very high level of maturity, as it is already used in commercial products, for example, electric tools and micro-cars. SIBs are even considered to potentially represent 15% of all batteries used for passenger vehicles in 2030 [3]. The principle of the SIB is fundamentally comparable to that of the LIB, with the charge carrier alkali metal cation being sodium instead of lithium. SIBs have a considerably lower energy density than the LIB; however, they offer other advantages thanks to employing abundant and cheap sodium as a replacement for the comparably scarce and expensive lithium. Sodium-

ion batteries are further characterized by enabling safe transport (transportation at 0 V is possible), long lifetime, limited ecological footprint and compatibility for high power applications, even at low temperatures [4–7]. In numbers, while having a limited energy density that is typically below 200 Wh/kg, they have rate capabilities of 4C and above, even at negative ambient temperatures [4].

The correlations between stress factors and the occurrence of thermal runaway and propagation are summarized in Figure 1. Even if the thermal runaway is, to the best of our knowledge, explained by two main degradation modes (short-circuit and exothermic self-heating), the chemical mechanisms involved are numerous and occur at five different levels in the cell with a possible cascading effect between them. Each mechanism can be induced by different causes and each cause can trigger several different degradation mechanisms.

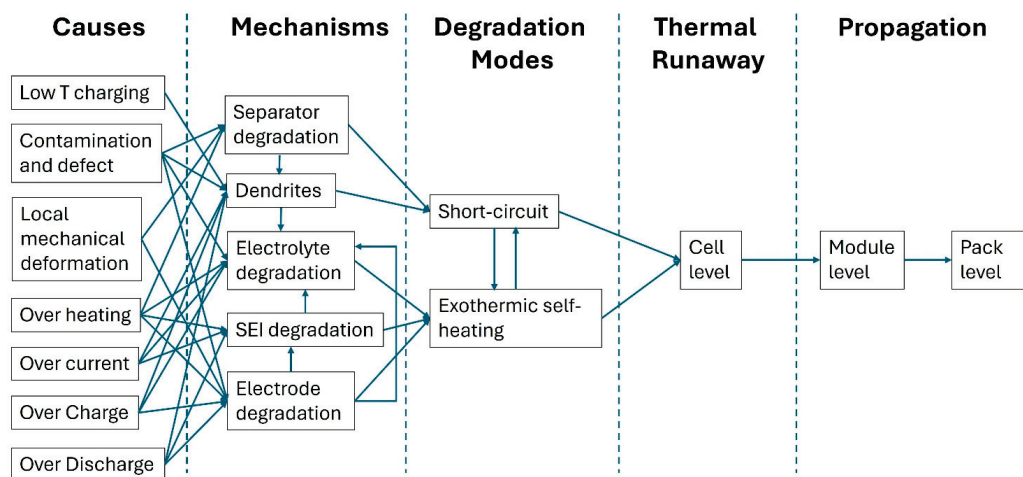


Figure 1. Overview of the relationships between causes and the thermal runaway and propagation mechanisms of a Li-ion battery (SEI = Solid Electrolyte Interphase, T = Temperature).

The presence of an NMC transition metal oxide in the cathode induces specific self-degradation phenomena in addition to the complex interplay of causes and mechanisms for LIBs during the cycling of the cells. Figure 2 illustrates in detail the chain reaction triggered by the NMC self-degradation, visualizing these reactions and their influence on the amplification of the cascading effect leading to a cell thermal runaway.

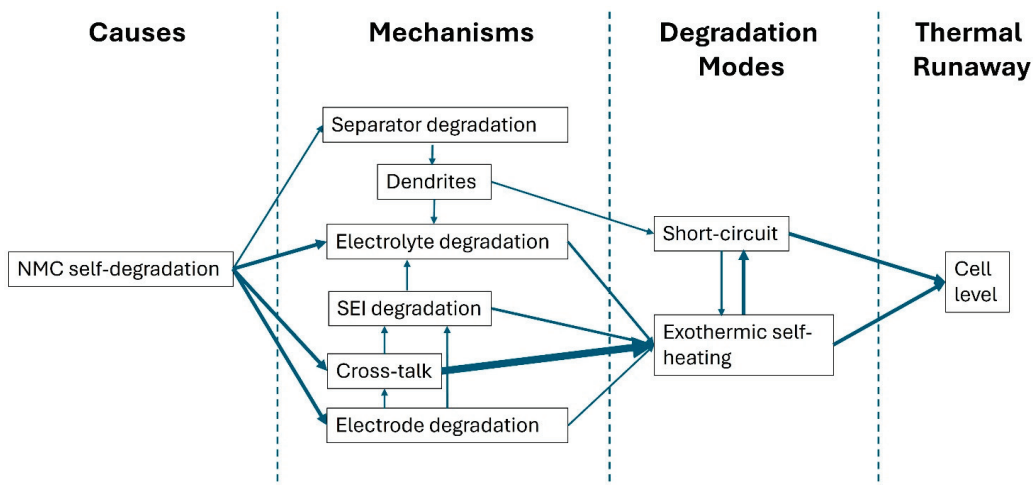


Figure 2. Overview of the relationships between NMC aging and degradation mechanisms in a Li-ion cell.

The process of a thermal runaway is influenced by many parameters. A well-known and important one is the chemistry of the cathodic material present in the LIB. The trend toward higher cell energy content and power has led to the use of high nickel content fractions in the NMC cathode materials usually labeled nickel-rich NMC materials. In terms of safety, NMC materials have important disadvantages. During a thermal runaway, the material-related specific heat release is one of the most important figures of merit [8]. Batteries containing LFP show a lower energy density, but the LFP material is characterized by superior chemical and thermal stability compared to transition metal oxide materials. LFP cathodes have been described to be stable for temperatures of up to 500 °C even in a charged state [9]. It has been observed that the higher energy density of NMC-based batteries relates to a higher risk of thermal runaway and more severe related consequences (peak temperature, gas exhaust, speed of propagation) [10,11]. This highlights the importance of building a knowledge basis for safety-related issues of these new battery technologies.

Compared to post-lithium chemistries such as sodium-ion, the thermal runaway mechanisms of LFP and especially NMC are considered well understood. A recent report noted the instability of the NMC811 material even under normal conditions [12]. When an NMC811/graphite battery is being charged, the NMC811 material starts to degrade at a voltage of 4.15 V by heat release, oxygen and transition metal ion solubilization in the electrolyte, crystal phase modification as well as creations of inactive and isolating layers [7,9]. Thus, the battery suffers from capacity loss and an increase in resistance. In addition, the dissolved oxygen and metal ions diffuse to the anode surface where they lead to further undesired reactions. The latter contributes to an accelerated aging of the Li-ion cell, a phenomenon recently described as “crosstalk” mechanism [13]. The heat released by the crosstalk mechanism is added to the heat released by other phenomena (see Figures 1 and 2) and can easily lead to the cell (or parts of it) reaching the critical self-heating temperature via a cascading effect of successive reactions.

The TR of a Li-ion cell is considered to take place following a typical pattern [14].

When the self-heating temperature for a typical Li-ion cell in the range of 90–120 °C is exceeded, the SEI on the anode surface (graphite and/or silicon) needed to passivate the anode, becomes unstable and degrades. The anodic material is consequently in direct contact with the carbonate electrolyte. Thus, a new SEI is continuously reformed and degraded with an important gas emission including carbon oxides, ethylene, ethane, and oxygen, resulting in an increase in internal cell pressure and cell swelling. These reactions are highly exothermic [15].

The heating of the cell is consequently self-perpetuating until reaching the trigger temperature where the polymeric polyolefin separator melts, leading rapidly to an internal short-circuit of the cell with a drop of its voltage as well as a discharge-related temperature rise. A huge electrolyte decomposition and consequent gas emission are initiated in the corresponding temperature range [14].

Consequently, temperature and pressure within the cell continue to increase, eventually reaching the venting point where the pressure valve of the cell opens, and venting occurs. The cell is still experiencing uncontrolled reactions and heating. The temperature can become sufficiently high so that cell materials, i.e., transition metal oxides, graphite, binders and electrolytes, decompose rapidly.

The thermal runaway starts rapidly at ca. 200 °C, triggering and/or amplifying the combustion of all reactive solid products present in the cell, leading to a quasi-exponential increase in cell temperature until reaching a maximum [13,14,16].

The TR scenario in the case of mechanical damage to the cell is slightly different. The heat source is created by the local short circuit, described as an internal hot spot by Ren et al. [17]. Finegan et al. [18] reported the penetration of the cell in the longitudinal direction

of 18,650 cylindrical cell and its effects. The TR initiates in the jellyroll around the nail location and expands to the whole cell in several seconds. Yoshima et al. [19] reported that the Joule heating at the short circuit location was due to the current flowing between the contact of the nail and the electrode. The heating causes gas generation.

Consequently, it appears logical to consider that the local short circuit formed by any sufficient mechanical damage generates enough heat to lead to the cascade reaction of the TR scenario, as described in the previous paragraph, in the vicinity of the short circuit, eventually expanding to the whole cell.

The cathode chemistry also has a high influence on the TR scenario. Liu et al. report that when the thermal runaway of NMC started, it could not be stopped, even by putting the 25 Ah single cell in liquid nitrogen ($T \approx -196^\circ\text{C}$) [13]. The same cooling procedure was effective just before the start of the thermal runaway. This information confirms that the thermal runaway of an NMC/graphite cell can be prevented but when started, it can hardly be controlled (“point of no return”). This behavior can be explained by the NMC high-temperature degradation reactions generating sufficient heat and oxygen to fuel its own and other combustion reactions until the reactions have consumed all reactive materials in the cell. The reaction in NMC materials is so violent that solid particles are emitted, while this is not the case with LFP [8,11,13,16,20]. Note that this last remark is based on a report with an isolated single-cell protocol.

Huge amounts of released heat and gas combined with the emission of particulate matter are very likely the reason why NMC cells, and more particularly Ni-rich NMC compositions, show a more dramatic thermal runaway behavior [11]. Generally, a higher Ni content in the cathode correlates with higher cell temperatures during TR and an increased gas volume [11]. The risk of propagation in a battery module and/or pack is consequently high and raises safety concerns for passengers of EVs. The state of charge of the cell (SoC) is an important factor impacting the thermal runaway scenario [15,17,21,22]. Even though differences can occur depending on the cell design and cell chemistry, it seems reasonable to consider that the higher the SoC of the cell, the more likely a TR is to occur (in a shorter time and/or at a lower temperature), and the more energy is released.

The goal of this work, in the first step, is to create an experimental base to evaluate the influence of both battery chemistry and trigger method on the characteristics of the thermal runaway. The trigger methods chosen aim to investigate scenarios representing the three main triggers of a thermal runaway event: (a) the heat–wait–seek method, mimicking internal self-heating, mainly due to internal failure, (b) the continuous heating method, representing the effect of an intense external heat source (i.e., close to a hot spot in the vicinity of the cell) and (c) nail penetration mimicking mechanical damage, for example, in case of a vehicle crash. The cell chemistries selected are NMC811, LFP, and SIB. NMC and LFP are the most popular LIB chemistries used to power BEVs and are expected to remain so at least until the end of this decade [3,23]. As previously mentioned, SIBs are an emerging technology and are projected to potentially account for 15% of the battery market used for BEVs by 2030 [3].

In the second step, the experimental results are used to develop a methodology to simulate, and thus predict, thermal runaway events even for advanced battery technologies, enabling the transfer of the presented methodology to investigations of thermal propagation phenomena in multi-cell configurations. Due to the high complexity of the thermal runaway phenomenon, we employ a combination of physical testing procedures with virtual development methods to drastically reduce the number of tests needed for the development of a “no thermal propagation” battery system and thus accelerate the development of safe and cheap electrical vehicles.

2. Materials and Methods

The cells considered in the experimental campaign presented in this work are cylindrical, manufactured in 18,650 format and have the main characteristics listed in Table 1. All cells tested were fully charged (SoC = 100%), which is state-of-the-art [8,9,11,16,24], and it is considered the worst possible case as explained in the introduction [15,21,22].

Table 1. Details of the three types of cells used for the TR investigations.

Cell	Manufacturer	Description	Nominal Capacity	Nominal Voltage	Cell Mass
			[mAh]	[V]	[g]
LFP	A123	APE18650M1-A	1100	3.2–3.3	39
SIB *	HAKADI	18650E-1500	1500	3.0	37
NMC811	LG Chem	INR18650-MJ15	3500	3.6	49

* Note that based on analysis of the SIB, the cathodic material is assumed to be a layered transition metal oxide with a chemical composition close to $\text{Na}_{0.8}\text{Ni}_{0.32}\text{Fe}_{0.34}\text{Mn}_{0.34}\text{O}_2$ [25].

The cells are positioned vertically in an autoclave filled with nitrogen with seven temperature sensors (thermocouples) mounted at different locations on the cell surface as shown in Figure 3. For the heating protocol, the cells are heated up with a heating pad (11 cm² surface area) directly positioned on the lateral surface. In addition, different (cell-type specific) thermal insulation measures have been applied to the cell canning as shown in Figure 3.

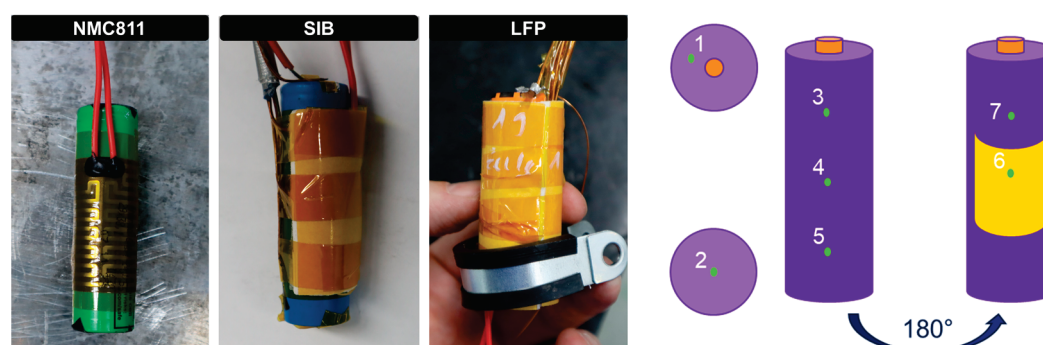


Figure 3. Position of the seven thermocouples (TCs) on an 18,650 cell. The yellow area represents the heating pad.

Two separate heating protocols were used for each cell chemistry to trigger the thermal runaway taking inspiration from the literature [2,8,11,16,24]:

- Constant heating (CH) with a continuously applied heating power of 27 W. The constant heating was applied until the occurrence of the thermal runaway
- Heat–wait–seek (HWS) tests with heating steps of 5 K and step time of 300 s.

Additionally, a standard nail penetration test was performed with the NMC and the SIB cells, penetrating the cell slightly off-centered in the bottom area (Figure A1).

The autoclave was equipped with temperature sensors (type-K sheath thermocouples) and a pressure transmitter. Processing and recording of the analog sensor readouts were performed with standard analog-to-digital data conversion software. For the qualification of the emitted volatile species, an MKS 2030 FTIR analyzer from MKS Instruments, Inc., Andover, MA, USA and an HSense mass spectrometer from V&F Analyse- und Messtechnik GmbH, Absam, Austria, were used. Furthermore, a camera was used to observe the visual progress during the thermal runaway tests. For the cell heating, standard polyimide heating pads were used. Control of the heating power for the heat–wait–seek tests was realized by a

PID controller referenced to the thermocouple located on the heating pad. Nail penetration tests were performed with a feed rate of 1 mm/s employing an in-house developed nail penetrator using a 3 mm steel nail with a 30° taper. For quantification of the gas amount after TR, the gas volume was calculated based on the ideal gas law using the autoclave pressure and temperature as input.

Modeling thermal runaway based on different, chemistry-specific reaction mechanisms in a high-fidelity 3D environment as typically employed for investigations of thermal propagation phenomena in multi-cell configurations was performed with the software CONVERGE CFD (Version 3.1.) [26]. The geometry employed in this study is a representation of the single-cell measurement setup as shown in Figures 3 and A2. It mainly includes the cell, the heating pad, the holding clamps, and insulation material if needed, as illustrated in Figure 4. For the simulation of TR triggered by nail penetration, a heat source was used to simulate the initially created short circuit. More specifically, no short circuits are considered in the simulation as such, but the heat generated is accounted for within the Arrhenius approach for the cell reactions. The model used has addressed heat loss from the cell to the environment by incorporating heat transfer to the ambient gas phases as well as heat transfer to the materials surrounding the cell, such as clamps and cell holders.

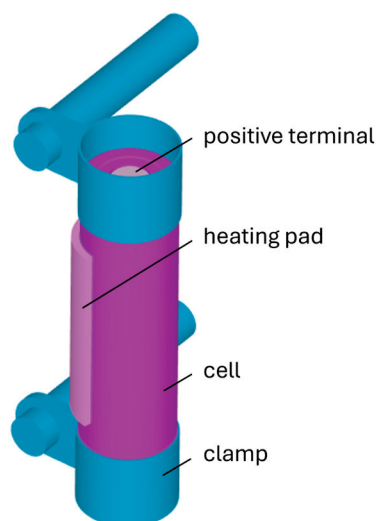


Figure 4. Geometry of single cell with clamps as employed in the 3D CFD simulation environment.

3. Results and Discussion

3.1. Individual Cell TR Tests

3.1.1. Cell Characteristics in Constant Heating Tests

Figure 5 depicts the thermocouple traces recorded during constant heating (CH) tests for the three investigated cell chemistries. The LFP cell shows the least critical thermal runaway behavior, as expected from the literature, with the lowest peak temperature [8,9]. However, the temperature still reaches 350–400 °C on the cell body, as evident from Figure 5. The smoke emission remains limited during the entire experiment. Figure 5a shows the different temperatures recorded along the cell body. Sensor TC6 on the heating pad records, as expected, the fastest warming and highest temperature during the heating step. The bottom and top of the cell remain significantly colder, attributed to the longer distance from the heating pad and possible cooling as they are not insulated. Regardless of the differences depending on the sensor location, a continuous and quasi-monotonous increase in the cell body temperature is recorded during the first 420 s of the test. The first noticeable event is a rapid increase in heating for TC6 at $t \approx 420$ s and the start of venting at $t = 460$ s. The rapid increase in the temperature of the other parts of the cell body (TC1 to TC5 and TC7) is

noticeable only after $t \approx 510$ s. A limited amount of smoke occurs after $t \approx 540$ s, which is the peak temperature for sensors TC6 (heating pad) and TC7 (closest to TC6) but not for the other sensors, TC1 to TC5. The latter reach their maximum temperature at $t \approx 575$ s (except TC1). All sensors finally cool down slowly at a similar rate. We interpret these phenomena as the CH leading to a local hot spot in the cell directly in contact with the heating pad ($t \approx 420$ s). The hot spot initiates electrolyte degradation, venting ($t \approx 540$ s), and a local TR event (maximum temperature for TC6 and TC7). The latter rapidly propagates through the cell and heats its whole body ($t \approx 575$ s). When the TR event ends, the cell cools down slowly.

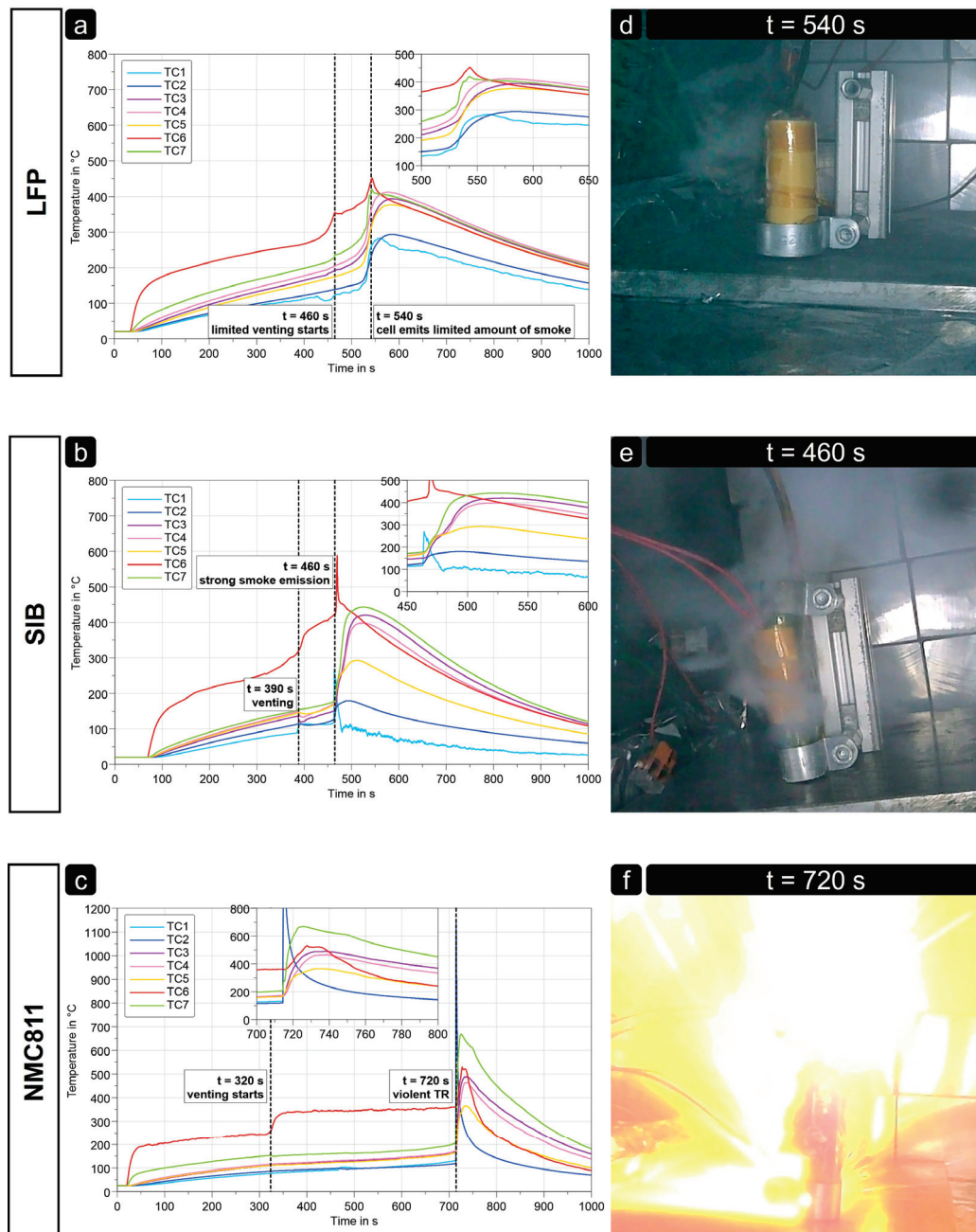


Figure 5. Temperature evolution during the CH experiments of (a) the LFP, (b) the SIB (b,c) the NMC811 cell, photo of (d) the LFP cell at 540 s, limited fuming, (e) the SIB cell at the thermal runaway at 460 s, and, (f) the NMC811 cell at the thermal runaway at 720 s. Note the fume was so dense for the SIB that rapidly nothing else was visible with the camera.

The SIB cell behavior is comparable to the LFP cell, with a more pronounced heating of the cell surface and temperatures reaching values between 400 and 450 °C. Venting and smoke emission of the SIB cell start after 390 s and 460 s, respectively. The latter is more pronounced compared to the LFP, even though no ignition of the volatile gases occurs (see Figure 5). Despite the limited differences observed, we believe that a similar TR scenario occurred in the SIB than the one described previously for the LFP. While having the earlier start of the venting at 320 s, the NMC811 cell needs a considerably longer time to heat up and to show a measurable effect of the TR Event with $t = 720$ s when compared to 540 s for LFP and 470 s for SIB. We believe the missing thermal insulation for the NMC811 on the outside of the canning can partially contribute to heat losses to the environment. The NMC cell is violently emitting sparks and flames through the venting opening (see Figure 5) with gas temperatures reaching 1100 °C (TC1 and TC2) while the cell body (TC2 to TC7) reaches peak temperatures above 650 °C (TC7; see Figure 5). These observations are in agreement with the literature [10–12], i.e., the nickel-rich NMC811 is a very reactive material, prone to react with and amplify the TR scenario. Note, the possible contribution to the TR scenario of the silicon present in the anode of the NMC811 cell should also be considered [27], even if its quantity in the anode is limited to several percent, is very likely to limit its impact.

The cell weight loss after TR shows a proportionality to the peak temperature of the cells, with the LFP cell losing around 14% of its mass, followed by the SIB with around 19% mass loss. The NMC cell showed the highest mass loss with nearly 65% of its mass ejected, supporting the contribution of the NMC811 material to the TR event, i.e., the NMC811 reacts and is consumed while the cathodic materials of the LFP and SIB cells appear stable. Venting events are present for all cells but are more visible for the SIB cells. These observations are also confirmed by the visual appearance of the TR events, as discussed earlier. Furthermore, we observe internal cell short-circuits, i.e., a potential drop of at least 3 V, occurring way before the venting and TR events, in agreement with the literature [14–16]. At this point, the observed cell surface temperatures are typically between 100–150 °C while the heating pad temperature reaches 220 and 250 °C.

Note that the LFP cell is finally emitting an important quantity of smoke at a significant time, starting ca. 928 s (15.5 min), after the occurrence of the thermal runaway; see Figure A3. Rapidly, the autoclave is full of smoke.

3.1.2. Cell Performance in Heat–Wait–Seek Tests

The results of the HWS tests, Figure 6, appear generally similar to the CH tests, with a gradual increase in the cell temperature up to a sudden increase in temperature at the point of thermal runaway. However, due to the test protocol, it takes longer for the thermal runaway to occur. The stair shape of the temperature warming is clearly visible on the TC6 sensor. The temperature dispersion for TC3 to TC7 appears narrower than for the CH test (Figure 5), in agreement with the difference between the warming protocols. TC1 and TC2 suffer from significant heat loss due to their positions. The LFP cell has the lowest lateral surface peak temperature (approx. 330 °C), followed by the SIB (around 500 °C) and NMC (around 600 °C) cells. For the latter, the gases emitted via the venting opening reached temperatures surpassing 1200 °C, comparable with the CH experiment (see Figure 5) with a similarly violent runaway behavior (see Figure 5). The observed weight loss of the LFP cell amounted to nearly 19%, while the SIB cell lost more than half of its weight. The NMC cell had the highest weight loss with more than 60% of its mass ejected during the test. The quantification of the mass loss recorded is similar between the CH and HWS tests for the LFP and NMC cells. However, it differs significantly for the SIB cell, suggesting the occurrence of another TR scenario for this cell chemistry depending on the triggering method. This point is discussed later in Sections 3.2 and 3.3.

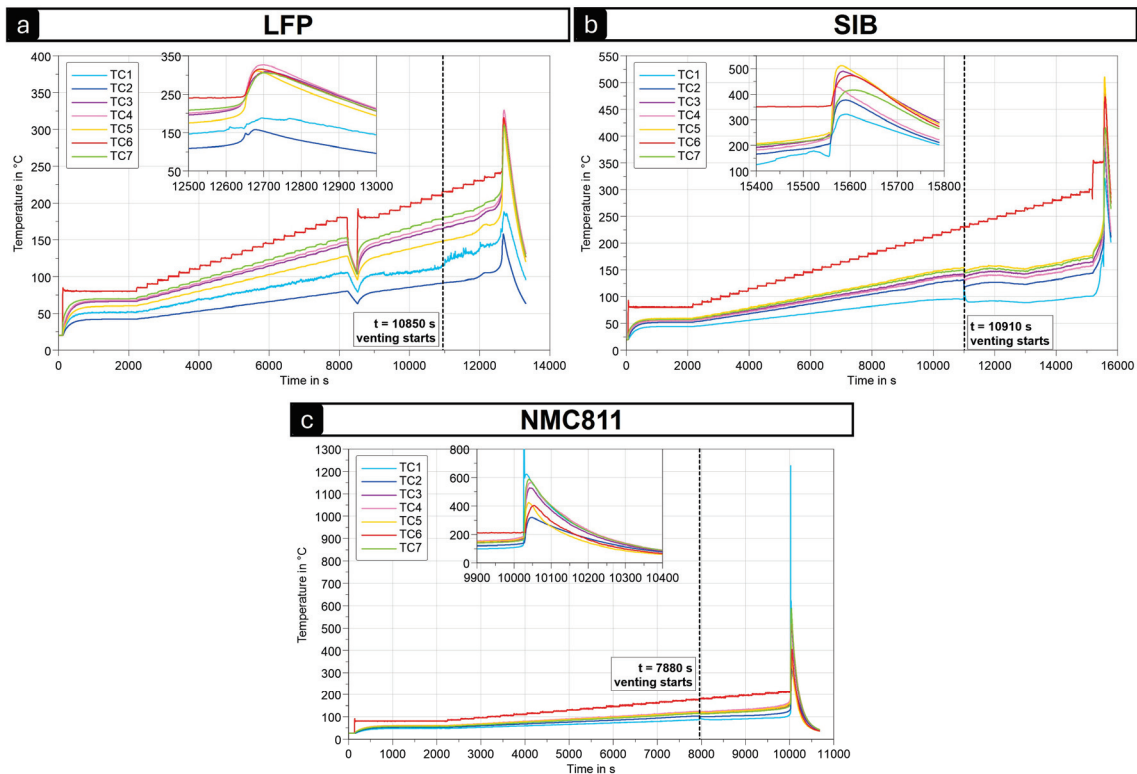


Figure 6. Temperature evolution during the HWS experiment of (a) the LFP, (b) the SIB cell and (c) the NMC811 cell.

3.1.3. Cell Performance in Nail Penetration Tests

Nail penetration tests were performed for both SIB and NMC chemistries (see Figure 7). The cell TR starts with the cells at an ambient temperature and is induced by the internal heat-up of the cell due to the short circuit caused by the nail. For both cells, the open circuit voltage (OCV) shows anomalies around 15 s before TR, visible as a deviation from its steady value before the nail penetration (see top panels of Figures A4 and A5), confirming the reliability of this test. Sensors on the bottom of both cells showed an exponential increase in temperature, followed by simultaneously occurring venting and TR events, as indicated by the sudden increase in pressure as well as temperature (see bottom panels of Figures A4 and A5). The cells reached peak temperatures shortly after nail penetration (see Figures A5 and A6). The peak temperature on the lateral surface of the SIB cell was recorded at around 380 °C (see Figure 7), while the NMC cell showed peak surface temperatures of nearly 450 °C (see Figure 7). Both cells ejected hot gas streams from the venting and puncture openings shortly after penetration in agreement with Finegan et al. [18] for similar nail penetration through longitudinal penetration of cylindrical cells. In addition, the NMC cell showed a very violent TR behavior, with sparks and flames emitted from the venting and puncture opening due to the violent reaction of the cell's internals (see Figure 7, and Figure A7). The high reactivity of the NMC chemistry compared to LFP and SIB is confirmed, regardless of the thermal trigger method used to initiate the TR.

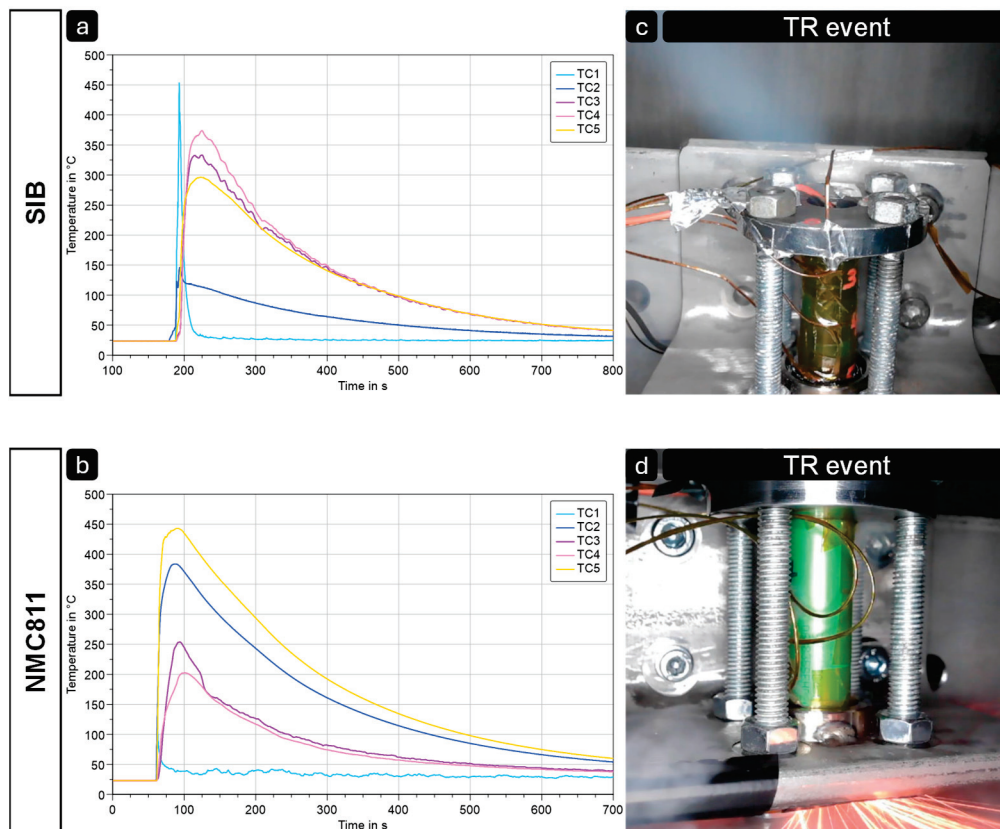


Figure 7. Temperature evolution during nail penetration test of (a) the SIB and (b) the NMC811 cells. Photos of the cells when visual change are recorded attributed to the TR event, i.e., (c) visible smoke for the SIB (from the top only) or (d) visible smoke (bottom left) and sparks for the NMC811.

3.2. Trigger Method Performance Across Different Cell Chemistries

In order to compare the cell chemistries during tests with a respective trigger method, the temperature gradient (temperature rise rate) as a function of the temperature was used, Figure 8.

During CH tests (see Figure 8), the NMC cell shows the highest temperature gradient (around 70 K/s), while SIB and LFP cells heat up more slowly and show comparable temperature gradients (below 20 K/s). LFP has been described to show stability superior to 500 °C [9], and we consequently consider that the LFP has not reacted during this TR event. Few data are available for the SIB cathodic material but based on the similarity of the data from the SIB and LFP cells in Figure 8a, it appears reasonable to consider that the $\text{Na}_{0.8}\text{Ni}_{0.32}\text{Fe}_{0.34}\text{Mn}_{0.34}\text{O}_2$ material has not reacted, or at least not significantly. Furthermore, the NMC cell shows a significant temperature rise rate above 400 °C, indicating an ongoing heat generation due to the reaction of the materials within the cell in this temperature range. Such observation agrees with an NMC 811 combustion phenomenon, taking into account the material stability limit to be inferior to 240 °C in a charged state [10]. Furthermore, Figure 8 shows two distinct local maxima of the temperature rise rate for the cells. This feature is most visible for the SIB and NMC chemistries, and only marginally appears for the LFP cell. We attribute this behavior to the non-uniform heating of the lateral surface of the cells. This leads to a partial overheating of the cell in the vicinity of the heating pad, initiating the TR locally. When the TR occurs, we intuitively consider that other parts of the cell body must be further heated before they can contribute to the TR too.

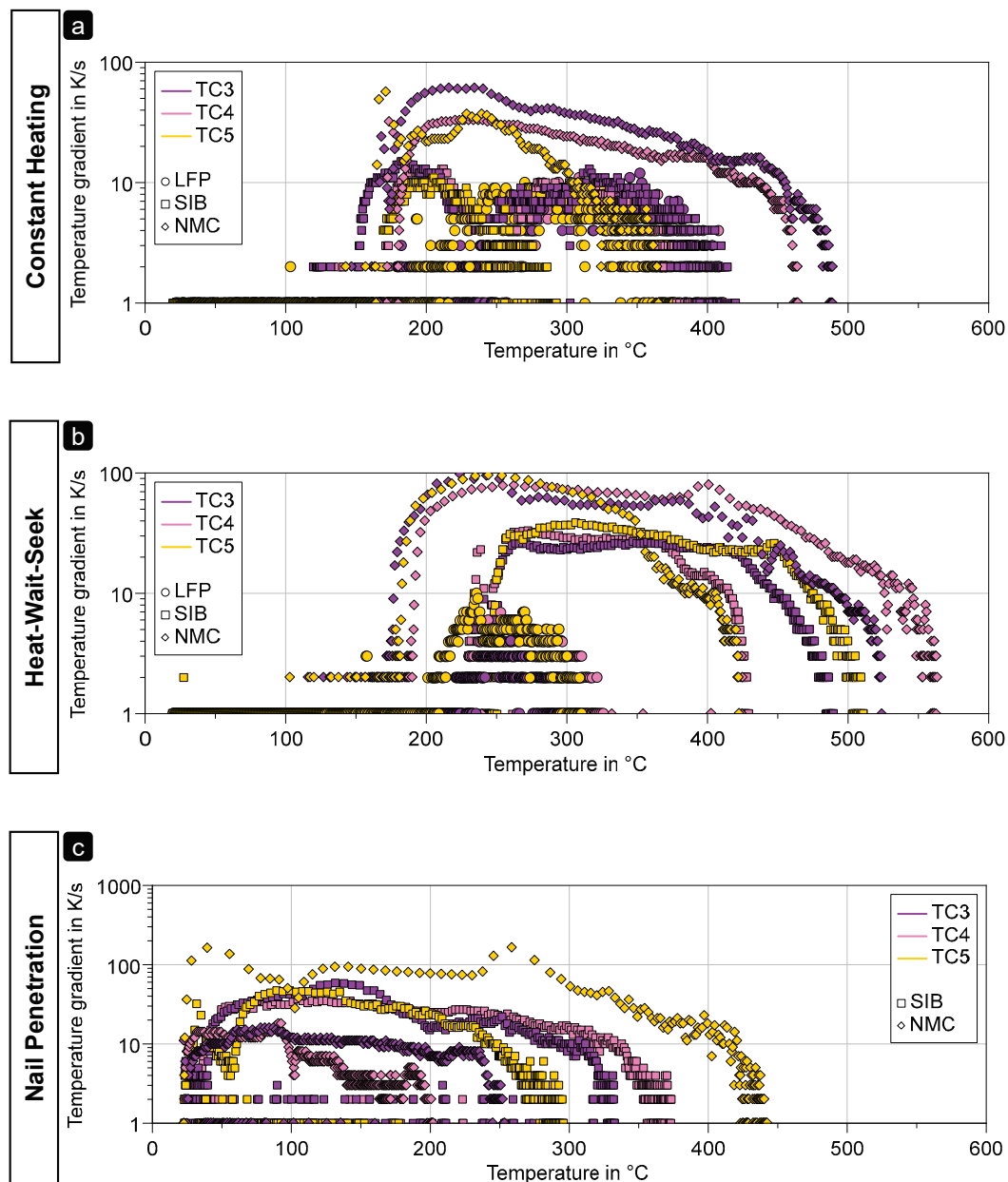


Figure 8. Temperature rise rates at the lateral surface depending on the cell chemistry (LFP, SIB and NMC) during a thermal runaway for each trigger method ((a) constant heating, (b) heat-wait-seek, (c) nail penetration). Note the logarithmic scaling of the temperature gradient as well as the different scaling of the temperature gradient in diagram °C.

The temperature gradients recorded during the HWS tests (see Figure 8) again show the highest gradient for the NMC cell (peaking around 100 K/s). Additionally, the temperature rise rate is increasing at lower temperatures (at around 170–190 °C) compared to the SIB and LFP chemistries (above 200 °C), while the temperature is further increasing at higher temperatures (above 500 °C) than for LFP and SIB cells. The SIB cell shows temperature gradients of up to 40 K/s, while the LFP cell shows temperature gradients peaking at 10 K/s. The results of both CH and HWS experiments are comparable in terms of the occurrence of the venting event prior to the TR of the cells. The temperature rise vs. temperature appears relatively unchanged for the LFP and the NMC cells between Figure 8a,b, but it is obviously not the case for the SIB cell. This will be discussed in the next Section 3.3. Furthermore, it is evident that the time between the occurrence of the

venting and TR events is significantly higher for the HWS tests, owing to the moderate heating ramp.

During nail penetration tests, the NMC cell again shows the fastest temperature increase on its lateral surface with the temperature rise rate peaking at nearly 165 K/s. The SIB cell on the other hand shows a lower temperature rise rate peaking at around 60 K/s. In any case, the nail penetration triggering method allows the earliest and fastest temperature increase in all experiments. Again, the NMC cell is still showing a temperature increase in a temperature region where the SIB cell is not heated up further (above 380 °C). It agrees with the visual observations, the NMC cell shows sparks and a flame (Figures 7d and A7) while only gas and smoke are released with the SIB cell (Figures 7c and A6). Due to the nature of the testing protocol, the nail penetration experiments conducted with SIB and NMC cells show a different temperature evolution than CH and HWS tests with steady temperature signals before TR. Furthermore, as venting and TR events appear to happen simultaneously, both pressure and temperature are not applicable as early detection methods. For these tests, the open cell voltage seems to be a reliable indicator of the impending thermal event (see Figures A5 and A6).

Comparing the peak lateral surface temperatures reached during the experiments of all three initiation methods, the measured peak temperatures during the nail penetration experiments are comparable to the CH tests and around 150 K lower than for the HWS tests, as the heat sources (internal for nail penetration and external for CH) are not homogeneously heating the cells during these tests. In terms of weight loss, no clear trend could be identified for the distinct trigger methods, as this parameter is highly influenced by cell chemistry.

The temperature rise rate of the HWS tests shows the highest homogeneity (see Figure 8), in agreement with the observation reported in Section 3.1, with the lateral surface sensors showing a close evolution for each chemistry. This homogeneity is not visible for the other initiation methods. We attribute this narrow temperature distribution within the cell to the highly homogeneous temperature distribution induced by the HWS method, in agreement with Figure 6. This allows more material to be able to reach a critical state simultaneously and thus contributes to heat generation at the same time.

3.3. Chemistry Performance Across Different Trigger Methods

Generally, the LFP cells showed the least severe TR behavior during the tests, followed by the SIB and NMC cells (see Figures 5–7). In terms of mass loss, this order is also evident, with the lowest mass loss for the LFP cells and the highest mass loss for the NMC cells. However, while the mass losses of both LFP and NMC cells are comparable for CH and HWS tests, the mass loss of the SIB cell during the HWS-initiated TR was significantly higher (more than half of the cell's mass) than that during the CH tests (less than 20%) as reported in Section 3.1. We attribute this to the more uniform heating of the cell during the HWS test, resulting in a more uniform conversion of the cell materials during TR.

Figure 9 confirms the very similar and limited temperature rise rate for the LFP cells both for the CH and HWS tests. We can claim the TR events of the LFP cell do not appear to be affected by the choice of the thermal trigger method. This limited temperature gradient is beneficial in terms of safety and thus enables reductions in temperature dissipation and thermal insulation measures, while significantly lowering the risk of thermal runaway propagation.

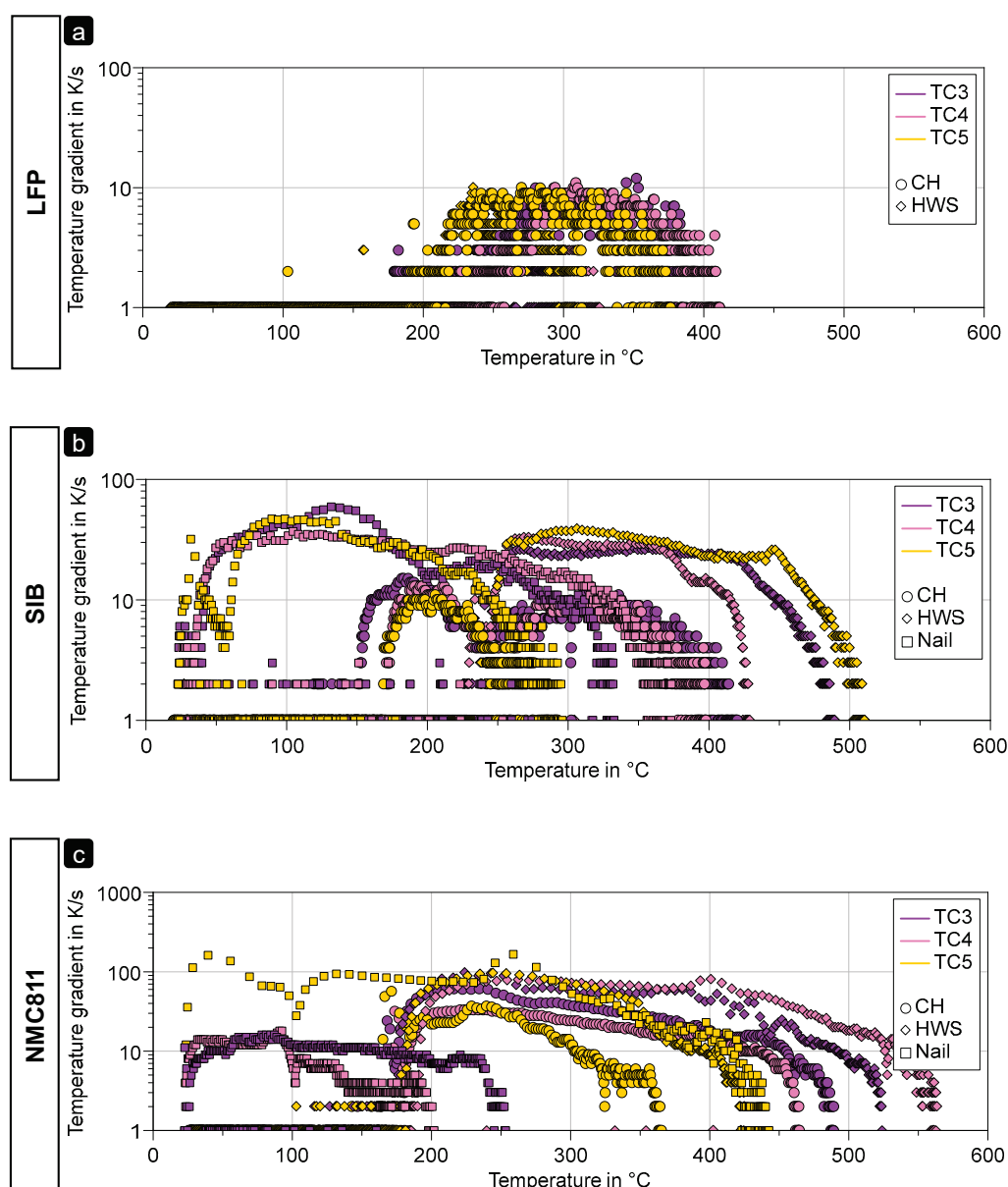


Figure 9. Temperature rise rates at different side surface locations during a thermal runaway depending on the trigger method for each cell chemistry ((a) LFP, (b) SIB, (c) NMC). Note the logarithmic scaling of the temperature gradient as well as the different scaling of the temperature gradient in diagram °C.

As previously stated in Sections 3.1 and 3.2, the SIB cell shows an obvious difference in behavior between the CH and HWS tests. The temperature gradient is very limited, <20 K/s, with the CH test. The values are even close to zero for temperatures above 410 °C. For the HWS test, a temperature gradient greater than 30 K/s is recorded at 450 °C. The highest temperature rise is observed with the nail penetration test, at 70 K/s. These differences in reactivity between the CH and HWS tests are also in agreement with the gas, as discussed in Section 3.4. (see Figure 9). These figures are considerably higher than for the LFP cells, necessitating more sophisticated measures in terms of heat dissipation and propagation mitigation.

The first observations always reported violent reactions of the TR scenarios with the NMC811 cells, i.e., sparks, flame and even explosion for the CH and HWS tests. The NMC811 cell shows the highest temperature rise rates with values higher than 160 K/s for the nail penetration, ca. 100 K/s for the HWS test and greater than 60 K/s for the CH

test (see Figure 9). The temperature gradient is significant in all cases above 400 °C. Consequently, NMC811 cells are the most demanding cells among all tested when considering the safety measures to be planned in a BEV application.

For all conducted NMC811 tests, the measured peak temperatures as well as the computed temperature rise rates align with the scenario of a very energetic auto-combustion of the NMC material, as reported by Liu et al. [10] and the very high temperature reached at the TR. The limited temperature of the TR as well as the low temperature rise rate during the TR of the LFP cell can be explained by the very stable thermal properties of the LFP cathode up to 500 °C even when fully charged [9]. Assuming a similar reactivity for the anode materials of LIBs and SIBs, a contribution of the SIB cathode material to the TR characteristics of the herein-tested SIB cell can be concluded. This is further supported by studies showing metal oxides other than NMC contributing to the cell TR [8,10].

To help the reader, a summary of the main data for different TR events is presented in Table 2. The weight loss illustrates the difference between cathodic material chemistry and the triggering method on the thermal runaway of the cells. Intuitively, we consider that high weight loss corresponds to an important loss of materials, either by combustion or by ejection, i.e., the more reactive the material, the more limited its thermal stability.

Table 2. Main data for different TR events. \$: in case of the nail penetration, t = 0 corresponds to the beginning of the nail penetration itself (see Figures A6 and A7).

Cells	Trigger Method	Vent Time (s)	TR Time (s)	Max. T_{gradient} (K/s)	T_{max} Cell Body (°C)	T_{max} Gases (°C)	Weight Loss (%)
LFP	CH	460	540	10	410	-	14
	HWS	10,850	12,650	10	330	-	19
SIB	CH	390	460	<20	450	275	19
	HWS	10,910	15,560	40	500	-	>50
	Nail	-	18 \$	60	370	450	-
NMC	CH	320	720	60	680	>1100	65
	HWS	7880	10,030	100	600	>1200	>60
	Nail	-	15 \$	>100	440	-	-

From the previous paragraph, we can summarize the cathodic material stability as LFP >> Na_{0.8}Ni_{0.32}Fe_{0.34}Mn_{0.34}O₂ (SIB) > NMC:

- The LFP, as a lithium metal phosphate, has a thermal stability superior to 500 °C [9] even in a fully charged state. Based on the maximum cell body temperature recorded, we can reasonably suppose that LFP did not contribute to any TR event (both CH and HWS) or very little, which agrees with the limited temperature gradient of ca. ≤10 K/s (Figure 9a and related discussion) and weight loss < 20%.
- NMC811 is described as very reactive, especially when fully charged, with thermal stability inferior to 240 °C [10], while the maximum temperature recorded of the cell body is always superior to 650 °C. Thus, combustion and/or ejection of the NMC811 during the TR events (see Figure 5f) are very likely to have occurred, in agreement with a high-temperature gradient (>60 K/s for CH and >90 K/s for HWS; see Figure 9c and related discussion) and a weight loss always superior to 60%.
- We suppose that the cathodic material of the SIB, Na_{0.8}Ni_{0.32}Fe_{0.34}Mn_{0.34}O₂, has a thermal stability relatively close to that of the alkali metal oxides used in the LIB:

- With the CH trigger method, the temperature in the SIB cell is probably not sufficient to lead to any significant degradation of the cathodic material, leading to a limited temperature gradient ≤ 20 K/s (Figure 9b and related discussion) and a weight loss inferior to 20%.
- With the HWS trigger method, the SIB cell is homogeneously heated, and more energy is released during the TR event, with a temperature gradient of ≈ 40 K/s (Figure 9b), allowing a reaction of the cathodic metal oxide, in agreement with a weight loss $> 50\%$ and significant gas release.

3.4. Gas Emission: Combined Impact of the Cell Chemistry and Trigger Method

The gases emitted during the venting of the cells were for all cells mostly composed of dimethyl carbonate (DMC), ethyl methyl carbonate (EMC), hydrogen (H_2), carbon dioxide (CO_2), and carbon monoxide (CO), with the rest represented by other hydrocarbons. These results are in line with the electrolytes being composed of organic carbonate compounds for all investigated chemistries [25,26,28].

The quantification of the amount of gas emitted by the cells during the test protocols shown in Figure 10 reveals unexpected results. Note that the values for the HWS tests have a higher margin of error due to the short sampling time after TR. As expected, the gas volume emitted by the cells after TR is dependent on both testing protocol and cell chemistry. The amount of gas is affected by the degradation path of the electrolyte. In agreement with the literature, the LFP cells show a much smaller capacity-normalized gas emission (L/Ah) compared to the NMC811 cells.

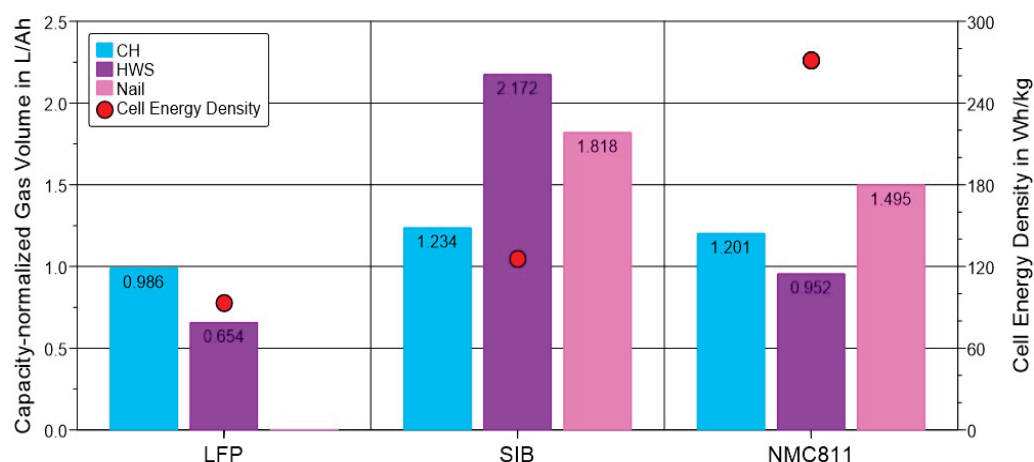


Figure 10. Cell energy density (red dots) in Wh/kg for the LFP, SIB and NMC811 cells as well as the capacity-normalized gas volume in L/Ah emitted during thermal runaway tests using different trigger methods.

Unexpectedly, the normalized gas emission of the SIB chemistry is for all testing protocols higher or at least equal to that of NMC cells and significantly higher than that of the LFP cells. The SIB cells are usually considered safer than the Li-ion cells, as evidenced by enhanced stability at 0 V [29,30]. However, our tests indicate that this may not be the case in the charged state. As previously reported, the electrolytes and anodes of the SIB [31], even if not identical, are very similar to their LIB counterparts [32], being carbonate-based and carbon-based, respectively. In the case of the investigated samples, however, the charged cathodic materials are quite different—a transition metal oxide for the SIB and the NMC811—while the LFP cell features polyanionic $Li_{1-x}FePO_4$. It is very difficult to predict the amount of gas released for each cell as it is influenced by numerous factors that remain unknown for the final user of the cell, for example, the cell design, the active materials

and the electrolyte present in the cell and their respective quantity, and the surface area of the electrodes.

Based on the established knowledge [14,15], during the heating of the cells, gas is emitted first by the continuous reaction of the electrolyte with the anode material when the SEI is not thermally stable anymore ($T > 110\text{--}120\text{ }^{\circ}\text{C}$). Subsequently, when a short circuit is created by the separator melting (this is also the case of nail penetration), the additional heat generated accelerates the electrolyte/anode reaction and electrolyte evaporation. At high temperatures, typically above $200\text{ }^{\circ}\text{C}$, the hot metal oxide present in the SIB contributes to the gas emissions during thermal runaway, similar to the reported degradation of NMC [8,11]. On the other hand, LFP-based cathode materials are known to be stable up to $500\text{ }^{\circ}\text{C}$ and thus to contribute poorly to the heat and gas release during thermal runaway [8,11].

When looking at the safety issues of thermal runaways, especially the safety of passengers, it appears obvious that there is no completely safe battery technology today. However, based on our experimental tests, the LFP cells appear to be less at risk compared to the SIB and NMC811 cells. SIBs are considered a safe technology compared to LIBs, but we have shown in the present study that this is not necessarily the case. Safety knowledge must always be adapted to the evolution of battery technology. Another important safety factor for BEVs is how the battery is designed to prevent, delay, or limit the consequences of TR and propagation phenomena, but this is not the topic of this work.

3.5. Thermal Runaway Simulation as a Basis for Propagation Studies

Modeling thermal runaway is performed based on different, chemistry-specific reaction mechanisms in a high-fidelity 3D environment as typically employed for investigations of thermal propagation phenomena in multi-cell configurations. In the modeling process, various solids are assigned temperature-dependent material properties such as density, specific heat, and thermal conductivity. The cell, Figure 4, is represented as a single solid with anisotropic thermal conductivity along the cell layers. Heat transfer is facilitated through interfaces between the heating foil and the cell, as well as between the clamps and the cell. The transport of heat is influenced by the geometry and material properties of the objects involved. Contact with the ambient fluid, e.g., nitrogen, is modeled using a convection boundary condition, incorporating a heat transfer coefficient and far-field temperature derived from experimental data. When the cell or clamps are insulated, the heat transfer coefficient is reduced to reflect the insulation.

To model chemical reactions during battery thermal runaway, detailed chemical mechanisms for gas-phase combustion kinetics are utilized [33]. Furthermore, established mechanisms, such as those by Hatchard and Kim [34] and Ren [35], are used to evaluate local reaction rates and the associated heat release during thermal runaway. These reaction rates follow the Arrhenius format, depending on local temperatures and material concentrations. Accurate representation of thermal abuse within the cell requires calibration of the employed chemical mechanism. For the NMC811 cell, the reaction mechanism proposed by Ren et al. [35] for NMC Li-ion batteries is selected. Due to the specific nature of thermal runaway behavior, calibration of individual reaction kinetic parameters is essential, using data from controlled tests such as differential scanning calorimetry (DSC), accelerated-rate calorimetry (ARC), heat–wait–seek, or constant heating tests. The goal is to develop a mechanism that, once calibrated, can represent thermal runaway behavior for any initiation method without re-adapting calibration parameters.

In this study, CH test results are used for calibration due to the faster thermal runaway process and lower computational effort. Additionally, a well-represented constant heating test model is expected to better match the thermal runaway triggered by nail penetration.

The calibrated model setup is subsequently employed for simulating the HWS and NP tests and thus confirms the validity of the selected calibration parameter values. To accurately calibrate the thermal runaway mechanism, the thermal behavior of the system—including thermal properties of different solids, heat transfer pathways, and heat losses—must be precisely modeled. Initial calibration involves adjusting the heat transfer coefficient along external walls to model convective heat losses to the ambient fluid, matching the initial temperature rise rate in the absence of exothermic reactions. Monitor points are selected to correspond with thermocouple positions in the experimental setup, ensuring adequate comparison (cf. Figure 3).

The convective evaporation process of the electrolyte, triggered after vent activation, plays a significant role in thermal runaway, as explained by Parhizi et al. [36]. The endothermic process of electrolyte vaporization, however, is absent in the Ren mechanism. To simulate this, a calibrated heat sink term is applied post-venting. The calibrated value aligns with the typical electrolyte heat of vaporization and available mass for 18,650 batteries. If detailed electrolyte data are available, alternatively, a dedicated custom reaction equation can be incorporated into the Ren mechanism [36,37]. While the Ren mechanism is calibrated to NMC811 cell data, a different NMC grade (NMC333, NMC622, etc.) would necessitate re-calibration of the cathode reaction [38]. Adaptations to reliably extend the mechanism's capabilities for various cathode chemistries are under investigation by the authors.

Validation of the NMC cell model employs a 3D single-cell model setup and calibrated Ren mechanisms for NMC811 CH, HWS, and NP single-cell experiments. Figure 11 illustrates a comparative analysis of temperature traces obtained from both measurement and CFD simulation for two distinct experimental setups: constant heating (a) and heat-wait-seek (b). The temperature traces are evaluated at various thermocouple positions, specifically TC3, TC4, and TC5, as depicted in Figure 3. The primary distinction between these two initiation scenarios, from a modeling standpoint, lies in the heating strategy employed in the boundary conditions, which is either continuous or stepwise. Temperature traces from measurements and CFD simulations for constant heating and heat-wait-seek experiments exhibit a good fit, with the model calibrated on CH tests accurately representing thermal runaway in HWS tests. The CH simulation accounts for the mass loss of the cell occurring during the TR due to venting, thereby ensuring that the cooldown phase aligns with the experimental data. The results of the CFD simulation in these two cases appear to be validated.

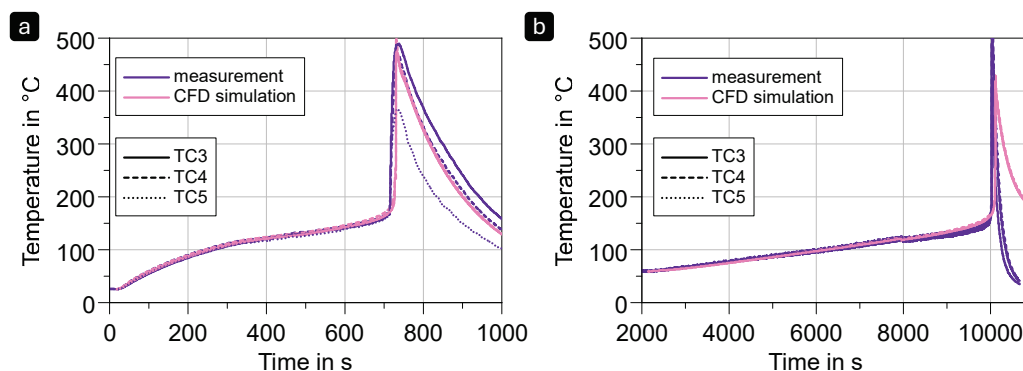


Figure 11. MC811 (a) constant heating, used for NMC model calibration, and (b) heat-wait-seek comparison between measurement and CFD.

For the nail penetration simulations, the same mechanism and model setup, calibrated for using the CH test data, are employed. The nail penetration event induces a local short-circuit, initiating the thermal runaway process within the battery, which initially remains localized [18]. This phenomenon is replicated in the 3D simulations by utilizing a calibrated

short-circuit energy source in the vicinity of the nail to locally trigger the thermal runaway. Figure 12 presents a comparison between the measured and CFD-simulated temperature traces for the monitoring positions nearest to the penetrating nail, for the NMC811 (a) and SIB (b) cells. Both chemistries were simulated under identical boundary conditions and geometrical configurations, with the only variation being the cell chemistry model. The results demonstrate a strong correlation between the measured and simulated temperature data, validating our model.

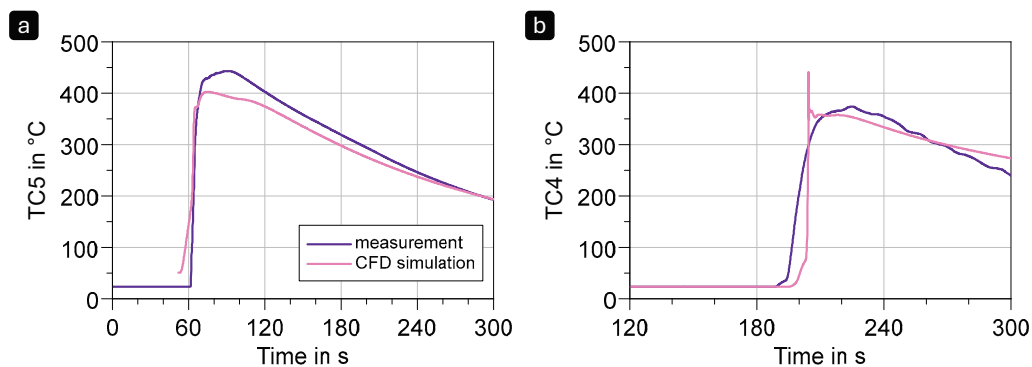


Figure 12. Nail penetration comparison for NMC811 (a) and SIB (b) between measurement and CFD.

Figure 13 depicts the temperature traces recorded by each thermocouple on the lateral cell surface during the heat–wait–seek measurement, alongside the corresponding values obtained from the CFD simulation at the respective monitoring points. Thermocouple TC6, located on the heating pad (cf. Figure 3), is significantly influenced by the electrical energy input and is therefore deemed irrelevant for this analysis. Additionally, thermocouples TC1 and TC2, positioned on the top and bottom canning surfaces of the cell, exhibit considerably lower temperatures during the cell heat-up phase due to their proximity to the clamps (refer to Figure 3). The clamps conduct heat away from the cell, resulting in lower temperatures in their vicinity, which significantly affects the temperature readings and renders the TC1 and TC2 traces unreliable indicators of the internal cell processes. Although thermocouple TC7 is also situated near the heating pad and thus affected by it, it is included in the comparison shown in Figure 13, along with the three thermocouples located on the side canning surface opposing the heating pad (TC3, TC4, and TC5). Among these, TC4 registers the highest temperature due to its central position along the height axis.

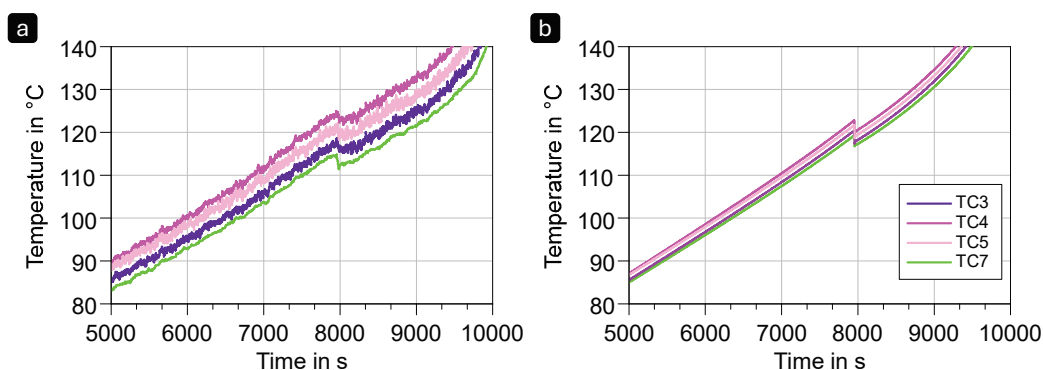


Figure 13. NMC811 heat–wait–seek comparison between different thermocouples in measurement (a) and CFD simulation (b).

Overall, Figure 13 reveals that the order of thermocouples from hottest to coldest in the CFD simulation aligns with the experimental observations. The scatter between the lowest and highest temperature values is also well-matched between the simulation and the experiment. This concordance underscores the CFD simulation’s accurate representation

of the heat exchange processes and the resulting temperature distribution within the cell. The standard Ren mechanism models six distinct reaction domains, each representing interactions within and between various materials present in the Li-ion battery. These domains include SEI decomposition (SEI), reactions between anode and electrolyte (AN-E), cathode and anode (CAT-AN), anode and binder (AN-B), cathode and binder (CAT-B), and cathode decomposition (CAT). The employed simulation approach enables the tracking of individual reaction progress, as illustrated in Figure 14 for the NMC811 constant heating test. The initial self-heating reactions that trigger the thermal runaway process are anticipated to be the SEI decomposition and the anode–electrolyte (AN-E) reactions, which occur at lower temperatures [15]. Subsequently, the binder-related reactions and the cathode decomposition reaction lead to the rapid temperature increase characteristic of the thermal runaway process, resulting in the observed peak temperature levels [15].

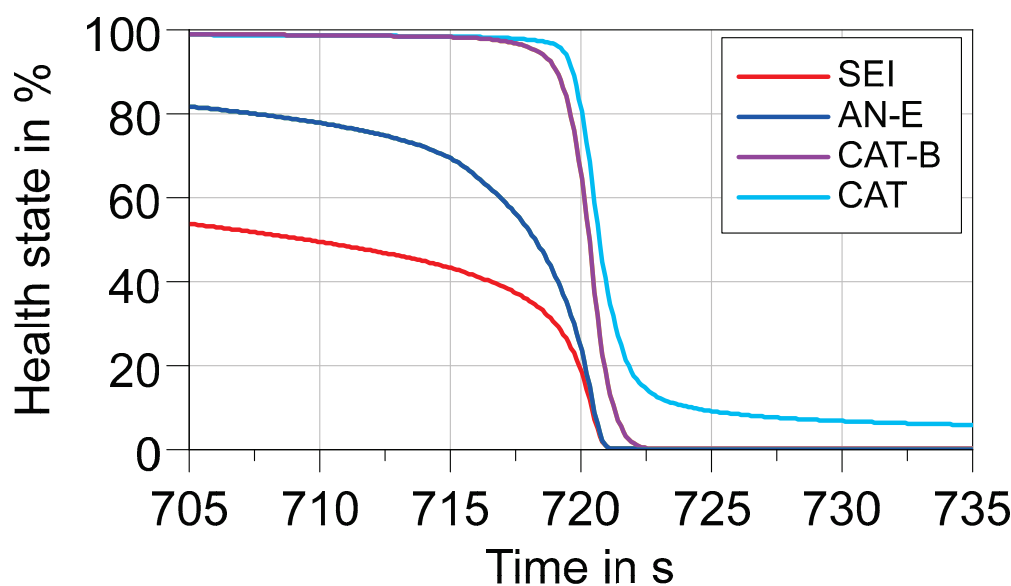


Figure 14. Health state evolution of the NMC811 cell CH thermal runaway reaction progress described with the calibrated Ren mechanism; 100% = pristine state material, 0% = wrecked material.

It is important to note that in this study, the NMC thermal runaway mechanism was calibrated using results from a single CH test of a single battery cell. Previous studies have demonstrated significant variation in thermal runaway behavior, even among cells with the same battery chemistry and from the same manufacturer [39]. Therefore, when applying a thermal runaway mechanism calibrated from one experiment to another, this inherent variation must be considered when compared with experimental data. If repeated tests or cell manufacturing tolerance data are available, statistical modeling of the thermal runaway behavior can also be performed [39,40]. In this study, the calibrated Ren mechanism shows good agreement when applied to different thermal runaway trigger methods, as evidenced in Figures 11 and 12, thereby confirming the validity of the calibration for multiple cell units of the same type.

Due to the differences in chemistry, simulating the thermal runaway of LFP and SIB cells necessitates the use of dedicated mechanisms that account for chemistry-specific effects. For this purpose, the Hatchard-Kim mechanism [34] has been investigated in previous works [41] and is employed for simulating the thermal runaway of LFP cells. The calibration process follows a similar approach to that described for the NMC cell, with model parameter adaptation performed solely for the CH experiment. The results, presented in Figure 15 demonstrate a good representation of the measured LFP thermal

runaway behavior in both the CH (used for calibration) and HWS tests for a randomly selected thermocouple.

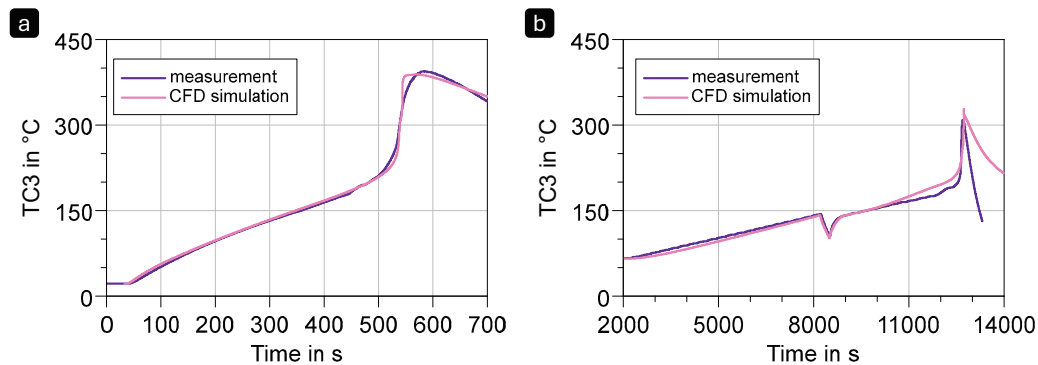


Figure 15. LFP constant heating ((a), used for LFP model calibration) and heat-wait-seek (b) comparison between measurement and CFD.

The absence of a dedicated mechanism for sodium-ion battery (SIB) chemistry in the literature can make the thermal runaway simulation of this chemistry challenging. Considering the numerous similarities between the chemistries of LIB and SIB, the simplest approach is to use an existing model for LIB, which is expected to provide sufficiently usable results for TR simulation. To demonstrate versatility in fitting different thermal runaway mechanisms to various, including new battery chemistries, the SIB model was calibrated using three different mechanisms, including one-step, two-step, and the complete Hatchard-Kim (four-step) mechanisms. Ultimately, the one-step Hatchard-Kim mechanism was selected as it provides good enough results and is less computationally expensive. Figure 16 illustrates an adequate agreement between the temperature traces of arbitrarily chosen thermocouples from both measurement and CFD simulation in the CH and HWS tests of the sodium-ion cell. While this approach provides a solid foundation for simulating thermal runaway in sodium-ion battery cells as an emerging chemistry, achieving a highly accurate representation of the phenomenon that is comparable to the NMC and LFP modeling results necessitates the development of dedicated mechanisms.

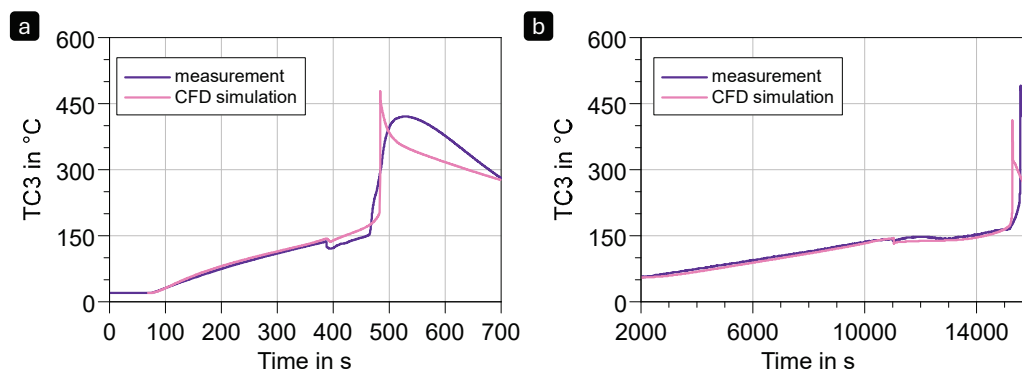


Figure 16. SIB constant heating ((a), used for SIB model calibration) and heat-wait-seek (b) comparison between measurement and CFD.

4. Conclusions

The concept of this study was divided into two steps. The first step was to create an experimental database to evaluate the role of both the battery chemistry and trigger method on the characteristics of the thermal runaway. The second step consisted of using experimental results to develop a simulation methodology for thermal runaway events and thus be able to predict them. The virtual development is flexible; the effect of different

cell chemistries and formats, trigger methods, and other parameters can be simulated in a faster and cheaper way than the equivalent experimental tests.

Different thermal runaway tests have been conducted to simulate the various possible causes for thermal runaway and propagation occurrence in electric vehicle batteries. The experimental campaign is based on three different battery chemistries—LIBs employing either LFP or NMC811 as cathodic material, and an SIB cell employing a cathode based on a transition metal oxide. The presented results clearly confirm the high influence of both the testing conditions and battery chemistry on the thermal runaway phenomenon, i.e., the duration, the venting, the peak temperature and gas release.

Among the three types of cells tested, only the NMC811 showed the most violent reaction with sparks and flames being emitted. As expected, the LFP chemistry appears more compatible with arising safety concerns compared to NMC811. Surprisingly, the fully charged SIB appears less safe than an LFP-based Li-ion battery in the same 18,650-cell format, which shows a considerably lower peak temperature and capacity-normalized gas release. This unexpected finding confirms the necessity for a comprehensive understanding of new battery technologies, with this knowledge necessary for guaranteeing the safety of battery applications.

The presented measurement results are a solid experimental basis that has been further employed for modeling in 3D and predicting the thermal runaway with chemistry-specific reaction mechanisms, with individual reaction rates represented by the typically employed Arrhenius approach. Especially considering the typical manufacturing tolerances and fluctuations of individual cells, it seems to be sufficient to model the cells with mass-averaged, but still cell-specific material properties to keep the data procurement and modeling effort as low as possible while omitting inherent stochastic effects. Coupled with accurate thermal properties of different solids, heat transfer pathways and heat losses, this approach yields an accurate 3D temperature field providing insight into physical processes that are not accessible with typical experimental methods.

Ultimately, this enables the models to accurately represent the occurrence of the thermal runaway phenomenon for different triggering methods (i.e., timing) and cell chemistries (i.e., temperatures) as a fundamental prerequisite for capturing the thermal propagation phenomenon in battery packs. Even though models will always be reliant on data gathered from real-world tests, our approach represents another step towards a reliable model-based battery module and pack development with optimized safety and a limited number of physical tests and decreases the cost, thus enhancing the overall economic viability of the development process.

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Conflicts of Interest: Sébastien Sallard and Brahim Soltani are employees of IAV France S.A.S, 4 rue Guynemer, 78280 Guyancourt, France. Oliver Nolte, Lorenz von Roemer, Alexander Fandakov, Karsten Mueller, Maria Kalogirou, and Marc Sens are employees of IAV GmbH, Carnotstrasse 1, 10587 Berlin, Germany. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

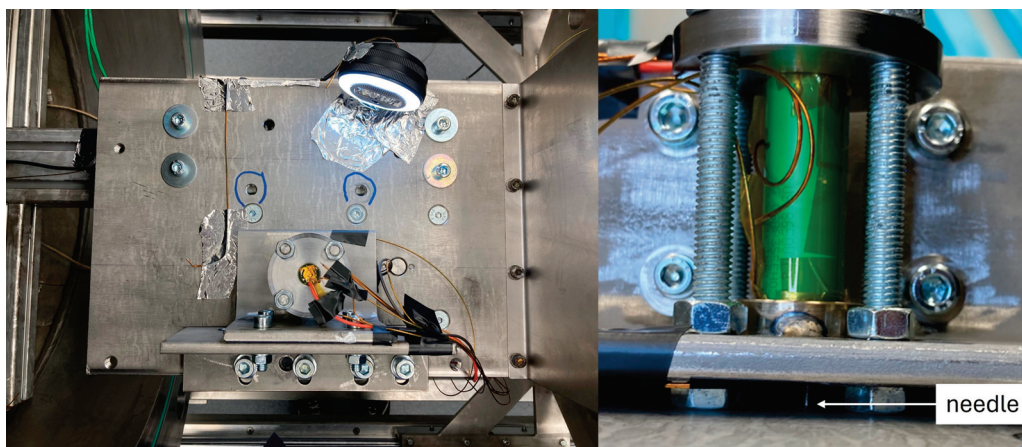


Figure A1. NMC811 cell located in the autoclave and with a specific cell holder for the nail penetration test.

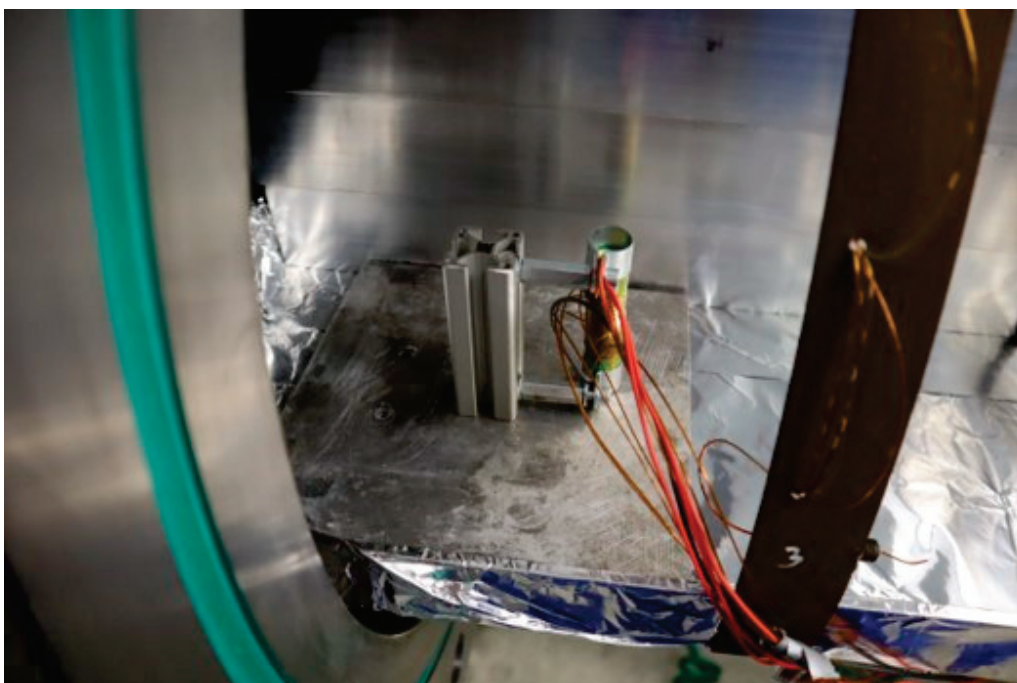


Figure A2. NMC811 cell with temperature sensors and one heating pad located in the autoclave before the thermal runaway experiment.



Figure A3. LFP cell during CH experiment at ca. 928 s after beginning of the experiment.

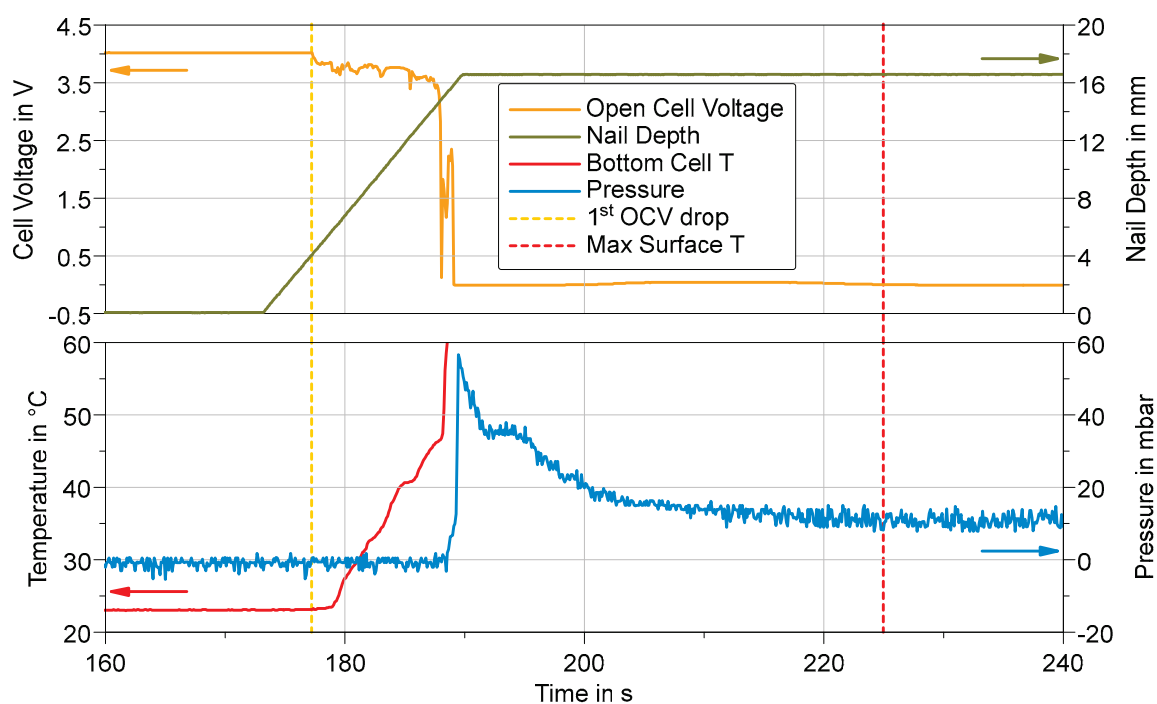


Figure A4. Overview of important sensor traces during the SIB nail penetration test. The top panel shows cell voltage and nail penetration depth, while the bottom panel shows the temperature at the cell bottom and the autoclave pressure, all as a function of time. The first detection of cell voltage deviations as well as the point of maximum temperature on the lateral cell surface are indicated by dashed lines.

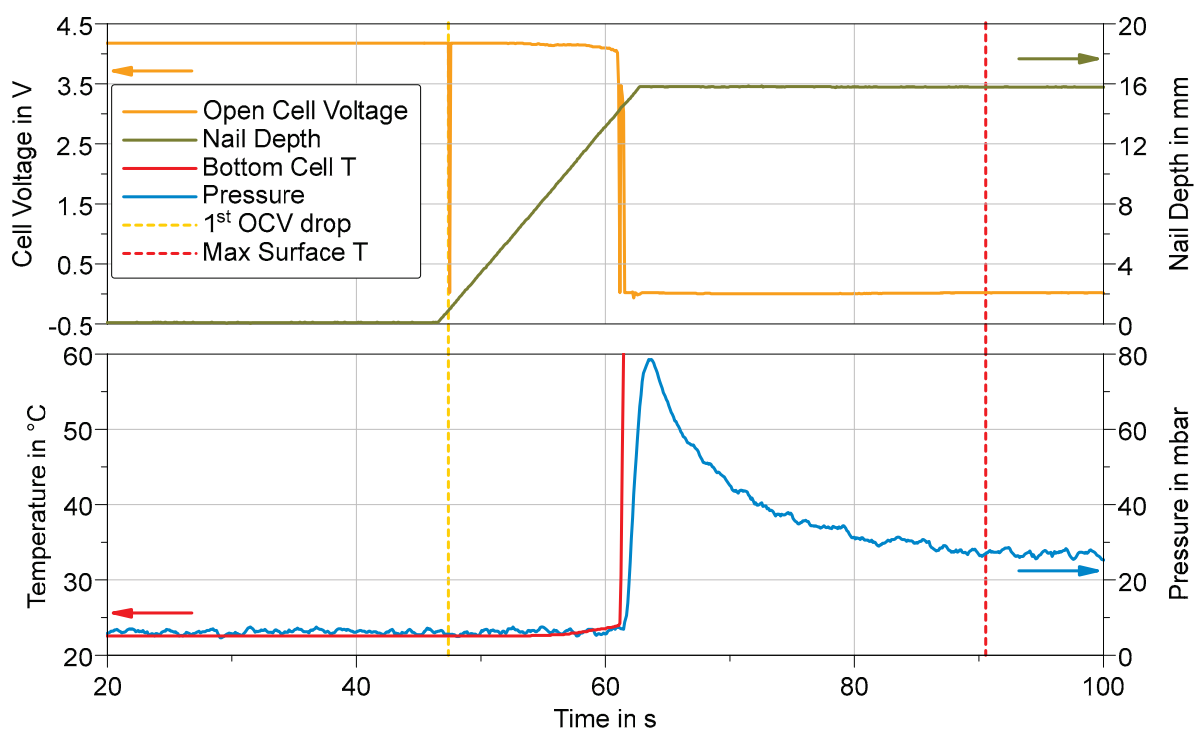


Figure A5. Overview of important sensor traces during the NMC nail penetration test. The top panel shows cell voltage and nail penetration depth, while the bottom panel shows the temperature at the cell bottom and the autoclave pressure, all as a function of time. The first detection of cell voltage deviations as well as the point of maximum temperature on the lateral cell surface are indicated by dashed lines.

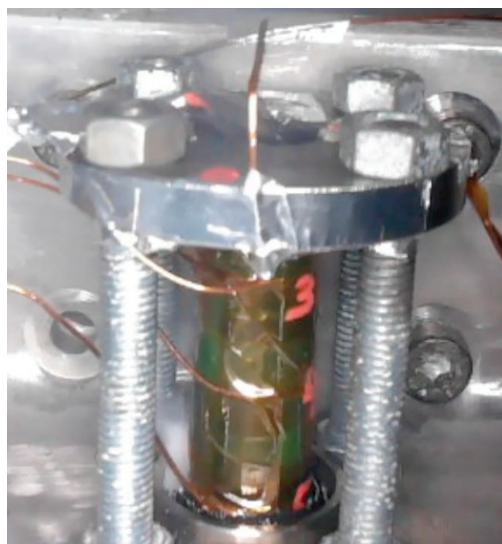


Figure A6. SIB cell during nail penetration test, ca. 1 s after Figure 7c. A small but dense white smoke emission is visible on the bottom left of the cell.

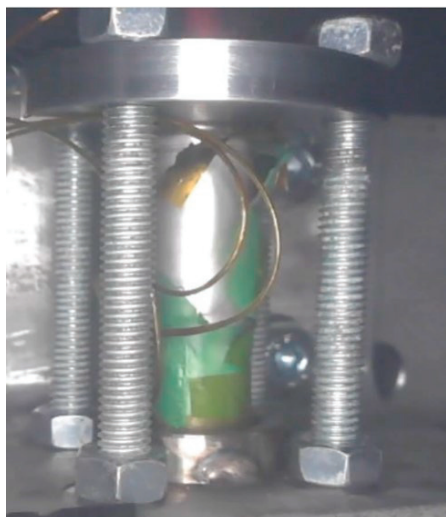


Figure A7. NMC811 cell during nail penetration test, ca. 1.5 s after Figure 7d. Flames become visible on the top of the cell holder and last for 2 more seconds. A tenuous smoke, emitted from the cell since the start of the TR, explains the blurry nature of the recording.

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Article

Synthetic Data Generation for AI-Informed End-of-Line Testing for Lithium-Ion Battery Production

Tessa Krause ^{1,2,*}, Daniel Nusko ^{3,4}, Johannes Rittmann ¹, Luciana Pitta Bauermann ³ and Moritz Kroll ³ and Carlo Holly ^{2,5}

¹ Precitec GmbH & Co. KG, Draisstraße 1, 76571 Gaggenau, Germany

² Chair for Technology of Optical Systems TOS, RWTH Aachen University, Steinbachstraße 15, 52074 Aachen, Germany; carlo.holly@tos.rwth-aachen.de

³ Fraunhofer ISE—Institute for Solar Energy Systems, Heidenhofstraße 2, 79110 Freiburg, Germany; moritz.kroll@ise.fraunhofer.de (M.K.)

⁴ Department of Sustainable Systems Engineering—INATECH, Faculty of Engineering, Albert Ludwigs University of Freiburg, Emmy-Noether-Straße 2, 79110 Freiburg, Germany

⁵ Fraunhofer ILT—Institute for Laser Technology, Steinbachstraße 15, 52074 Aachen, Germany

* Correspondence: tessa.krause@tos.rwth-aachen.de

Abstract: Lithium-ion batteries are a key technology in supply chains for modern electric vehicles. Their production is complex and can be prone to defects. As such, the detection of defective batteries is critical to ensure performance and consumer safety. Existing end-of-line testing relies heavily on electrical measurements for identifying defective cells. However, it is possible that not all pertinent information is encoded within the electrical measurements alone. Reversible expansion in lithium-ion cells is an indicator of lithiation within the cell, while irreversible expansion is a consequence of the ageing process; unexpected expansion may indicate the presence of undesirable defects. By measuring expansion in addition to electrical measurements, we aim to make better and faster quality predictions during end-of-line testing, thereby facilitating the early detection of potential defects. To make these predictions, we implement artificial intelligence algorithms to extract information from the measurements. Training these networks requires large training datasets, which are expensive to produce. In this paper, we demonstrate a first-order physical modelling approach for generating synthetic data to pre-train artificial intelligence algorithms that perform anomaly detection on lithium-ion battery cells at the end-of-line. The equivalent circuit model used to generate voltage curves could be fit to real data with a mean absolute error of less than 1 %, and the expansion model could be fit to a mean absolute error of less than 2 % of the measured values. By pretraining the artificial intelligence network using synthetic data, we can leverage existing physical models to reduce the amount of training data required.

Keywords: lithium-ion battery; end-of-line testing; system modelling; artificial intelligence; cell expansion; cell defects

1. Introduction

The production of lithium-ion batteries is a critical process in the manufacturing of modern electric vehicles. Lithium-ion battery technology requires complex, multi-step processes to generate cells, in which defects are likely to arise in various stages. These defects can have effects ranging from poor electrical performance to catastrophic thermal runaway, both of which must be avoided. Even a small number of defective cells can pose significant dangers to people and infrastructure; this underscores the necessity to identify

and mitigate potential safety risks as much as possible to avoid both loss of trust in the technology and economic consequences for manufacturers.

As such, end-of-line testing is an important step in ensuring the safety and performance of products that contain lithium-ion battery cells. Existing end-of-line testing approaches typically rely on electrical and temperature measurements during battery cell testing. Lithium-ion battery cells experience reversible swelling due to the intercalation and deintercalation of lithium-ions into and out of the active materials within the cell. In addition to the unavoidable ageing process, irreversible expansion can occur due to undesirable gas formation, formation of the solid electrolyte interphase (SEI) and lithium plating, among other undesirable events within the cell. Characterizing the volume expansion of these cells—in addition to standard electrical and temperature measurements—creates the possibility of gaining additional insights into the quality of cells during final testing.

The resulting data from these end-of-line tests will be composed of complex multivariate time series. Artificial intelligence algorithms have shown promise in extracting meaningful information from multivariate time series data, such as those we are collecting. These algorithms typically require a large amount of training data, which for end-of-line battery testing are expensive and time-consuming to generate. In this paper, we propose a first-order physical model to generate synthetic cycling data for pre-training and evaluating the usefulness of artificial intelligence networks. These synthetic datasets are intended to be used for the pre-training and evaluation of unsupervised methods; therefore, we only must consider the modelling of normal, and not defective, lithium-ion battery cells.

2. Background

End-of-line testing is a ubiquitous step performed at the end of the battery manufacturing process to not only remove defective cells but also to assign grades indicating performance. End-of-line testing can involve visual inspection and various electrical measurements to ensure the cell meets design requirements [1–3]. Currently, there is no universally accepted standard for these end-of-line tests, and each cell manufacturer employs its own procedures.

In addition to electrical measurements, one could also measure the volume expansion of the battery cell to gain greater insights. Volume expansion in lithium-ion cells has irreversible and reversible manifestations; both modes of expansion provide valuable information regarding potential performance and manufacturing defects. Manufacturing defects could include issues such as uneven electrode coating, metal particle contamination, poor electrode sheet alignment, and compromised separator material, among others [4]. Irreversible expansion can be caused by the formation of the SEI layer, as a result of gas formation, or by lithium plating, all of which are a consequence of undesirable electrochemical reactions occurring within the cell [5,6]. Reversible expansion is inherent during charge/discharge cycles because it is a product of the intercalation of lithium ions between the positive and negative electrodes [7]. A number of researchers have measured battery expansion during ageing. However, the goal of their research was to validate battery expansion models rather than to identify defects within the cells [8,9].

To extract information from the multivariate time series generated during end-of-line tests, artificial intelligence methods have shown promise in both anomaly detection and classification applications [10,11]. Artificial intelligence is already being used for assessing performance and quality in lithium-ion batteries. When large amounts of training data are available, artificial intelligence (AI) algorithms can glean more information from datasets than is possible with more traditional data analysis techniques [12]. One of the most common use cases for AI in lithium-ion battery applications is remaining useful lifetime (RUL) predictions [13,14]. In RUL applications, large datasets can be generated using

relatively few batteries. These datasets typically include information on time, current, voltage, and temperature, and are collected over several months through continuous charging and discharging of the batteries. Some researchers have attempted to use artificial intelligence to improve quality assurance. In comparison with RUL prediction, in which multiple datasets can be generated from a single battery, quality assurance prediction necessitates one battery cell for every training sample. Generating a dataset that includes both normal and abnormal cells is particularly challenging and costly because it is rare to find multiple cells displaying the same type and position of defects. Additionally, these cells must be managed under the strictest safety conditions because of the potential risk of fire and explosion [4,15]. The controlled introduction of relevant defects is also very time-consuming and safety-critical [16]. To circumvent expensive and time-consuming dataset generation, some researchers are developing quality assurance predictors trained on synthetic data. Jia et al. created an internal short circuit classifier, trained on nearly exclusively simulation data [17]. Another example is the work of Turetskyy et al., who trained a neural network to solve for unknown parameters in electrochemical models using simulated voltage and current curves, as well as electrode information [18]. Both works achieved accurate predictions on computer-generated training data.

3. Methods and Materials

3.1. Measurement During Cell Cycling

The pouch cells used in this study have a nominal capacity of 1 Ah and are composed of a $\text{LiNi}_{0.6}\text{Mn}_{0.2}\text{Co}_{0.2}$ (NMC622) cathode and an artificial graphite anode. The cells have dimensions of 66 mm by 51 mm by 3 mm. Cycling was performed using a Basytec CTS Standard battery tester. To avoid inducing thermal expansion, cycling was performed with 0.5 C charge current and 1 C discharge current. Data from the battery tester were acquired with a sampling rate of 1 Hz. The recorded cycles are conducted on new, unaged cells.

In our previous study, the pouch cells were cycled without any external pressure [19]. These measurements were performed to assess the homogeneity of swelling across the cell's surface during cycling. However, in practice, pouch cells are nearly always cycled under compression to prevent delamination and ensure good contact between the various components within the cell [20–22].

A testing setup developed by Fraunhofer ISE [23] was used to compress the battery cell in a vertical position. The apparatus is shown in Figure 1. To achieve compression, the test rig is composed of two pressure plates: one fixed and one moveable. A pneumatic cylinder applies a defined force against the moveable pressure plate and holds it in place. A ball joint is utilized at the connection point between the movable pressure plate and the pneumatic cylinder piston. This ball joint allows the pressure plate to move in the direction of the piston as the cell expands uniformly and rotate with respect to any non-uniform expansion of the battery cell. Three displacement sensors, which are connected to the fixed pressure plate, can measure this uniform or non-uniform movement of the moveable pressure plate. We utilised chromatic confocal point sensors produced by Precitec Optronik GmbH with a 2 mm measurement range, a linearity of 260 nm, and a measurement spot size of 6 μm . This design enables the measurement of the spatially resolved expansion and contraction of the battery cell.

To ensure constant temperature conditions, the entire cycling program was performed in a climate chamber, a KB 720 produced by Binder GmbH, held at a temperature of 25 °C.

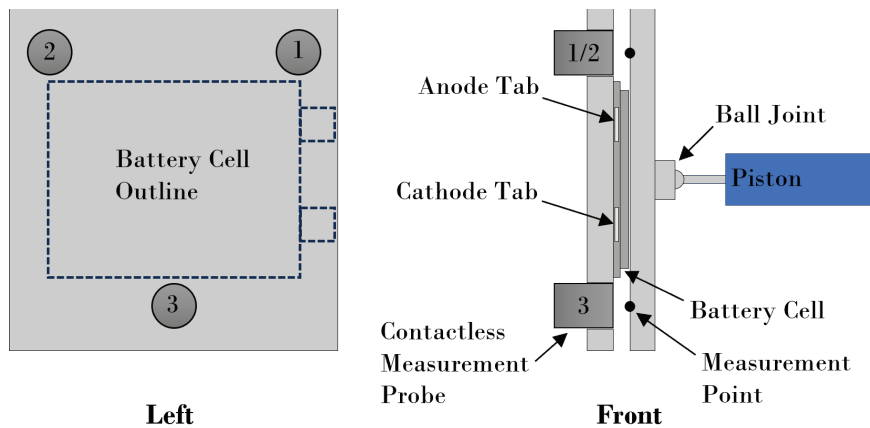


Figure 1. Simplified drawing of battery cell test rig (patent pending: [23]). The left drawing shows a side view of the test stand. The dashed line represents the outline of the battery cell. Points 1, 2, and 3 indicate the sensor positions for contactless distance measurements using chromatic confocal point measurement. The right drawing shows the front view of the test stand, where components, such as the piston and ball joint—required for cell compression—are illustrated. Points 1, 2, and 3 again represent the projected positions of the contactless measurement probe.

3.2. Cell Characterization

To perform equivalent circuit modelling, an open circuit voltage (OCV) curve is necessary. This curve was generated by charging the battery cell up to its upper cut-off voltage of 4.2 V with a charging rate of $C/10$. A resting phase of 1 h was implemented to ensure thermal equilibrium after charging the battery cell. Discharging was then carried out with a discharge rate of $C/10$ in steps of 2 % depth of discharge (DoD) until reaching the lower cut-off voltage of 3.0 V. These DoD steps were determined using coulomb counting. After every 2 % DoD discharge step, a resting phase of 1 h was performed. A voltage drop can be seen at the beginning of the rest phase. This resting phase was then used to determine a thermal equilibrium as well as a load-free voltage level. At the end of the rest phase, the voltage level was taken to be the OCV at the corresponding state of charge (SoC). The measurement used to generate the OCV curve discharge is shown in Figure 2.

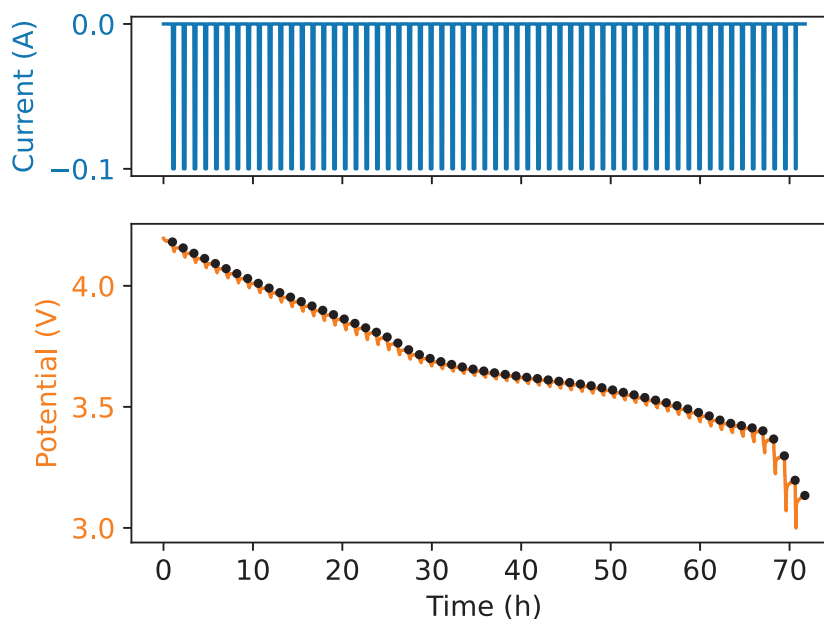


Figure 2. Current and voltage measurement data for open circuit voltage curve generation. Black dots denote points where open circuit voltage values were taken.

3.3. Modelling

To simplify the modelling and reduce the effects of thermal expansion in the battery cell, the cycling was performed at relatively low currents, which minimizes heat generation during the measurements. As such, no thermal modelling was performed, and thermal contributions were not considered in the electrical or expansion models.

3.3.1. Equivalent Thevenin Circuit Model

When modelling the electrical behaviour of lithium-ion cells, one could use either an electrochemical model or an equivalent circuit model [24,25]. The most common approach to electrochemical modelling is to utilise a pseudo 2-dimensional (P2D) interpretation of the dynamics inside the cell [26–28]. While P2D models offer a physical way to model the electrical behaviour of the cell, developing these models is complex and computationally expensive. The goal of this publication is to develop a first-order method for generating synthetic data rather than to generate the most accurate representation of the electrochemical dynamics within a lithium-ion cell. We therefore opt to implement an equivalent circuit model (ECM) to generate synthetic electrical data in favour of making use of an electrochemical model. ECMs are widely used to model the voltage output of a cell under different loading conditions [25,29–31]. The circuit diagram for the ECM is shown in Figure 3, where an integer number, n , of resistor-capacitor (RC) pairs in series are used to reproduce the transient voltage response of the cell during charge and discharge.

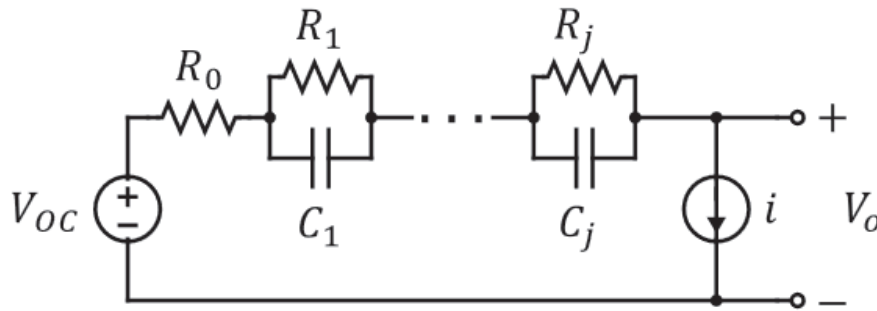


Figure 3. Equivalent circuit model for a lithium-ion battery with an arbitrary number of resistor-capacitor elements.

Starting from Kirchoff's second rule, we generate the following expression for the output voltage:

$$V_o(k) = V_{OC}(SoC) + R_0 i(k) + \sum_{j=1}^{n_{rc}} R_j(SoC) i_j(k). \quad (1)$$

It has been demonstrated that the resistors in the RC pairs, R_j , have a SoC dependency [25,30,31], and we therefore must select an expression $f(SoC)$ such that

$$R_j(SoC) = f(SoC), \quad (2)$$

where $f(SOC)$ will be selected during model fitting.

Next, we require an expression for the current through the resistive element in the j^{th} RC pair. This gives

$$i_j(k+1) = \exp(-T_s/\tau_j) i_j(k) + (1 - \exp(-T_s/\tau_j)) i(k), \quad (3)$$

where T_s is the sampling period, k is the integer-valued time step, i_j is the current through the j^{th} resistive element, τ_j is the time constant for the j^{th} RC pair, and i is the applied current [30]. For any RC pair, the time constant is given by

$$\tau = \frac{1}{RC}. \quad (4)$$

The state of charge is updated using current counting. This gives the expression

$$SoC(k+1) = SoC(k) + \frac{T_s}{3600 C_n} i(k), \quad (5)$$

where C_n is the nominal capacity of the battery cell in Ah, which is multiplied by 3600 to convert the measurement to As.

3.3.2. Expansion Model

To develop an expansion model, we first consider the expansion behaviour of an unconstrained cell, as outlined in Krause et al. [19], prior to considering the expansion behaviour of a compressed cell.

Before considering the expansion of the composite cell, we first look at the expansion behaviour of the individual electrode materials during lithiation. The cell being modelled has a graphite anode and an NMC622 cathode. The electrode deformation as a function of lithiation is taken from Clerici et al. [32] for graphite and Quilty et al. [33] for NMC622. The lithiation curves for both electrode materials were taken at 1 C. Electrode deformation is plotted as a function of SoC in Figure 4. Note that NMC622 demonstrates a linear relationship between expansion and lithiation. In addition, this material exhibits no hysteresis between charge and discharge. In contrast, the expansion of graphite is more complex due to the different stages of graphite lithiation.

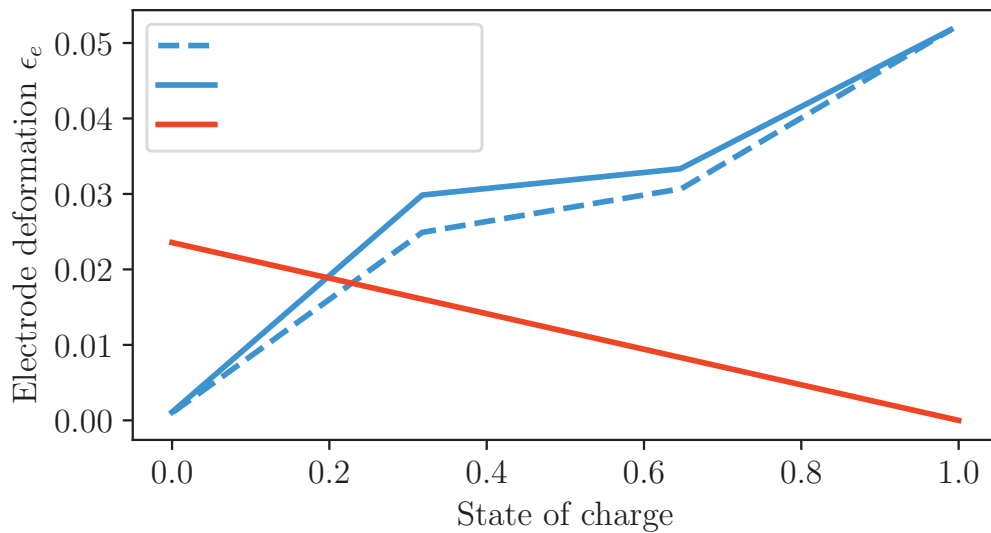


Figure 4. Volume deformation ratios ϵ_e , for graphite and NMC622 as a function of state of charge. Curves are generated from data in [32] for graphite, and from [33] for NMC622.

The expansion of an uncompressed cell is given by

$$\Delta t_{unc} = M C_{case} (\epsilon_{an} \xi_{an} t + \epsilon_{ct} \xi_{ct} t_{ct}), \quad (6)$$

where M is the number of electrode pairs, C_{case} is the constraint ratio of the battery case, ϵ_{an} and ϵ_{ct} are the electrode deformation for the anode and cathode, respectively (shown in

Figure 4 for a graphite anode and an NMC622 cathode), ξ_{an} and ξ_{ct} are the active volume fractions for the respective electrodes, t_{an} and t_{ct} are the respective electrode thicknesses.

Now that we have an expression for the expansion of an uncompressed cell, we can consider the effect of the application of a compressive force on the total expansion. We start with the balance of forces in the system at an arbitrary point $p(x, y)$, as shown in Figure 5. This yields the balance of forces

$$F_{net} = F_{plate} - F_{cell}. \quad (7)$$

If the plate was not moving and the system were in equilibrium we would have

$$0 = F_{plate} - F_{cell}. \quad (8)$$

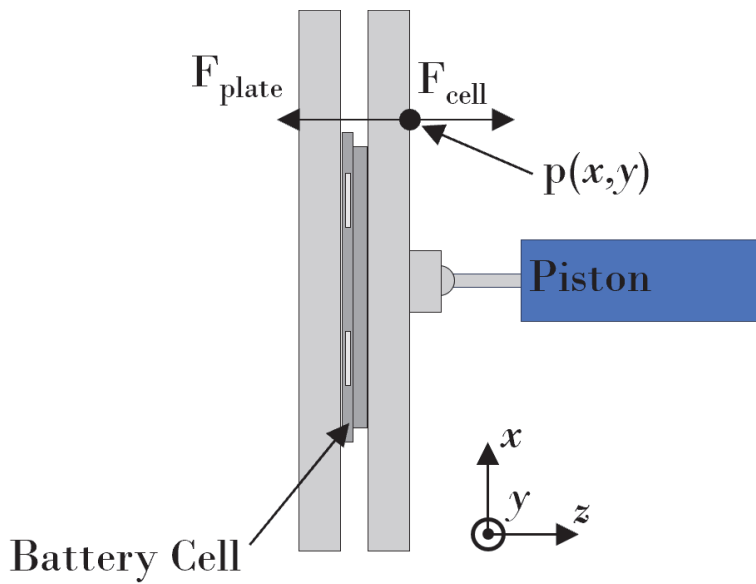


Figure 5. Force diagram at a point $p(x, y)$ on the pressure plate (right), which is compressing a battery cell against a fixed plate (left).

However, the system is not in equilibrium, so we must develop representations for all forces within it. While we could model F_{pis} as an air spring, because the displacement is relatively small, we assume that F_{pis} is a constant. F_{cell} is dependent on the unconstrained expansion calculated in Equation (6). We treat the cell as an expanding object with Young's modulus E and area A , to give

$$F_{cell} = EA\Delta t_{unc}. \quad (9)$$

We are ultimately measuring the movement of a plate with mass m . This gives the differential equation

$$m\ddot{z} = F_{plate} - F_{cell}. \quad (10)$$

Since this equation is difficult to solve analytically, we implement Euler's method, yielding

$$\begin{bmatrix} z_{n+1} \\ \dot{z}_{n+1} \\ \ddot{z}_{n+1} \end{bmatrix} = \begin{bmatrix} z_n + h\dot{z}_n \\ \dot{z}_n + h\ddot{z}_n \\ \frac{1}{m}(F_{plate} - F_{cell}) \end{bmatrix} \quad (11)$$

where z is the displacement at point $p(x, y)$ in the z direction, $\dot{z}$ and $\ddot{z}$ represent the first and second derivative with respect to time, and h represents the step size, also with respect to time.

3.3.3. Model Fitting

The models for both the electrical and expansion behaviour have now been established. Next, we must develop a fitting methodology, starting with the parameters that must be fit. It is useful to split the fitting process by whether the cell is charging or discharging. This will leave us with two sets of fitting parameters. For clarity, we further split the parameters into those needed for the electrical and expansion models. For the electrical model, we need to fit the parameters, with all variables being defined above. In total, there are 27 parameters that need to be fit for the electrical model, as SOC_{init} is fit only for either charge or discharge, depending on which is performed first.

$$P = \begin{bmatrix} R_0 \\ R_1(a_1, b_1, c_1) \\ R_2(a_2, b_2, c_2) \\ R_3(a_3, b_3, c_3) \\ \tau_1 \\ \tau_2 \\ \tau_3 \\ SOC_{init} \end{bmatrix}. \quad (12)$$

Out of convenience, R_j is chosen to be of the form

$$R_j(SoC) = c_j \exp(-a_j SoC) + b_j, \quad (13)$$

where a_j , b_j , and c_j must be fit for each RC-pair.

For the expansion model, we fit a separate set of parameters for each of the three sensor positions. In the expansion model, we bundle some of the variables in the expansion model to single parameters to be fit. This is shown below.

$$P = \begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ \dot{z}_0 \\ SOC_{init} \end{bmatrix} = \begin{bmatrix} F_{pis} \\ EAMC_{case} \zeta_{an} t_{an} \\ EAMC_{case} \zeta_{cat} t_{cat} \\ \dot{z}_0 \\ SOC_{init} \end{bmatrix} \quad (14)$$

Since there are three sensors, and we need a set of parameters for both charge and discharge, this gives 30 parameters that need to be fit for the expansion model.

In total, we have 57 parameters that need to be fit. Fitting is performed using the Scipy optimize package using the Nelder–Mead method.

4. Results and Analysis

4.1. Measurement

For the purpose of generating model parameters for synthetic data generation, we cycle nine cells. To obtain equivalent circuit model parameters, voltage curves from all nine cells were utilized. For the expansion model, the information from two of the nine cells is used. The electrical data collected in the original campaign are used to both verify the model fitting and generate parameters for synthetic data generation. At this time, the limited expansion data are only used to verify model fitting.

4.2. Model Fitting

To verify that the models developed in the previous section accurately represent the experimental data, we fit the models using data from the two cells that provided both

voltage and expansion curves. In Figure 6a, we present the fitted model alongside the experimental voltage curves. The results clearly show a strong agreement between the model and the data. We next examine the residuals, shown in Figure 6b. While it is clear that there are certain segments of the voltage curve that fit better than others, the mean absolute error is less than 6 mV with a maximum residual of 24 mV.

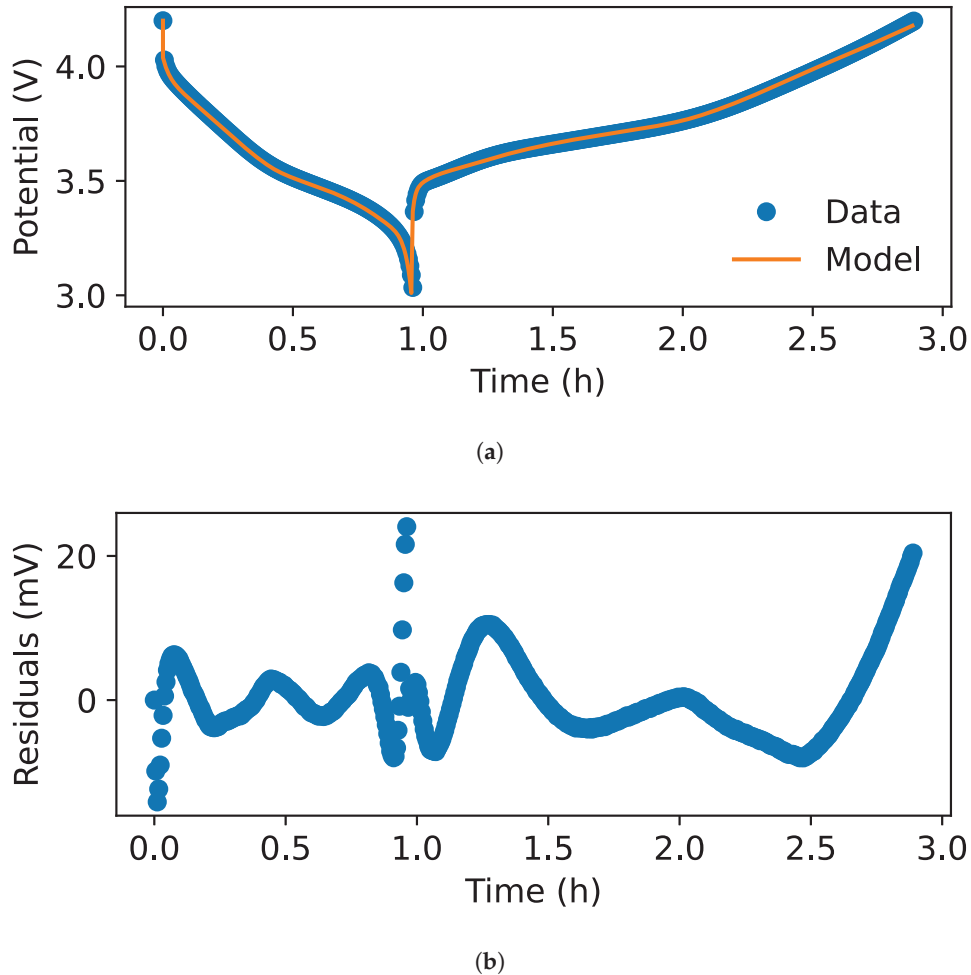
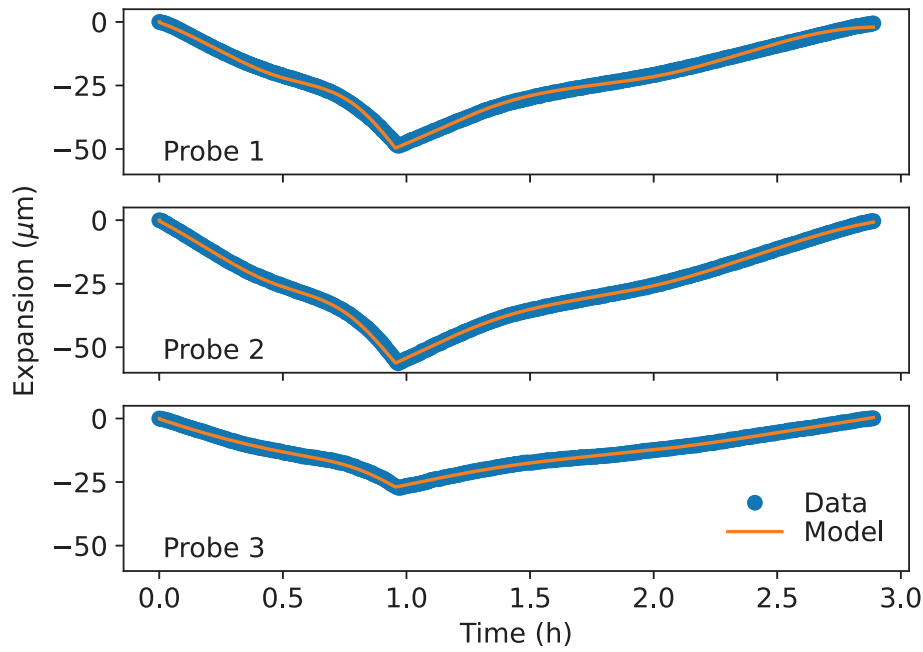
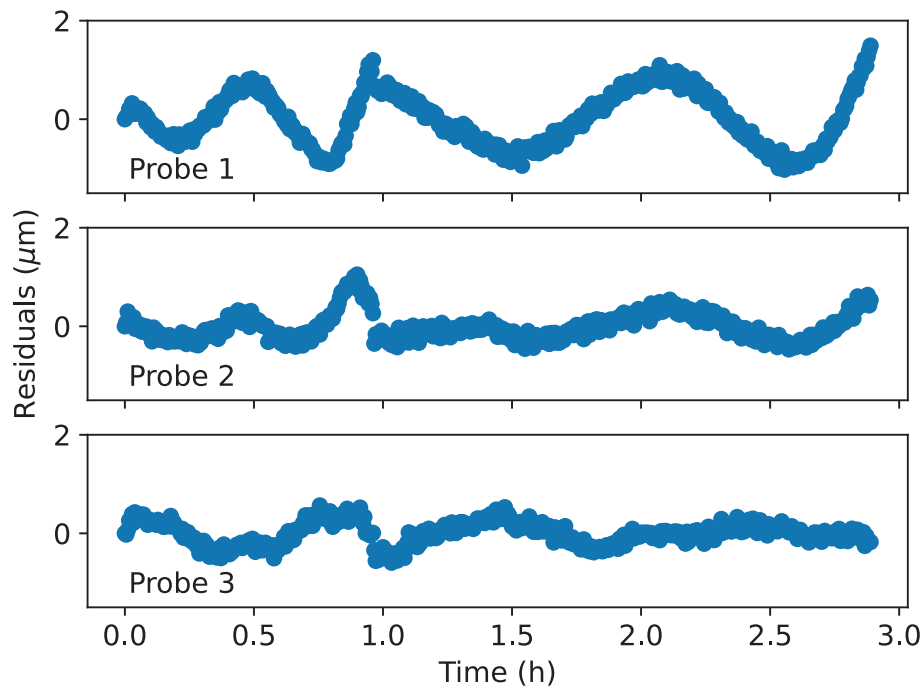


Figure 6. (a) Voltage measurements, plotted in blue, and the fit model (V_o), plotted in orange, for a lithium-ion battery cell discharged at 1 C and charged at 0.5 C. (b) The residuals corresponding to the difference between the experimental data and the model shown in (a).

We next fit the model developed for cell expansion during cycling. As we measure cell expansion at three points, we must fit the model to the data taken at each of the measurement locations. The overlay of the model on the measurement data taken using the three optical probes is shown in Figure 7a. The corresponding residuals are shown in Figure 7b. The mean absolute errors between the model and the measurement data are 0.4 μm , 0.2 μm , and 0.2 μm for data taken using measurement probes 1, 2, and 3, respectively. The maximum residuals are 1.5 μm , 1 μm , and 0.6 μm for data taken using measurement probes 1, 2, and 3, respectively. The mean absolute error corresponds to a percentage error of 2 %, 0.9 %, and 1 % relative to the average measurement for probes 1, 2, and 3 respectively. The residuals are evenly distributed around zero, implying a good fit to the measurement data.



(a)



(b)

Figure 7. (a) Expansion measurements taken at three different points, plotted in blue, and the fit model, plotted in orange, for a lithium-ion battery cell discharged at 1 C and charged at 0.5 C. (b) The residuals corresponding to the difference between the experimental data and the model shown in (a). For details on the positioning of the probes, see Figure 1.

4.3. Synthetic Data Generation

To demonstrate the synthetic data generation methodology, the electrical model is fit using data from nine identical battery cells, generating nine different sets of fitting parameters. During an initial inspection of values, it was discovered that the model could be simplified for this specific battery cell type. During charge, the values fit for the a_j terms

were on the order of less than 10^{-4} . Due to the small a_j terms, the input to the exponential function used to calculate R_j approaches zero. This means that the transient resistance values can be represented as

$$R_j \approx c_j + b_j. \quad (15)$$

This simplification does not hold during discharge, and Equation (13) continues to be a reasonable representation of the transient resistance values when fitting the model to data taken during discharge.

To assess how the model is being fit to data taken from different battery cells, it is useful to visualize the distribution of parameter fits in each instance. Plotting the distributions is also useful in assessing whether any of the cells being used for model fitting are outliers. In order to effectively visualise the distribution of each fitting parameter, we scale each parameter to the mean and represent each individual fit parameter as a percentage deviation from the mean.

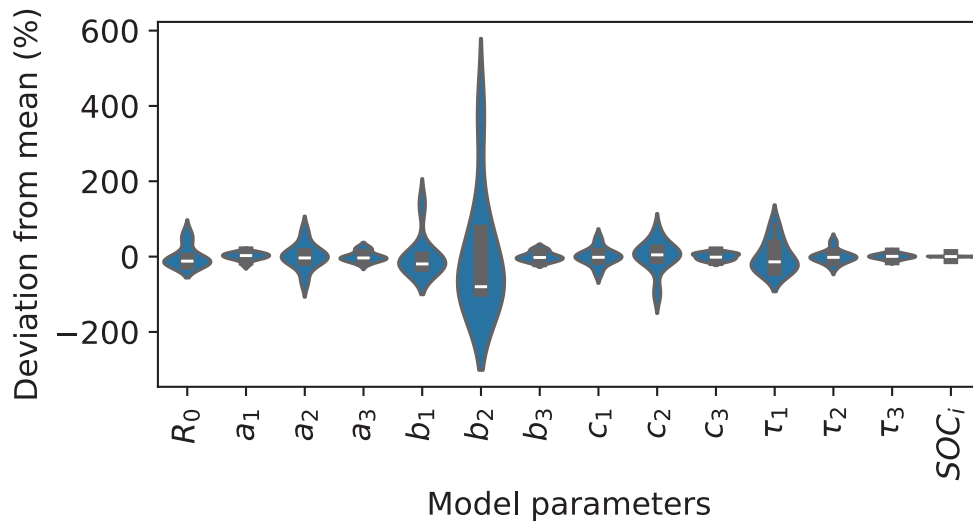
Figure 8 shows violin plots for both discharge and charge parameters, as detailed in the previous section. The distributions demonstrate that there is at least one battery cell with fit parameters that appear to be outlying. When looking at these distributions, it may be useful to consider that the mean values of each of these parameters are of different orders of magnitude. The mean and standard deviations of the model parameters are shown in Tables 1 and 2.

Table 1. Mean and standard deviation of model parameters for the discharge mode generated by fitting voltage curves of nine lithium-ion battery cells

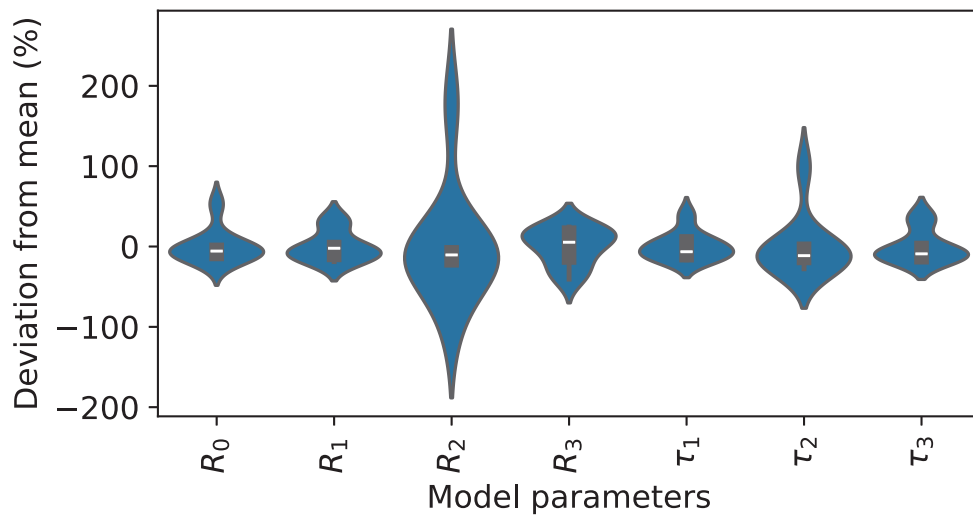
	Mean	Std
R_0	$4.96 \times 10^{-3} \Omega$	$1.42 \times 10^{-3} \Omega$
a_1	4.61×10^1	0.44×10^1
a_2	5.17	1.73
a_3	1.92	0.25
b_1	$9.20 \times 10^{-8} \Omega$	$4.86 \times 10^{-8} \Omega$
b_2	$4.57 \times 10^{-4} \Omega$	$7.15 \times 10^{-4} \Omega$
b_3	$8.04 \times 10^{-2} \Omega$	$0.94 \times 10^{-2} \Omega$
c_1	$2.17 \times 10^1 \Omega$	$0.49 \times 10^1 \Omega$
c_2	$7.86 \times 10^{-3} \Omega$	$3.25 \times 10^{-3} \Omega$
c_3	$1.27 \times 10^{-1} \Omega$	$0.11 \times 10^{-1} \Omega$
τ_1	$1.35 \times 10^3 \text{ s}$	$0.57 \times 10^3 \text{ s}$
τ_2	$8.19 \times 10^1 \text{ s}$	$1.40 \times 10^1 \text{ s}$
τ_3	$8.12 \times 10^1 \text{ s}$	$0.54 \times 10^1 \text{ s}$
SOC_i	1.044	0.007

Table 2. Mean and standard deviation of model parameters for the charge mode generated by fitting voltage curves of nine lithium-ion battery cells

	Mean	Std
R_0	$2.37 \times 10^{-1} \Omega$	$0.50 \times 10^{-1} \Omega$
R_1	$1.57 \times 10^{-1} \Omega$	$0.27 \times 10^{-1} \Omega$
R_2	$4.66 \times 10^{-2} \Omega$	$3.33 \times 10^{-2} \Omega$
R_3	$1.33 \times 10^{-1} \Omega$	$0.31 \times 10^{-1} \Omega$
τ_1	$3.12 \times 10^4 \text{ s}$	$0.54 \times 10^4 \text{ s}$
τ_2	$1.24 \times 10^{-3} \text{ s}$	$0.47 \times 10^{-3} \text{ s}$
τ_3	$3.91 \times 10^1 \text{ s}$	$0.79 \times 10^1 \text{ s}$



(a)



(b)

Figure 8. Violin plots for model parameters for the discharge (a) and charge (b) mode generated by fitting voltage curves from nine lithium-ion battery cells.

The distributions, plotted in blue, are generated by fitting a kernel density estimation to the values generated by refitting the electrical model for each of the nine battery cells. Practically, this is achieved using the `gaussian_kde` function from the Python Scipy package.

From these distributions, we can then randomly generate parameters to be fed back into the electrical model, generating a synthetic voltage curve for a battery cycle. An example of this is shown in Figure 9, where voltage curves measured from three cells during discharge are plotted alongside the synthetically generated curve, demonstrating our approach to synthetic data generation.

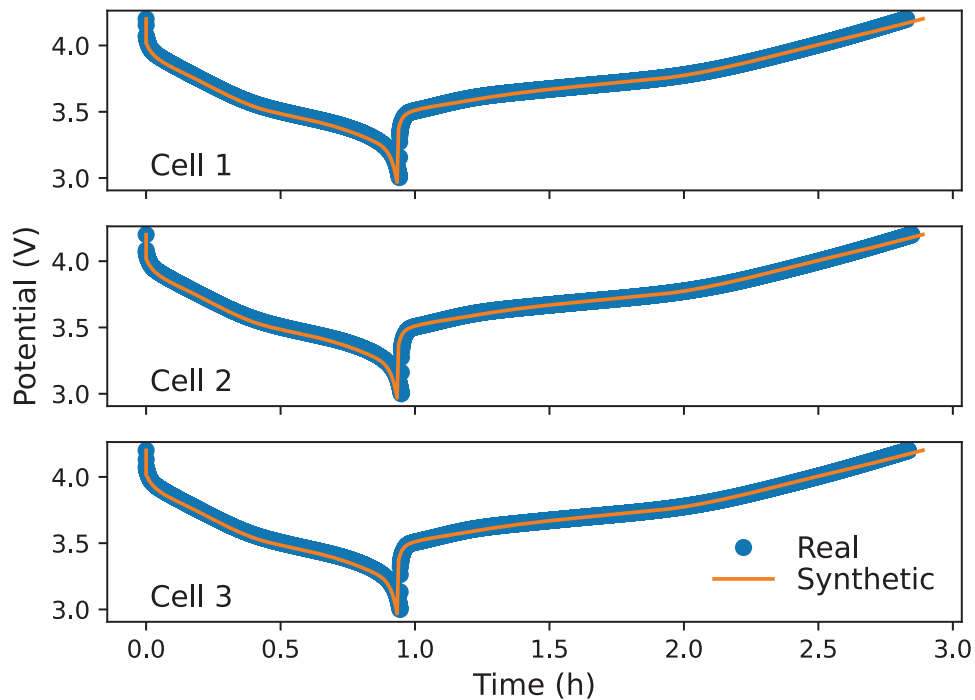


Figure 9. A comparison of voltage curves taken from three real battery cells during cycling (plotted in blue), each overlaid with the same synthetically generated voltage curve (plotted in orange).

5. Discussion

We have demonstrated models that are capable of representing the changes in electric potential and thickness that occurs when lithium-ion cells are cycled. The models proposed are relatively simple when compared to others in the literature. It is assumed that simplifying a model may result in reduced accuracy. When considering the electrical behaviour of a lithium-ion cell, P2D models offer a more physical representation than is possible with an equivalent circuit model; however, they are far more complex to implement [26,27]. Similarly, researchers such as Clerici et al. have demonstrated more sophisticated approaches to modelling cell expansion. However, these approaches require techniques such as finite element analysis, a computationally expensive endeavour [32]. In this work, we accept that a decrease in complexity comes with a decrease in accuracy. That being said, the models developed are suitable for our use case.

In principle, these models, and by extension the synthetic data generation methodology, could be applied to other lithium-ion battery chemistries and formats and other cycling conditions. Both the electrical and expansion models would need to be adjusted to account for the varying electrode and electrolyte materials. In the case of prismatic and cylindrical cells, the casing itself applies the required pressure during cycling rather than relying on external forces to apply pressure. This would likely require revisions in the expansion model. When considering other cycling conditions, particularly at higher charge and discharge rates, it is important to note that neither the electrical nor expansion models take into account the effects of temperature. In our use case, slow cycling is desirable, as it prevents premature ageing in the cells [34]. As a result of cycling slowly, we see negligible fluctuations in temperature. Therefore, we are free to ignore temperature effects. If one wanted to cycle the cells at a higher current or in an environment with fluctuating temperatures, a thermal model would need to be developed.

The goal of developing the models presented in this work is not to generate the most accurate representation of lithium-ion battery cell behaviour across all cycling conditions but to create an easily deployable model for the purpose of generating synthetic data.

Synthetic data are ultimately used to help an artificial intelligence algorithm learn features that it can expect to encounter in real data and, therefore, does not need to be a perfect representation of the real system.

It is, however, important that the parameters we sample from are representative of battery cells exhibiting normal behaviour. From the violin plots shown in Figure 8, it becomes apparent that the width of the distribution for each parameter is parameter dependent. The differing widths of the parameter distributions can at least partially be attributed to varying orders of magnitude for each parameter, as shown in Tables 1 and 2. Parameters with a very small magnitude are more likely to have a wider distribution. This is the case when we examine the R_2 value in Figure 8b and Table 2. It is also useful to consider how a given parameter contributes to the output of the model. For instance, b_2 in Figure 8a has a wide distribution compared with that of other parameters. When we examine how b_2 contributes to the eventual calculation of V_o , we must recall its use as a bias term in Equation (13), where a_2 , b_2 , and c_2 are used to calculate R_2 during discharge. In the case of the R_2 term, the $c_2 \exp(-a_2 SOC)$ component is an order of magnitude larger than b_2 . Therefore, the model output, V_o , is relatively insensitive to the value of b_2 , leading to a wider distribution. Variance in the widths for different parameters is therefore explainable and is not a cause for concern in generating synthetic data from the parameter distributions.

It is important to consider the possibility of outliers in the distributions, as this could cause a deviation from normal cell behaviour in synthetically generated data. Upon further inspection of the fit parameters, it appears that two battery cells contribute to the non-symmetric shape of the parameter distributions. More battery cells will be cycled to assess whether the two identified cells are outliers or if the true parameter distributions are wider than those generated by fitting to only nine cells. By fitting the models using more cells, we can minimise the effect of outliers and ensure the quality of the distributions that the parameters are sampled from.

6. Conclusions

We have established the need for end-of-line testing in lithium-ion battery production, the benefits of an expansion measurement in addition to existing electrical measurements, and the suitability of AI algorithms for extracting information from multi-sensor testing data. The limitations of using real battery cells to generate sufficient training data for the effective use of AI algorithms have also been introduced.

To address these limitations, we have established a methodology for generating synthetic data that can be used to train unsupervised AI algorithms. We first conducted expansion and voltage measurements on nine compressed 1 Ah lithium-ion cells under low current cycling conditions. These measurements were then used to parametrise an equivalent circuit model and model for compressed cell expansion. Finally, the distribution of parameters from fitting models with data from multiple cells was then sampled and passed back to the models to generate synthetic data.

This work allows for the production of large datasets without having to cycle a large number of battery cells. Anomaly detection algorithms for the purpose of identifying abnormal cells during end-of-line testing in lithium-ion battery production can then be pre-trained using the synthetic dataset. Real data can then later be used to retrain the models, reducing the number of cells that ultimately need to be cycled to train algorithms for end-of-line testing.

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Abbreviations

The following abbreviations are used in this manuscript:

Acronyms

AI	artificial intelligence
DoD	depth of discharge
ECM	equivalent circuit model
NMC622	$\text{LiNi}_{0.6}\text{Mn}_{0.2}\text{Co}_{0.2}$
OCV	open circuit voltage
P2D	pseudo 2-dimensional
RC	resistor-capacitor
RUL	remaining useful lifetime
SEI	solid electrolyte interphase
SoC	state of charge

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Article

Developing a Simple Electricity Consumption Prediction Formula for the Pre-Introduction Prediction for Electric Buses

Yiyuan Fang *, Wei-hsiang Yang, Yuto Ihara and Yushi Kamiya

Faculty of Science and Engineering, Waseda University, Tokyo 169-8555, Japan

* Correspondence: fyy@aoni.waseda.jp

Abstract: This study aims to develop a theoretical formula to help bus operators easily predict electricity consumption while introducing a certain type of electric bus on a pre-determined route. The formula requires vehicle-side information (such as air resistance coefficient, rolling resistance coefficient, vehicle weight, powertrain efficiency, kinetic energy recovery rate, auxiliary equipment electricity consumption, and other vehicle-related data) for construction and road-/operation-side information (such as average driving speed, number of starts and stops, road gradients, and other road-/operation-related data) for prediction. First, herein, as a basic study to construct the theoretical formula, a developed electric bus and its vehicle electricity consumption simulator are employed. We then perform a comparative analysis considering the comparison of loss between the actual operation on public roads and the assumed constant velocity when running on flat roads. Next, we develop theoretical equations for the generalization of velocity and gradient changes and simplified modeling of electricity consumption prediction. Considering the burden of information collection on operators, we categorize it into three stages. In this paper, we first organize the minimum necessary road-/operation-side information (route/operational indicators). Next, we propose a theoretical formula for electricity consumption prediction constructed based on vehicle-side information. Finally, we validate the validity and accuracy of the constructed formula using electric buses and their on-road operational data that we developed earlier. The verification results showed that, after obtaining vehicle-side and road-/operation-side information, the theoretical formula constructed in this study achieved an electricity consumption prediction with an average error of 6% (high-accuracy method). This result demonstrates the practicality of using the theoretical formula to predict the electricity consumption/range of electric buses operating on specific routes.

Keywords: electricity consumption prediction; prediction formula; electric vehicle; simple method

1. Introduction

Concerns about climate change (global warming) and the depletion of fossil fuels have prompted many countries and regions around the world to take active measures in reducing carbon dioxide emissions and saving energy [1,2]. The transportation sector consumes approximately 20% of global energy and accounts for about 25% of global carbon dioxide emissions, most of which come from the road transport sector [3,4]. Therefore, in order to achieve the emission reduction targets set out in the Paris Agreement under the United Nations Framework Convention on Climate Change in 2015, the road transport sector needs to make significant contributions [5,6]. Against this backdrop, the electrification of vehicles has been rapidly advancing in recent years across various regions of the world, including Asia, Europe, and the Americas [7–10].

Recently, we have seen an increasing number of electric buses and trucks [11–13]. However, owing to the difficulty of predicting the performance of electric buses during actual operation, many companies have ultimately been hesitant to act or have abandoned the idea of introducing electric buses by weighing this idea. In this study, we aim to develop a theoretical formula that enables operators to easily predict and calculate the most basic performance indicator, namely the electricity consumption of the vehicle(s) [kWh/km] [14,15].

Previous formulas for vehicle pre-introduction electricity consumption prediction include the following aspects. The most reliable method measures the electricity consumption data obtained through field test runs using the vehicles to be deployed. However, the implementation cost represents a major obstacle. As another method, there are cases where vehicle electricity consumption simulations are used [16]. Specifically, this method uses diesel vehicles that are already owned by the operator to test run the route to be introduced (to collect the velocity change data) and calculates the electricity consumption by simulating the process in combination with route gradient data collected from maps and other sources. However, vehicle simulation is a complex, interdisciplinary task involving multiple fields such as mechanical engineering, electrical engineering, control engineering, and computer science. Vehicle simulation requires skilled technical personnel with expertise and costly simulation tools (both hardware and software) [17,18]. At present, this approach is typically applied in automotive R&D departments or research institutions [19]. Therefore, while this method is effective in predicting electricity consumption, it requires specialized knowledge and technical capabilities, making it challenging to adopt.

Therefore, in this study, we developed a method (simplified method) that enables the operators to predict the electric power cost of vehicles to be introduced based only on the estimated average velocity information. Additionally, we shall look at measures that enable even better forecasts (medium- and high-accuracy methods) if additional information on acceleration/deceleration and the road gradient of the route to be introduced is available.

First, herein, as a basic study to construct the theoretical formula, a developed electric bus and its vehicle electricity consumption simulator are employed. We then perform a comparative analysis considering the comparison of loss between the actual operation on public roads and the assumed constant velocity when running on flat roads. Based on the approximate proportional relationship between the two electricity consumption values, we propose a simple electricity consumption prediction formula that requires only the average velocity for practical use. Next, we develop theoretical equations for the generalization of velocity and gradient changes and simplified modeling of electricity consumption prediction. Finally, we construct various methods and summarize the same.

2. Comparison and Discussion of Losses Between the Actual Operation on Public Roads and Constant Velocity Driving on Flat Roads

The purpose of this study is to develop a simplified method that will enable operators to predict the cost of electricity for the vehicles they plan to install. Here, it is desirable to use only the “average velocity” expected during operation for the input information when considering the burden on the operator. Therefore, we first consider the “electricity consumption when driving at a constant velocity on a flat road”, which can be easily obtained after determining the vehicle to be deployed. This uses the “average velocity” described above. Following that, we can construct a method that considers the effects of acceleration and deceleration that occurred during actual operation and overlay the

“electricity consumption deterioration rate” on this value. This is positioned as a simplified method (using only average velocity information).

2.1. Various Information Obtained During Actual Operation of the Developed Electric Bus

In this section, we proceed with the basic study for the electricity consumption prediction formula; here, the vehicle selected as an example was the Waseda Electric Bus-3 (WEB-3), a small electric bus previously developed by our research group [20]. This bus is based on a small diesel bus manufactured by Hino Motors, which was converted into an electric bus and equipped with a wireless battery charger. The basic vehicle specifications are shown in Table 1. WEB-3 has been used in various regions in the past. Consequently, we first used the measured velocity change, road slope, and electricity consumption obtained in these areas to derive the aforementioned “electricity consumption deterioration rate” coefficient.

Table 1. Waseda Electric Bus-3 basic vehicle specs.

Mass when empty	kg	5990
Equivalent inertial mass	kg	162
Max motor output	kW	145
Passenger capacity (average)	people	25 (10)
Front projected area	m ²	5.91
Auxiliary consumption power	W	600
Motor inverter average efficiency (when cruising)		85% (75%)
Gear efficiency		85%



Information related to the past operation using the same vehicle is summarized in Figure 1. Figure 1a is the Nagano–Gururin route, which is a community bus route that circles an 8.5 km route in the central city area in about 50 min, and travels in the order of A, B, . . . H. Points B, C, and G in the figure are the higher elevation points, with a difference in elevation of ~30 m. Figure 1b is the Nagano–Hirabayashi route. Shuttles are operated on this route of ~11.5 km one-way (~45 min) that links the stop in front of Nagano station to the Nagaden Bus Yanagihara office. As the Nagano station side is ~30 m higher in elevation than that of the Yanagihara office side, the trip from Nagano station is downhill, whereas the return from the Yanagihara office is uphill. Subsequent studies will be conducted on round-trip runs.

Figure 1c is the Saitama–Honjo route. This is an 11.2 km round-trip route that links Honjo station and the Waseda Honjo campus (~35 min), and it is virtually flat. Figure 1d is the Saitama–Kumagaya route, which is a 5.1 km circuit of the central city area that takes ~20 min to complete and is virtually flat. Figure 1e in the same figure is the Saga–Karatsu route, which is a 3.3 km circular circuit of the central city area that also takes ~20 min to complete.

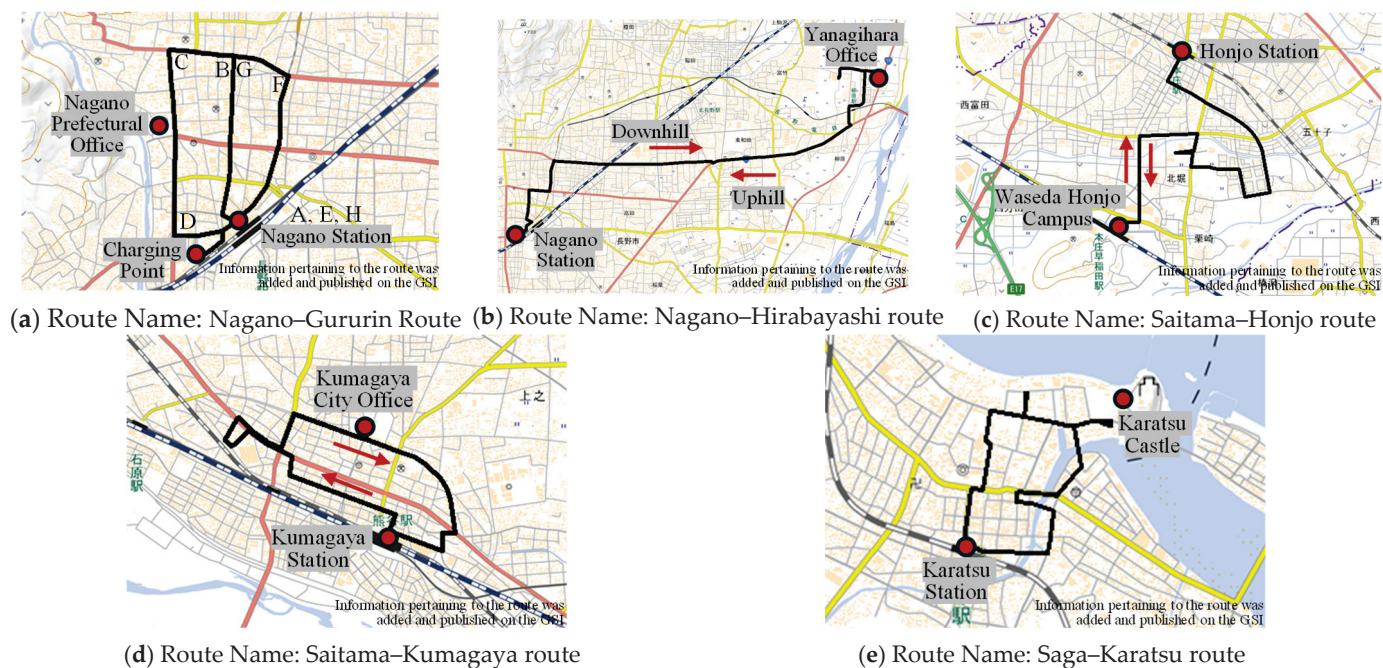


Figure 1. Overview of actual operational routes to which WEB-3 was introduced. In this study, for each route, the authors attempted to use data that closely reflects typical traffic conditions, excluding cases of congestion from the analysis. The buses in this study do not operate on dedicated lanes but share lanes with general traffic. The energy consumption values presented for each route are final averages (Table 2).

Table 2. Basic information from each route in actual WEB-3 operation.

Route	Driving Distance	Driving Time	Actual Measured Average Electricity Consumption	Route/Operational Indicators				
				Average Velocity V	Start/Stop Times n	Stop Time Ratio α	Gained Uphill Elevation $\frac{\sum h^+}{X}$	Gained Downhill Elevation $\frac{\sum h^-}{X}$
	km	s	kWh/km	km/h	Times/km	%	m/km	m/km
Nagano–Gururin	8.5	2975	0.83	10.3	4.9	41%	6.5	−6.5
Nagano–Hirabayashi	23	5411	0.68	15.3	2.2	33%	2.7	−2.7
Saitama–Honjo	11.2	2210	0.74	18.2	2.0	20%	1.8	−1.8
Saitama–Kumagaya	5.1	1145	0.70	15.9	3.2	17%	2.4	−2.4
Saga–Karatsu	3.3	1185	0.72	10.1	3.9	32%	5.4	−5.4

Next, the basic information on each route obtained during actual operation is summarized in Table 2. Here, in addition to the measured electricity consumption values, the following five road/operational indicators that have a significant impact on the same values are included, such as average velocity, start/stop times, stop time ratio, and gained uphill/downhill elevation (Figure 2) [21]. This information shall be used in subsequent studies.

$$\frac{\sum h^+}{X} = \frac{h_1 + h_3}{X} \quad \frac{\sum h^-}{X} = \frac{h_2 + h_4}{X} \text{ (negative value)}$$

X : Driving distance

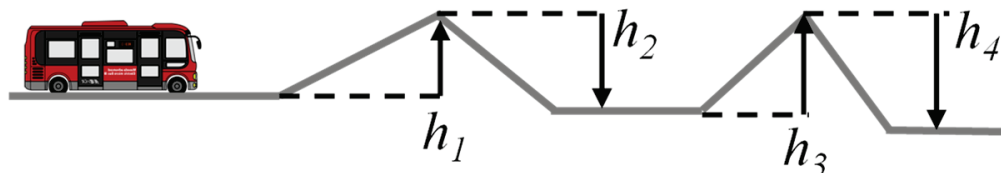


Figure 2. Image of derived gained uphill/downhill elevation value.

2.2. Vehicle Electricity Consumption Simulator Used in This Chapter

In the simplified method developed in this study, it is necessary to derive the “electricity consumption deterioration rate” as described above, and to acquire this value, a detailed comparison of the “power consumption values when running at a constant velocity on a flat road” and the “power consumption values during actual operation (acceleration/deceleration and hill climbing/descent)” is necessary. Therefore, we constructed a vehicle electricity consumption simulator [16] to derive these two values and analyze the contribution to electricity consumption deterioration. Figure 3 shows a conceptual diagram of the constructed backward simulator. This method, by inputting the vehicle velocity, can be used to obtain the final battery power consumption. The cost values derived by the constructed simulator and the measured cost values are shown in Table 3. The mean error is 2.4%, which was determined to be reasonable.

Table 3. Comparison of WEB-3 electricity consumption values for each route.

Route	Actual Measured Electricity Consumption	Vehicle Electricity Consumed Energy Simulator (Study in Section 2)		Electricity Consumption Prediction Formula (High-Accuracy Method) (Study in Section 3)	
		Electricity Consumption	Error	Electricity Consumption	Error
	kWh/km	kWh/km	%	kWh/km	%
Nagano–Gururin	0.83	0.80	3.6%	0.84	1.2%
Nagano–Hirabayashi	0.68	0.66	2.9%	0.72	5.9%
Saitama–Honjo	0.74	0.73	1.4%	0.67	9.1%
Saitama–Kumagaya	0.70	0.72	2.9%	0.68	2.9%
Saga–Karatsu	0.72	0.71	1.4%	0.66	8.3%
Mean error	-	-	2.4%	-	5.5%

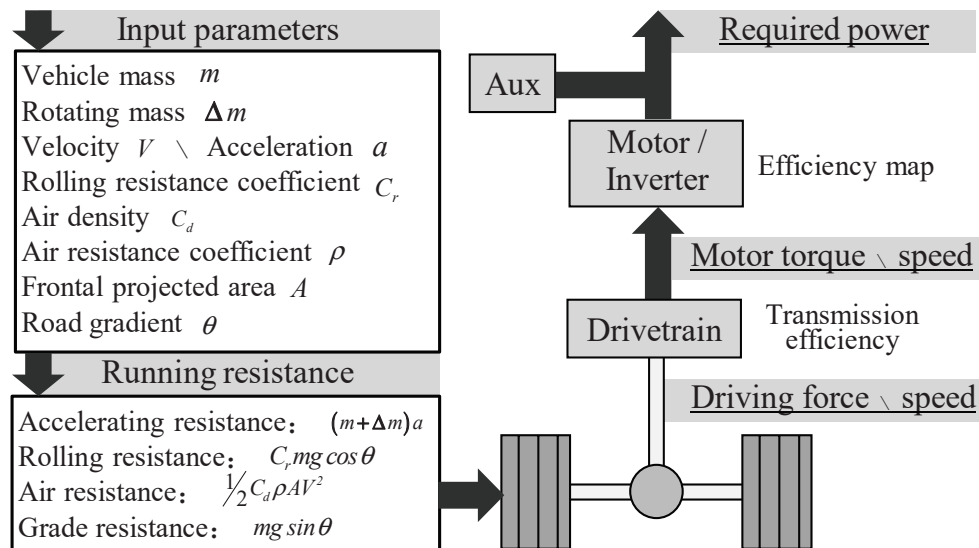


Figure 3. Constructed vehicle electricity consumption simulator, reprinted from Ref. [22].

2.3. Energy Analysis Using a Simulator When the Vehicle Is in Actual Operation and a Comparison Between It and When Driving on a Flat Road with a Constant Velocity

Using the vehicle consumed energy simulator constructed in this study, we calculated the loss breakdown that occurs during actual operation. The results are shown in Table 4. Considering the loss that occurs at a constant velocity over the flat road, the effects of acceleration/deceleration and uphill/downhill driving during actual operation are compared.

Table 4. Derivation of the loss that occurs during actual operation on each route using the constructed simulator and a comparison based on the assumption of running at a constant velocity on a flat road.

Route		Nagano–Gururin		Nagano–Hirabayashi		Saitama–Honjo		Saitama–Kumagaya		Saga–Karatsu	
Driving Situation		Fixed Velocity	Actual Operation	Fixed Velocity	Actual Operation	Fixed Velocity	Actual Operation	Fixed Velocity	Actual Operation	Fixed Velocity	Actual Operation
Average velocity	km/h		10.3		15.3		18.2		15.9		10.1
Electricity consumption	kWh/km	0.42	0.80	0.41	0.66	0.41	0.73	0.41	0.72	0.43	0.71
Auxiliary equipment consumption	kWh/km	0.06	0.06	0.04	0.04	0.03	0.03	0.04	0.04	0.06	0.06
Rolling resistance	kWh/km	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
Air resistance	kWh/km	0.00	0.04	0.01	0.05	0.01	0.05	0.01	0.03	0.00	0.02
Mechanical brake loss	kWh/km	0.00	0.24	0.00	0.14	0.00	0.20	0.00	0.21	0.00	0.20
Drive section loss	kWh/km	0.03	0.06	0.03	0.05	0.03	0.06	0.03	0.06	0.03	0.05
Motor loss	kWh/km	0.12	0.18	0.12	0.16	0.12	0.17	0.12	0.17	0.12	0.16
Electricity consumption deterioration rate (average value +74%)		+87%		+60%		+79%		+76%		+67%	

Mechanical brake loss only occurs during actual operation and has a high impact. The kinetic energy that decreases during deceleration and the potential energy that decreases during downhill driving are converted to calculate the same loss. Additionally, although the motor loss and drive loss worsen during actual operation, this phenomenon is caused

by the increased load on the same component during acceleration/deceleration and up-hill/downhill driving. There is also deterioration in the aerodynamic drag consumption. However, as this consumption is proportional to the square of the velocity, when the maximum velocity increases compared to the same average velocity during actual operation, this consumption also increases.

Figure 4 is a comparison of the loss breakdown of the Nagano–Gururin and Saga–Karatsu routes at approximately the same average velocity. Given the road/operational indicators for the two routes (Table 2), the former has a larger number of “start/stop times” and “gained uphill elevation” than the latter, and this leads to an increase in motor/drive unit/mechanical brake loss compared to the latter. These calculation results are considered reasonable. The former also has a higher “stop time ratio,” which has the effect of increasing the maximum velocity and correspondingly worsening the aerodynamic drag. The electricity consumption deterioration rate for both lines is +87% and +67%, respectively.

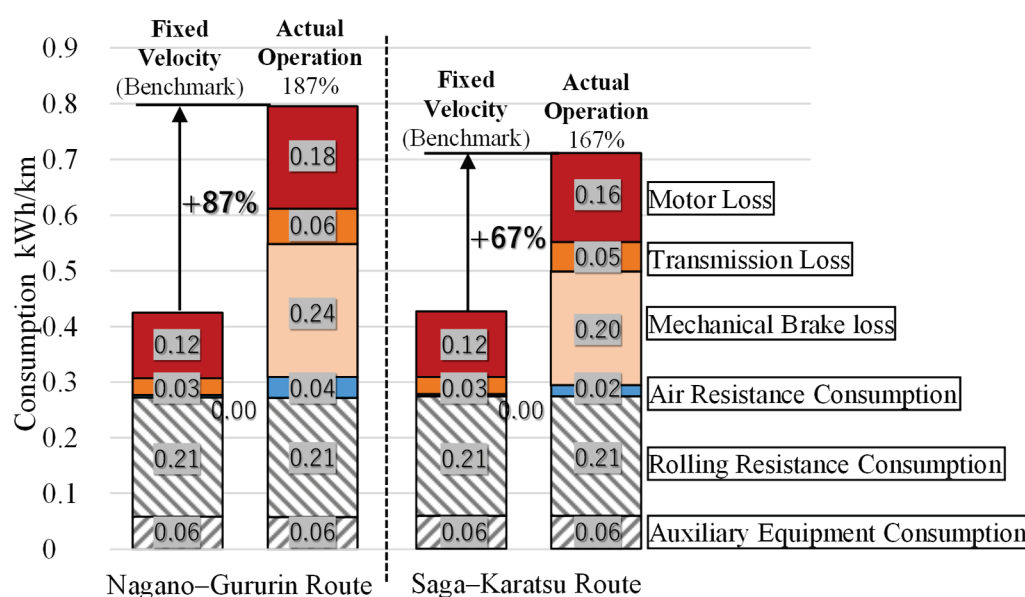


Figure 4. Comparison of loss between two routes at virtually the same average velocity.

Figure 5 is a graphical representation of the average velocity dependence of the various cost values listed in Table 4. The actual measured values are also shown, and the electricity consumption when driving at a constant velocity on a flat road is assumed to be a continuous line. Although the electricity consumption values during actual operation are greatly deteriorated compared to the continuous line of electricity consumption at a constant velocity, they converge relatively close to the continuous line. Thus, the continuous line for electricity consumption during constant-speed driving was adjusted by a constant multiplier so that it reflects the average rate of electricity consumption deterioration for the five routes analyzed in this study. The adjusted continuous line was then added to the figure. By using this corrected electricity consumption continuous line, it was possible to predict the electricity consumption to a certain degree when the average velocity information was provided by the operator. Therefore, for the “electricity consumption deterioration rate”, which is a representative value for the subject vehicle, the average value (+74% in this study) was set, and a method for predicting electricity consumption based on the corrected electricity consumption continuous line is used as the “simplified method”. The appropriateness of this method is discussed in Section 4 after constructing the theoretical formula.

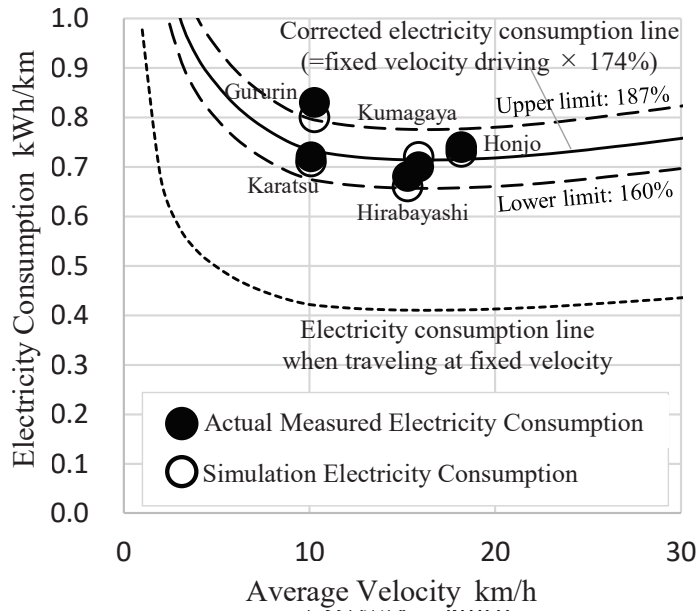


Figure 5. Attempt to predict electricity consumption using a corrected electricity consumption continuous line.

3. Construction of a Theoretical Formula for Simplify Modeling of Electricity Consumption Prediction

In the previous chapter, an attempt was made to derive a detailed comparison between the “electricity consumption values in actual operation” and the “electric power consumption at assumed constant velocity on flat roads” by analyzing various data obtained while the developed electric bus was running on the aforementioned five routes using a vehicle energy consumption simulator. Additionally, the “electricity consumption deterioration rate” representing the ratio between the two was calculated. We further generalize and simplify these studies in this chapter. Specifically, we use triangulated waveforms to generalize complex velocity changes in actual operations, substituting the effect of gradient changes with gained uphill/downhill elevation and adopting theoretical equations that simplify the modeling of electricity consumption estimation. Here, we shall investigate formulation strategies for regenerative energy that have been challenging in the past, and the results of this study should lead to the development of medium- and high-accuracy methods that can be used in situations where additional information on acceleration/deceleration and the road gradient of the route to be introduced can also be easily obtained.

First, we develop a theoretical formula for simplifying electricity consumption prediction monitoring. A generalized vehicle consumed energy theoretical formula [15] is described as follows:

$$E = E_{Air} + E_{Roll} + E_{Mech} + E_{Aux} \quad (1)$$

Here,

E Vehicle consumed energy [J];

E_{Roll} Rolling resistance consumed energy [J];

E_{Aux} Auxiliary equipment consumed energy [J];

E_{Air} Air resistance consumed energy [J];

Mechanical brake consumed energy [J].

(Mechanical braking directly consumes the vehicle’s kinetic energy, and since this kinetic energy is supplied by the power system during acceleration, mechanical braking indirectly increases the vehicle consumed energy.)

This is a generalized formula established not only for electric vehicles but also for internal combustion engine vehicles, and we will proceed with our study based on this formula.

3.1. Construction of a Formula When Driving at a Constant Velocity on Flat Roads

In this section, we shall construct an electricity consumption prediction theoretical formula that assumes cruising at a fixed velocity on flat roads. As acceleration, deceleration, and stopping do not occur in this case, driving resistance only consists of air resistance and rolling resistance. Thus, the mechanical breaking term from Formula (1) does not exist and it becomes

$$E = E_{Air} + E_{Roll} + E_{Aux} \quad (2)$$

For the air resistance term, if we consider power system efficiency (gear efficiency/motor inverter efficiency), it becomes

$$E_{Air} = \frac{1}{\eta_G \eta_{Mot}} \int F_{Air} V dt = \frac{1}{\eta_G \eta_{Mot}} \int \frac{1}{2} \rho A C_d V^2 V dt = \frac{1}{\eta_G \eta_{Mot}} \frac{1}{2} \rho A C_d V^2 X \quad (3)$$

Here,

- η_G Gear efficiency;
- F_{Air} Air resistance [N];
- t Time [s];
- A Front projection area [m²];
- η_{mot} Motor inverter efficiency;
- X Driving distance on the whole route [m];
- ρ Air resistance [kg/m³];
- C_d Air resistance coefficient;
- V **Average velocity [m/s]**
(Table 2 Road/operational indicators).

In the same way, the rolling resistance term is described as

$$E_{Roll} = \frac{1}{\eta_G \eta_{Mot}} C_r (m_{Car} + m_{Pas}) g X \quad (4)$$

Here,

- C_r Rolling resistance coefficient;
- m_{Pas} Passenger vehicle mass [kg];
- m_{Car} Vehicle mass [kg];
- g Weight acceleration [m/s²].

Finally, the auxiliary equipment consumed energy term is described as

$$E_{Aux} = P_{Aux} \cdot T \quad (5)$$

Here,

- T Driving time on whole route [s];
- P_{Aux} Auxiliary equipment consumption power [W].

Finally, the electricity consumption prediction formula is derived as

$$EC = \frac{E}{X} = \frac{1}{\eta_G \eta_{Mot}} \left[\frac{1}{2} \rho A C_d V^2 + C_r (m_{Car} + m_{Pas}) g \right] + \frac{P_{Aux}}{V} \quad (6)$$

3.2. Construction of a Formula When Accelerating/Decelerating on Flat Roads

For the theoretical formula constructed here, we added the “start/stop times” and “stop time ratio” to the “average velocity” used in the previous section, making variables

of these three information points. These correspond to the road/operational indicators for each route used in Table 2. By introducing the same values, we can reflect the vehicle acceleration and deceleration, which were ignored in the study of the previous section. For generalization, the velocity change monitored in this study is assumed to be a “triangular wave velocity change” [23] (Figure 6). With the same triangular wave as the main trip, this is repeated for the entire route distance.

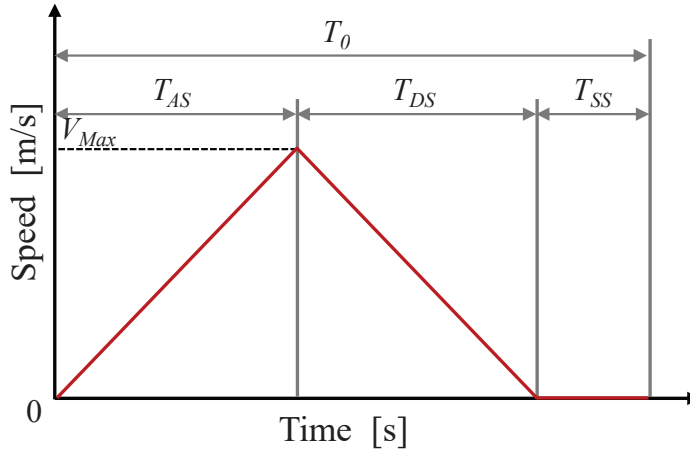


Figure 6. Triangular velocity change pattern basic trip.

We shall start by describing the method of determining the basic trip. The total time, acceleration time (=deceleration time), stop time, and maximum velocity for the basic trip are derived as follows.

$$T_0 = \frac{T}{N} = \frac{T}{n \cdot X/1000} = \frac{1000}{n \cdot V}, T_{AS} = T_{DS} = \frac{(1-\alpha)T_0}{2}, T_{SS} = \alpha T_0, V_{Max} = \frac{2V}{(1-\alpha)} \quad (7)$$

Here,

- T_0 Basic trip total time [s];
- T_{DS} Basic trip deceleration time [s];
- V_{Max} Maximum velocity [m/s];
- T_{AS} Basic trip acceleration time [s];
- T_{SS} Basic trip stop time [s];
- N Number of start/stop times on the entire route [times];
- n **Start/stop times (per unit driving distance) [times/km]**
(Table 2 Route/operational indicators);
- α **Stop time ratio**
(Table 2 Route/operational indicators).

Below, based on the basic trip velocity change patterns, as shown in Figure 6, we can construct the electricity consumption prediction theoretical formula based on Formula (1).

First, the air resistance term is

$$E_{Air} = E_{Air_AS} + E_{Air_DS} = 2E_{Air_AS} = 2 \frac{1}{\eta_G \eta_{Mot}} \int_0^{T_{AS}} F_{Air} v(t) dt = \frac{1}{\eta_G \eta_{Mot}} \cdot \frac{1}{4} \rho A C_d V_{Max}^2 X_0 \quad (8)$$

Here,

- E_{Air_AS} Air resistance consumed energy (acceleration interval) [J];
- E_{Air_DS} Air resistance consumed energy (deceleration interval) [J];
- $v(t)$ Velocity time function [m/s];
- X_0 Basic trip total driving distance [m].

In the same way, the rolling resistance term is

$$E_{Roll} = \frac{1}{\eta_G \eta_{Mot}} C_r (m_{Car} + m_{Pas}) g X_0 \quad (9)$$

Moving forward, we can formulate the energy consumed by the mechanical brake during deceleration, or “regenerative energy”. When decelerating the vehicle (on flat roads), the operational energy possessed when deceleration starts is used effectively by the drive resistance in the beginning (rolling resistance, air resistance), and the remaining portion, excluding mechanical brake losses and power system losses, is the regenerated energy (to simplify the discussion here, rare cases of deceleration, etc., are ignored). Therefore, in this study, we consider this phenomenon as we define the operational energy usage rate η_K . The same value is the ratio of (iii) aerodynamic drag consumption (effective use)/(iv) rolling resistance consumption (effective use)/(vi) regenerative energy to (i) kinetic energy possessed at the start of deceleration and consisting of the sum of the three (Figure 7).

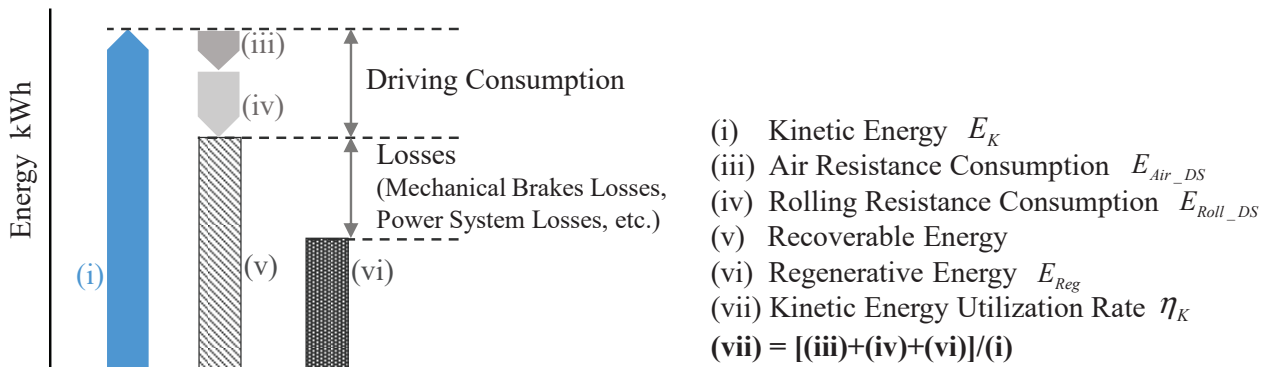


Figure 7. Definition of power energy usage rate when decelerating the vehicle (on flat roads).

It is shown below:

$$\eta_K = \frac{E_{Air_DS} + E_{Roll_DS} + E_{Reg_K}}{E_K} \quad (10)$$

Here,

- E_K Operational energy possessed at the start of deceleration [J];
- E_{Air_DS} Air resistance consumed energy (deceleration interval) [J];
- E_{Roll_DS} Rolling resistance consumed energy (deceleration interval) [J];
- E_{Reg_K} Deceleration regenerative energy [J].

For ease of calculation, if we include the power system loss, etc., in the mechanical brake consumption, the mechanical brake consumption E_{Mech} based on the same figure is

$$E_{Mech} = \frac{1}{\eta_G \eta_{Mot}} E_K - (E_{Air_DS} + E_{Roll_DS} + E_{Reg_K}) = \left(\frac{1}{\eta_G \eta_{Mot}} - \eta_K \right) (m_{Car} + m_{Pas} + m_{Rot}) a X_{AS} \quad (11)$$

When deriving the above formula, the relationship of

$$E_K = (m_{Car} + m_{Pas} + m_{Rot}) a X_{AS}, a = \frac{V_{Max}}{T_{AS}} = \frac{nV^2}{250(1-\alpha)^2} \quad (12)$$

Here,

- m_{Rot} Equivalent inertial weight [kg];
- X_{AS} Driving distance (acceleration interval) [m];
- α Acceleration (acceleration interval) [m/s²].

Finally, there is the auxiliary equipment consumed energy term, which is

$$E_{Aux} = P_{Aux} T_0 \quad (13)$$

The final electricity consumption prediction formula is

$$EC = \frac{1}{\eta_G \eta_{Mot}} \left[\rho A C_d \frac{V^2}{(1 - \alpha)^2} + C_r (m_{Car} + m_{Pas}) g \right] + \left(\frac{1}{\eta_G \eta_{Mot}} - \eta_K \right) (m_{Car} + m_{Pas} + m_{Rot}) \frac{n V^2}{500 (1 - \alpha)^2} + \frac{P_{Aux}}{V} \quad (14)$$

This formula is a “medium accuracy method” electricity consumption prediction formula.

3.3. Construction of a Formula When Accelerating/Decelerating on Gradient Roads

In the previous section, we constructed an electricity consumption prediction theoretical formula that assumed starting, accelerating/decelerating, and stopping on flat roads. In this section, to create a formula with a higher level of prediction accuracy, we shall add simple monitoring of situations where there is positional energy changes associated with uphill and downhill driving to the formula. Specifically, we shall consider ways to substitute the effect of gradient change with the gained uphill/downhill elevation.

Naturally, the increased positional energy amount becomes electricity consumption on uphill roads. If we consider power system efficiency, this becomes

$$E_{Up} = \frac{1}{\eta_G \eta_{Mot}} (m_{Car} + m_{Pas}) g \sum h^+ \quad (15)$$

Here,

E_{Up} Consumption of positional energy related to going uphill [J];
 $\sum h^+$ Total uphill elevation [m].

Next, we looked at a downhill road. First, we define the positional energy utilization rate η_p by considering the same phenomenon as the kinetic energy utilization rate η_K , as introduced in the previous section. As shown in Figure 8, this value is the ratio of (iii) air resistance consumption (effective use)/(iv) rolling resistance consumption (effective use)/(vi) regenerative energy to the (ii) position energy held at the start of the descent, which comprises the sum of the three. (To simplify the discussion here, rare cases of downhill driving, etc., are ignored.) As the same values are used, the reused amount (negative value) of the positional energy stored while driving uphill is

$$E_{Down} = \eta_p (m_{Car} + m_{Pas}) g \sum h^- \quad (16)$$

Here, we have

E_{Down} Reused positional energy related to descent [J];
 $\sum h^-$ Total downhill elevation [m] (negative value) [m].

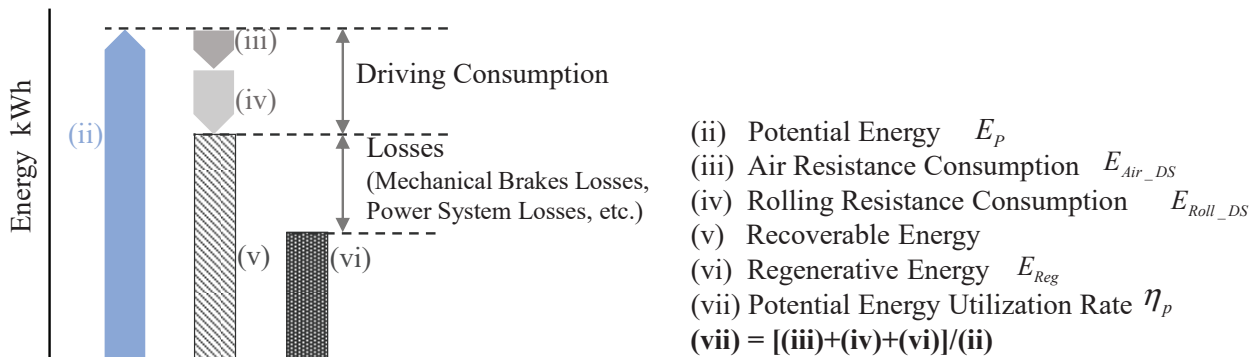


Figure 8. Definition of positional energy rate when driving downhill (cruise regenerative driving).

By summing the two terms described above, the electricity consumption amount change caused by the slope is derived as follows:

$$\Delta EC_{Slp} = \frac{E_{Up} + E_{Down}}{X} = (m_{Car} + m_{Pas})g \left(\frac{1}{\eta_G \eta_{Mot}} \frac{\sum h^+}{X} + \eta_P \frac{\sum h^-}{X} \right) \quad (17)$$

Here, we have

ΔEC_{Slp} Electricity consumption change amount when driving downhill [J/m];

$\frac{\sum h^+}{X}$ **Gained uphill elevation [m/m]**
(Table 2 Route/operational indicators);

$\frac{\sum h^-}{X}$ **Gained downhill elevation (negative) [m/m]**
(Table 2 Route/operational indicators).

By simply adding these formulas to the medium-accuracy method's cost prediction formula derived in the previous section, the following formula is finally achieved. The same formula is used as the cost prediction formula for the "high-accuracy method".

$$EC = \frac{1}{\eta_G \eta_{Mot}} \left[\rho A C_d \frac{V^2}{(1 - \alpha)^2} + C_r (m_{Car} + m_{Pas})g \right] + \left(\frac{1}{\eta_G \eta_{Mot}} - \eta_K \right) (m_{Car} + m_{Pas} + m_{Rot}) \frac{nV^2}{500(1 - \alpha)^2} + \frac{P_{Aux}}{V} + (m_{Car} + m_{Pas})g \left(\frac{1}{\eta_G \eta_{Mot}} \frac{\sum h^+}{X} + \eta_P \frac{\sum h^-}{X} \right) \quad (18)$$

3.4. Application of the Formula to the Developed Vehicle and Verification of Its Accuracy

In this section, we apply the theoretical formula for predicting electricity consumption that we developed earlier to a developed electric bus running on an actual operational route, as was studied in a previous chapter. We also investigate the accuracy of this formula.

Regarding the electricity consumption prediction theoretical formula assuming constant velocity on flat roads (Formula (7)), accelerating/decelerating on flat roads (Formula (14)), and accelerating/decelerating on a slope (Formula (18)), the theoretical formulas for the subject vehicle obtained by substituting the various coefficients listed in Table 1 are summarized below:

$$EC = 0.00091V^2 + 0.35 + \frac{0.17}{V} \text{ [kWh/km]} \quad (19)$$

$$EC = \frac{0.0016V^2}{(1 - \alpha)^2} + 0.31 + \frac{(0.0052 - 0.0022)nV^2}{(1 - \alpha)^2} + \frac{0.17}{V} \text{ [kWh/km]} \quad (20)$$

$$EC = \frac{0.0016V^2}{(1 - \alpha)^2} + 0.31 + \frac{(0.0052 - 0.0022)nV^2}{(1 - \alpha)^2} + \frac{0.17}{V} + (25 \cdot \frac{\sum h^+}{X} + 11 \cdot \frac{\sum h^-}{X}) \text{ [kWh/km]} \quad (21)$$

Here, based on driving results obtained until now, the power energy usage rate and positional energy usage rate were set to 60%. Here, the medium-accuracy method was obtained from Formula (20) and the high-accuracy method was obtained from Formula (21). Next, as shown in Table 2 for Formula (21), the predicted electricity consumption obtained by inputting the road and the operational indicators for each route were enlisted in the previously discussed Table 3. The mean error when compared with actual measured values was found to be 5.5%, which is considered sufficient accuracy for practical use.

Figure 9 is a graph that can be used to confirm the differences between the actual measured values/calculated values from the vehicle electricity consumption simulator (studied in Section 2) and the values calculated using the constructed theoretical formula (Formula (21)). In the same figure, the continuous line of electricity consumption and the corrected continuous line of electricity consumption (derived using the same process as the previous chapter) for constant-velocity running on a flat road derived by Formula (19)

are also compared with those obtained by the vehicle electricity consumption simulator. The generalized and simplified studies performed in this chapter (triangulation for generalization of velocity change, adoption of a strategy to substitute gained uphill/downhill elevation for gradient change, and adoption of a theoretical formula to simplify the modeling of electricity consumption prediction) were all considered to be appropriate.

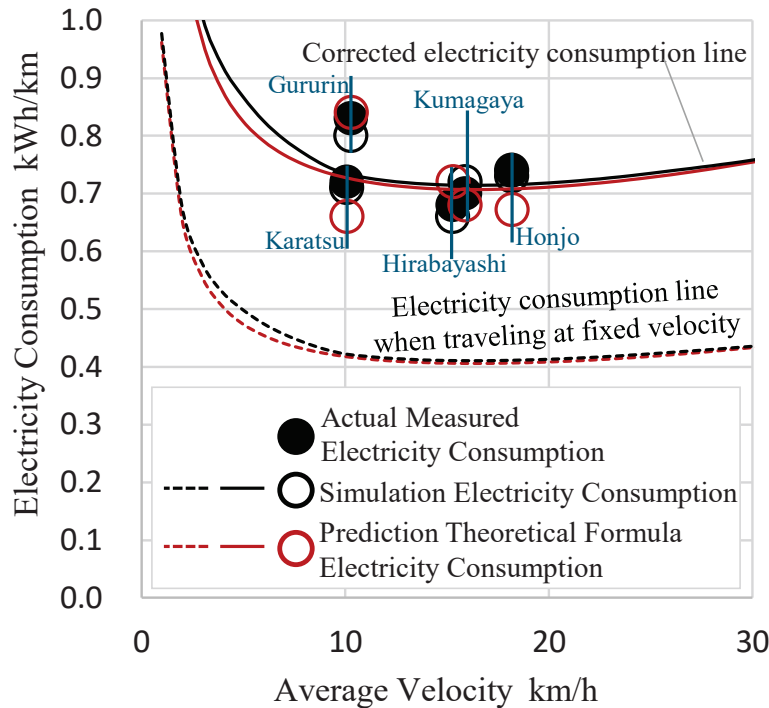


Figure 9. Derivation of various electricity consumption values using constructed formulas.

4. Discussion on the Appropriateness of a Simplified Method Using Only Average Velocity Information Using a Theoretical Formula

The simplified method we developed previously corrects the continuous line of electricity consumption of the vehicle at a constant velocity through the average of the deterioration rate of electric consumption over the five routes used in this study (introduction of a corrected continuous line of electricity consumption) and thus enables us to forecast electricity consumption only from average velocity information. In this chapter, we discuss the validity of our method using the cost prediction formula for the high-accuracy method developed previously. Additionally, even when driving at the same average velocity, the same high-accuracy formula can be used to predict the variation range of electricity consumption that can be expected in other areas with different road and operational conditions.

To prepare for this study, we first generalize the road/operational indicators (start/stop times, stop time ratio, and gained uphill/downhill elevation) and clarify the range of variation. To guarantee its accuracy, the target vehicles should be operated in a large number of regions and the distribution of these indicators should be determined before starting the study. However, as the main goal of this study is method establishment, only the information on the abovementioned five routes will be used.

The distribution status of the “start/stop times” indicator and the status of the “stop time ratio” are summarized in Figure 10a,b, respectively. Given the average velocity dependence of the two values, usually they have a negative first-order correlation [24], and the same tendency can be read from the information on the five aforementioned routes.

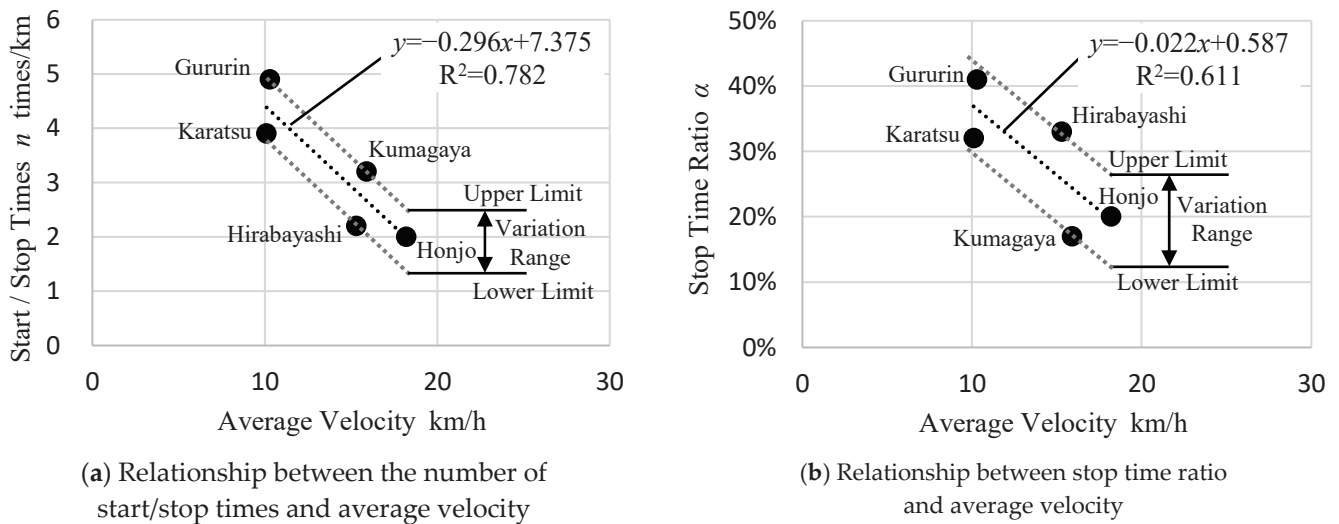


Figure 10. Generalization of road/operational indicators and clarification of the variation range during WEB-3 actual operation.

Additionally, from the same figure, estimates of the upper and lower limits for each average velocity for both values, that is, the variation range of the indicators assumed when operating, can be predicted to a certain extent. Given the fact there is no average velocity dependence for the gained uphill/downhill elevation, the variation range discussed below is from the highest to the lowest value of the information in Table 2 (6.5–1.8 m/km).

Next, in the same way as the previous study, we took the Nagano–Gururin route and the Saga–Karatsu route to be traveling at virtually constant velocity for our example routes, and we discussed in detail based on this. Figure 11 is an expansion of the area around an average velocity of 10 km/h in Figure 9. As mentioned above, the electricity consumption value based on the prediction theoretical formula (high-accuracy method) is obtained by substituting the road and operation indicators for each route into Formula (22), and the following equation is used to calculate the electric cost value. This value is obtained by substituting the road/operational indicators for each route into Formula (22).

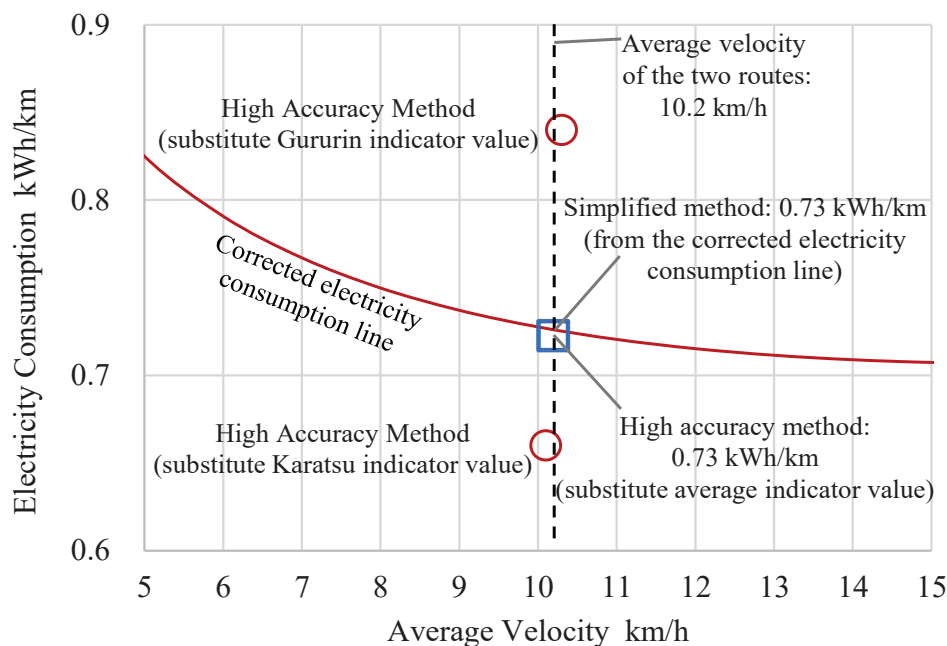


Figure 11. Study using the high-accuracy method regarding the electricity consumption values derived from the simplified method.

The electricity consumption value (high-accuracy method), as previously described, was obtained by substituting the respective road/operational indicators for each route into Formula (22) (Gururin: 0.84 kWh/km, Karatsu: 0.66 kWh/km) and was found to be 0.73 kWh/km by the simplified method by taking the value on the corrected electricity consumption continuous line. The ideal situation would be obtained if the latter electricity consumption values were representative of the consumption values obtained under the standard road and operating conditions at the same average velocity. Hence, to confirm this situation, we compared the average values of the indicators for the five routes in this study to the consumption values obtained by substituting the average values into the same equation. The electricity consumption value using the same method was 0.72 kWh/km, achieving a good match with the value obtained from the simplified method. This suggests that the electricity consumption values obtained for the average state of the five roads and operations are equivalent to those obtained by the simplified method, thereby demonstrating the utility of the method.

Next, we tried to predict the range of electricity consumption values that would occur in the case of operation in other regions with similar average velocity but where the road and operating conditions were different. Specifically, we first derived the best and worst values for electricity consumption obtained in Formula (22) and then arbitrarily moved the values within the variation range of each of the indicators assumed from the results of the previous study, as shown in Figure 10. Figure 12 shows the results of the study for the three average velocity groups (Gururin and Karatsu routes, Kumagaya and Hirabayashi routes, and Honjo route). The variation range is distributed almost symmetrically in the upward and downward directions of the electricity consumption values obtained from the corrected electricity consumption continuous line; thus, this can be considered appropriate. Furthermore, this range matches that of the maximum error range expected when using the simplified method.

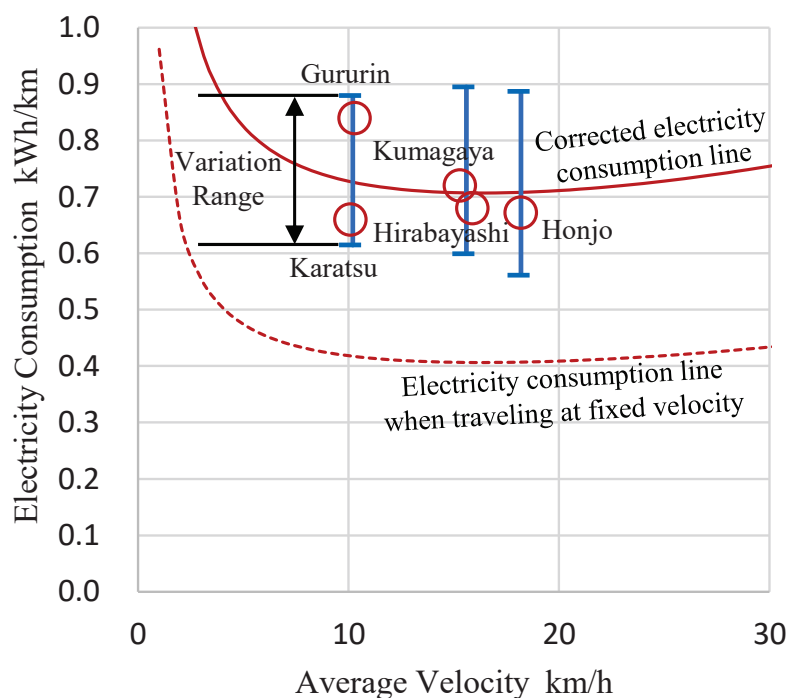


Figure 12. Prediction of the range of expected electricity consumption variation when driving in other regions with different road and operational conditions.

Therefore, a simplified method can be used to obtain approximate values for electricity consumption prediction provided that road/operational indicators do not deviate

considerably from the standard ones. However, when predicting electricity consumption for routes with specific values for the start/stop times, the stop time ratio, and the gained uphill/downhill elevation, it is preferable to use medium- or high-accuracy methods once the necessary information has been achieved.

5. Summary

In this study, we have developed a range of methods that enable operators to easily predict the electricity consumption of electric buses and trucks to be introduced on new routes. This is achieved using only basic information on the planned routes and operation methods.

First, we have constructed a simplified method. This is a method that uses only one type of road and an operational indicator (average velocity) to make a power cost prediction. This is based on the power consumption of the vehicle that is planned to be introduced when driving at a constant velocity on a flat road. The approach considers the effects of acceleration/deceleration and uphill/downhill driving that occurs during actual operation by multiplying the “power cost deterioration rate” by the power cost. We discussed the reasonability of the method based on the theoretical formula using a separately developed high-accuracy method. It was pointed out that approximate electricity consumption values can be obtained for routes where road/operational indicators do not deviate substantially from the standard ones.

Next, we have developed a medium-accuracy method. It is capable of predicting electricity consumption based on three types of road/operational indicators (average velocity, start/stop times, and stop time ratio) while assuming triangular-wave velocity changes. Notably, the same formula should be used after additional information on the operational status of the proposed installation site is obtained from the operator.

Finally, we have constructed a high-accuracy method. This is based on the medium-accuracy method and is capable of predicting electricity consumption using four types of road/operational indicators, with gained uphill/downhill elevation. Moreover, the appropriateness and validity of the method are verified based on the electricity consumption prediction simulator and actual measurements using the test vehicle.

In this study, the WEB-3 electric bus developed by our research group have been used as a specific example for a wide variety of studies. Notably, the equations and methods developed here can be applied to other electric vehicles if the relevant constants that are used are replaced. Herein, we have attempted to develop a method based on information from only five routes that have been operated in advance. However, in the future, we plan to increase the sample size to better align with the diverse operational conditions in different regions. Additionally, regarding future directions for this research, we believe that a more detailed discussion on the calculation method for kinetic energy recovery could be beneficial. Kinetic energy recovery significantly impacts the energy consumption of electric vehicles. The medium-accuracy and high-accuracy formulas we proposed consider kinetic energy recovery at a certain ratio based on measured data. However, to improve the accuracy of electricity cost predictions for different vehicles, adopting varying ratios for different vehicle types or establishing new calculation terms for kinetic energy recovery based on the braking system could be effective. Of course, detailed calculations for kinetic energy recovery might become complex, and balancing the complexity of the formulas with prediction accuracy will be key when developing new calculation terms for kinetic energy recovery.

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Article

Design, Analysis, and Comparison of Electric Vehicle Electric Oil Pump Motor Rotors Using Ferrite Magnet

Huai-Cong Liu

Hwaseong Powertrain R&D Center, Hyundai-Transys, 95, Hyundaikia-ro, Namyang-Eup,
Hwaseong-si 18280, Republic of Korea; hcliuh@hyundai-transys.com; Tel.: +82-010-3076-9989

Abstract: With the recent proliferation of electric vehicles, there is increasing attention on drive motors that are powerful and efficient, with a higher power density. To meet such high power density requirements, the cooling technology used for drive motors is particularly important. To further optimize the cooling effects, the use of direct oil-cooling technology for drive motors is gaining more attention, especially regarding the requirements for electric vehicle electric oil pumps (EOPs) in motor cooling. In such high-temperature environments, it is also necessary for the EOP to maintain its performance under high temperatures. This research explores the feasibility of using high-temperature-resistant ferrite magnets in the rotors of EOPs. For a 150 W EOP motor with the same stator size, three different rotor configurations are proposed: a surface permanent magnet (SPM) rotor, an interior permanent magnet (IPM) rotor, and a spoke-type IPM rotor. While the rotor sizes are the same, to maximize the power density while meeting the rotor's mechanical strength requirements, the different rotor configurations make the most use of ferrite magnets (weighing 58 g, 51.8 g, and 46.3 g, respectively). Finite element analysis (FEA) was used to compare the performance of these models with that of the basic rotor design, considering factors such as the no-load back electromotive force, no-load voltage harmonics ($<10\%$), cogging torque (<0.1 Nm), load torque, motor loss, and efficiency ($>80\%$). Additionally, a comprehensive analysis of the system efficiency and energy loss was conducted based on hypothetical electric vehicle traction motor parameters. Finally, by manufacturing a prototype motor and conducting experiments, the effectiveness and superiority of the finite element method (FEM) design results were confirmed.

Keywords: EOP; ferrite magnet; surface permanent magnet; interior permanent magnet; spoke-type IPM; finite element method

1. Introduction

EOPs play a crucial role in modern vehicles, primarily in the following ways. For traditional fuel vehicles, EOPs are mainly used for starting assistance: during the vehicle startup, the EOP can quickly establish the fuel pressure, helping the engine to start quickly [1,2]. EOPs are also used for lubrication and cooling: they lubricate and cool all types of transmissions, such as automatic transmission (AT), dry or wet dual-clutch transmission (DCT), dedicated hybrid transmission (DHT), continuously variable transmission (CVT), and manual transmission (MT), and reducers, including gears, clutches, and electric drives, as well as providing a lower proportion of the drive (clutches, hydraulic shifting, and hydraulic parking locks) [3–5]. In pure electric vehicles, especially in some high-performance vehicles, EOPs are mainly used to cool and lubricate the motor end-winding coils and reducer gear sets, preventing overheating and wear [6,7]. The design of EOPs needs to consider multiple

key factors to ensure their efficient, reliable, and safe operation. One major issue with the use of electrical products in the engine compartment is that the maximum temperature can reach 130 °C. Compared to general fuel vehicles, the ambient temperature for EOPs is slightly lower, but for some high-performance drive motors with speeds exceeding 16,000 rpm, the coil temperature often exceeds 150 °C to 180 °C [8,9]. Therefore, EOPs must directly spray a cooling medium onto the heat-generating components, such as reducer gears and motor stator end-windings. The structure of the direct oil-cooling system is shown in Figure 1. Excessive coil temperatures can rapidly increase the oil temperature, raising the heat-resistance requirements of the EOP. Therefore, the design of EOPs must consider high-temperature demagnetization under such high temperatures. To further prevent motor demagnetization in high-temperature environments, heavy rare earth elements, including Dy and Tb, must be added to the permanent magnets. However, with the rising prices of rare earth permanent magnets, there are concerns about the stability of the supply of Nd and Dy raw materials. In severe cases, exports may be restricted. Therefore, the use of rare earth permanent magnets should be reduced [10–13]. To reduce the dependence on rare earth permanent magnets, various motors that do not use rare earth permanent magnets, such as induction motors, synchronous reluctance motors (SynRMs) [14,15], and concentrated flux synchronous motors (CFSMs), have begun to be developed. Among the various motors that do not use rare earth permanent magnets, those using ferrite permanent magnets provide an optimal solution. The residual induction of ferrite permanent magnets is one-third that of rare earth permanent magnets [16]. On the other hand, the cost of ferrite permanent magnets is about one-tenth that of rare earth permanent magnets, and a stable supply of ferrite permanent magnets is easily obtained. Additionally, in high-temperature applications similar to those of EOPs, the low-temperature demagnetization characteristics of ferrite can be utilized to save magnet costs. As mentioned earlier, due to the lower residual induction of ferrite permanent magnets, it is necessary to increase the size of ferrite permanent magnets to meet the power and torque performance requirements [10–13,17–19]. This means an increase in the motor size. Therefore, selecting the optimal rotor magnet arrangement and structure is crucial. This paper analyzes various types of rotor arrangements with ferrite combinations and identifies the most suitable ferrite arrangement for an EOP rotor among the proposed rotor structures. It comprehensively compares the rotor shapes of SPM, IPM, and spoke-type IPM motors to establish design standards. This paper provides an important reference for the initial consideration of using ferrite magnet design methods for oil-cooled EOPs in EVs, the application scope, and the selection of ferrite rotor types, including a comparison of their advantages and disadvantages. The rest of this paper is organized as follows: Section 2 introduces the main parameters of ferrite motor rotors and the three analyzed rotor models. Section 3 compares the basic characteristics of each rotor and analyzes the torque and efficiency of the rotors. Finally, prototypes were manufactured based on the design structures. Section 4 shows a comparison of the model simulation and the experimental results. Concluding remarks are provided in Section 5.

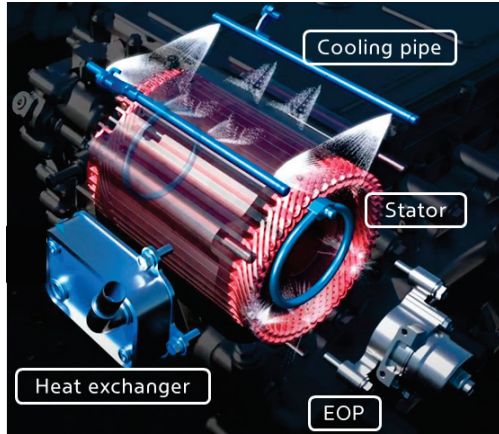


Figure 1. A diagram of the direct cooling of the end-winding in an oil-cooling drive motor for electric vehicles, reprinted with permission from Ref [20]. Copyright 2020 Hyundai-transys.

2. Electrometric Performances

2.1. Winding Factor

EV and HEV electronic oil pump motors generally use fractional slot concentrated windings (FSCWs). A typical characteristic of FSCW motors is the richness of the harmonic components, which greatly affects the various electromagnetic performances of the motor. In addition, the torque capacity of the motor is directly related to the fundamental winding factor. The winding factor of motors with different pole–slot combinations and double-layer windings is expressed as follows:

$$K_{wv} = \sin\left(\frac{vP}{Z}\pi\right) \frac{\sin(vp\alpha)}{N \sin\left(\frac{vp\alpha}{N}\right)} \quad (1)$$

In the formula, P is the number of pole pairs of the motor, $v = k/P$, k is the harmonic order, Z is the number of slots, $N = Z/r$, r is the greatest common divisor of the number of slots, poles, and phases, and α is the electrical angle between adjacent slots. From Formula (1), it can be seen that the winding factor of FSCW motors has periodicity and symmetry, which is the main reason for the generation of low-order harmonics and their irreducibility in FSCW motors. The winding factor can be used to derive the three-phase magnetomotive force (MMF) of the motor, as shown in Formula (2). Additionally, calculations were performed for three different pole–slot combinations (8/12, 10/12, and 14/12), and the results are shown in Figure 2.

$$K_v = \begin{cases} \frac{K_{wv}}{v} & v \neq (3*j)/p \\ 0 & v = (3*j)/p \end{cases} \quad j \in N^+ \quad (2)$$

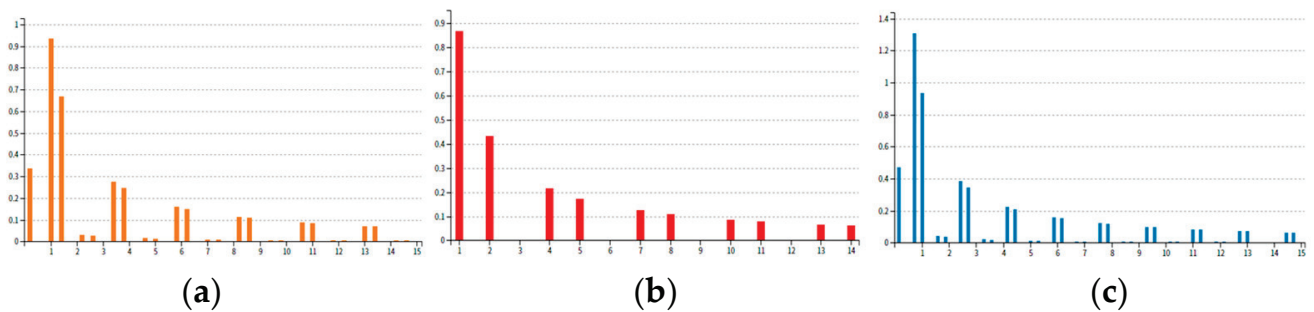


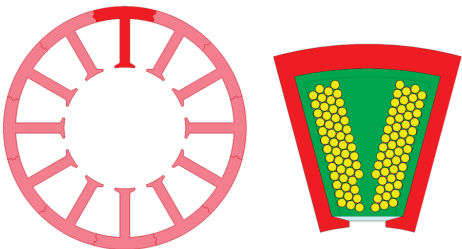
Figure 2. The three-phase MMF factor for the three pole–slot combinations, (a) 10/12, (b) 8/12, and (c) 14/12.

From Figure 2, it can be seen that all the motors contained rich harmonic components in the low-order harmonics. The 10/12 and 14/12 motors had larger subharmonics, which were the main reasons for motor losses and vibrations, while the 8/12 motor had no subharmonics. The over-harmonic amplitude of the 10/12 motor, except for the 7/5 harmonic amplitude, was smaller than that of the 14/12 motor, and the over-harmonic amplitude of the 12/8 motor was much smaller than that of the other two motors. However, the fundamental winding factor of the 10/12 and 14/12 motors was higher at 0.933, much higher than the 0.866 of the 8/12 motor, which helped to improve the output torque. Ultimately, after comprehensive consideration, we selected the 8/12 motor as the basic comparison model.

2.2. Stator Model for Analyzing Rotor Properties

Table 1 lists the specifications of the motor stator model used in this study. The rated DC voltage was 12 V. It is particularly noteworthy that the low magnetic flux density of the ferrite motor necessitated minimizing the back iron and tooth of the stator to provide the maximum slot area for the winding, thereby increasing the power density. Additionally, to increase the fill factor, a segmented stator was used. Finally, to secure the coil and for insulation, this design employed a 0.7 mm thick bobbin insulation.

Table 1. Main parameters of stator.

Item	Unit	Value	8/12 Stator, Slot of Stator
Outer and Inside Diameter	mm	60, 30	
Stack Length	mm	40	
Air Gap	mm	0.4	
Coil Size (bare)	mm	0.71	
No. of Turns, Strands	-	52, 1	
Phase Resistance@20 degC	Ω	0.076	
Fill Factor	%	43	
Bobbin Insulation Thickness	mm	0.7	

2.3. Analysis Models of Motor Rotor

To analyze the relationship between the characteristics of various motors and rotor shapes, the outer diameter of each rotor was fixed to ensure the same conditions and minimize the number of variables. Additionally, the arrangement of the rotor magnets was adjusted to standardize the size and shape of the stator and winding, allowing for the analysis of characteristics under similar conditions. To ensure the accuracy of the analysis using different magnet arrangements and rotor shapes, the typical rotor shape and ratio of the EOP were maintained as much as possible. The final design and the main parameters are listed in Table 2.

Table 2. Comparison of rotors.

Item	Unit	Model 1	Model 2	Model 3
No. of Magnet Poles	-		8	
PM Grade			NMF-12E	
Outer and Inside Diameter	mm	28.6, 9, sleeve (0.3)	29.2, 11	29.2, 9
Stack Length	mm		40	
Magnet Thickness	mm		4.5	
Magnet Weight	g	58.0	51.8	46.3

Generally, due to the low residual magnetic flux density of ferrite magnets, larger magnets must be used to achieve a greater torque density in EOPs. In the case of the IPM-type rotor, larger magnets could not be used structurally because barriers and ribs had to be added. Additionally, to obtain demagnetization characteristics and compare similar performances, the magnet thickness was 4.5 mm. Furthermore, for the SPM-type rotor, a sleeve had to be added to the outer layer of the motor rotor to prevent the magnets from flying off during high-speed rotation. In this paper, the sleeve used was made of stainless steel with a thickness of 0.3 mm. For the spoke-type IPM rotor, the inner diameter of the rotor was particularly important because the magnetization direction of the magnets was not radial towards the air gap but tangential to the air gap. Therefore, the iron core connection between the N and S poles needed to maximize the rotor's inner diameter to minimize it, thereby minimizing the magnetic leakage. Finally, all optimized rotors had to meet the rotational strength requirements. The different shapes of the ferrite magnet rotors were as shown in Figure 3.

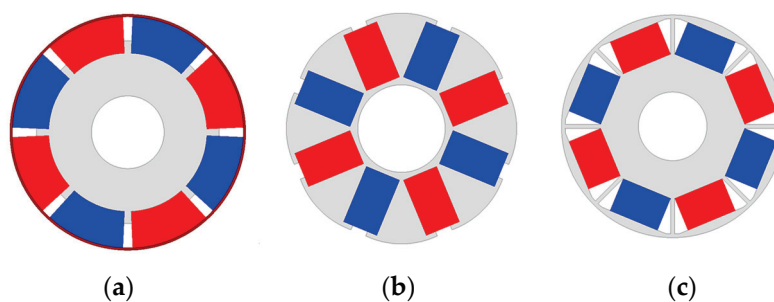


Figure 3. Three different shapes of ferrite magnet rotors: (a) model 1 (SPM with sleeve), (b) model 2 (spoke-type IPM), (c) model 3 (IPM).

3. Comparison of Electromagnetic Performance

3.1. No-Load Analysis of Three Models

The no-load back electric motive force (B-EMF) is an important parameter for analyzing the motor flux and power density. Figure 4a shows the peak line-to-line B-EMF at different speeds. It was found that due to the pole piece structure between the ferrite magnet and air gap of the IPM model, there was leakage flux, resulting in a low no-load back EMF. Meanwhile, although the spoke-type IPM also had a pole piece structure, the magnets caused the magnetic flux to converge in their arrangement, increasing the air gap flux density. In the SPM structure, the ferrite magnet was closest to the air gap, resulting in minimal leakage flux. Even with a sleeve structure, it could still achieve a high air gap flux density. Under the conditions of 1000 rpm and an ambient temperature of 20 degrees, the maximum phase-to-phase B-emfs for model 1, model 2, and model 3 were 2.13 V, 2.19 V, and 0.69 V, respectively. Figure 4b shows the B-EMF Fourier transform (FFT) analysis results. From the FFT analysis, under the same speed and temperature conditions, the fundamental B-EMFs for model 1, model 2, and model 3 were 2.13 V, 2.18 V, and 0.66 V, respectively. It is evident that these values are almost the same as the phase-to-phase back EMF, indicating that the harmonic components were very low. The total harmonic distortion (THD) was approximately 4.93%, 5.37%, and 9.08%, respectively. Additionally, Figure 4c shows that the cogging torque of each motor was calculated to be 0.054 Nm, 0.055 Nm, and 0.009 Nm, respectively.

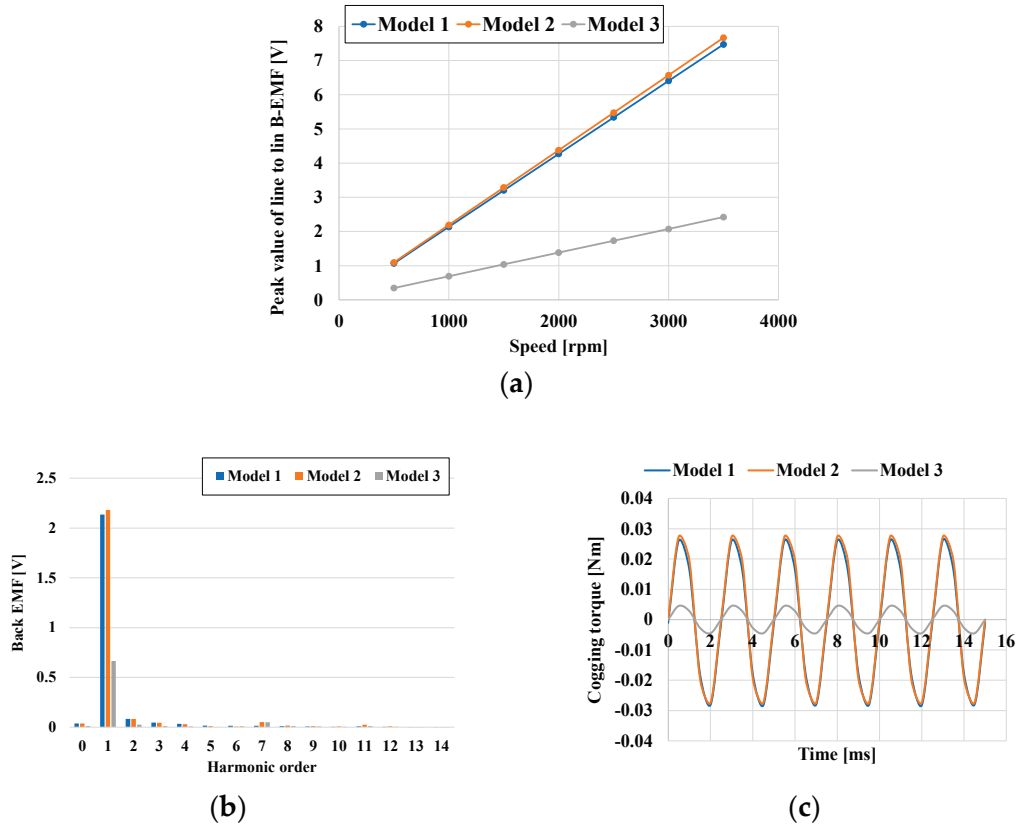


Figure 4. (a) The phase B-EMF of the three models. (b) The FFT analysis of the three models. (c) The cogging torque for the three models.

3.2. Speed–Torque and Speed–Efficiency Analysis

Another type of electromagnetic analysis was performed by applying a constant current at different speeds. Considering the B-EMF, the traction motor required a cooling flow and pressure for the oil pump, with the analysis range being up to the maximum speed of 3500 rpm. Initially, the analysis used the magnet torque without controlling the phase angle. It is well known that the reluctance in IPM motors, i.e., the salient poles, generates additional torque components. The spoke-type IPM, being a salient pole, increased the torque for a given current amplitude through phase angle control. It was found that the maximum torque occurred for the IPM at a current phase of 35–45°, for the spoke-type IPM at 15–20°, and for the SPM, which had no salient pole structure, the maximum current phase angle was generally 0°. This study conducted comparative analyses using different current phase angles in each motor to examine the characteristics of the maximum torque. As shown in Figure 5, to analyze the effects of the d-axis and q-axis, the analysis indicated that under the same current input, the spoke-type IPM configuration had the highest torque (0.46 Nm) due to its large magnet volume and effective magnetic flux generation. In contrast, the ferrite magnet in the IPM had the smallest effective magnetic flux. Figure 6 compares the magnetic field densities of the different models. It is important to note that not only was the rotor lamination significantly different, but the stator core saturation of the models also varied under load operation (as seen in Figure 6).

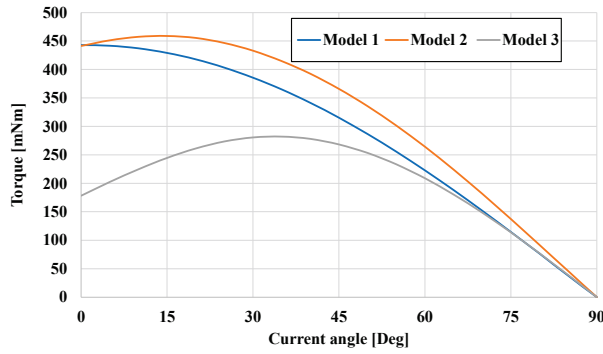


Figure 5. FEM torque value at different current angles (phase current I_a : 12 arms).

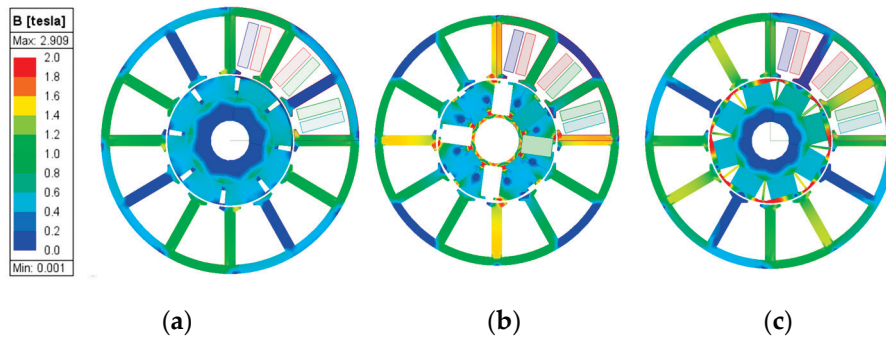


Figure 6. Cross section and flux density distributions of three models in MPTA condition. (a) Model 1, load condition (I_a : 12 arms; β : 0°). (b) Model 2, load condition (I_a : 12 arms; β : 15°). (c) Model 3, load condition (I_a : 12 arms; β : 35°).

Figure 7 compares the torque and power characteristics at different rotational speeds. The analysis shows that model 2 had the highest basic speed torque. This is because, as mentioned earlier, the ferrite magnetic flux was concentrated, and there was minimal magnetic leakage. The air gap magnetic flux density of model 2 was very high.

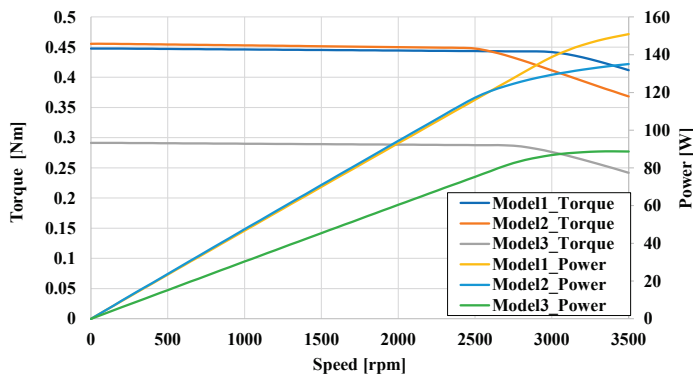


Figure 7. Comparison of torque and power according to speed.

Model 1 also had a high torque density. Due to the proximity of the ferrite to the air gap, the air gap magnetic flux density was increased. Additionally, even within the range of high-speed magnetic field weakening and Maximum Torque Per Volt (MTPV) control, model 1 did not exhibit a rapid torque drop in the high-speed range (2700–3500 r/min). This is attributed to the high initial basic speed and the low residual magnetic field strength of the ferrite, making it easy to modulate weak magnetic control. Finally, the power curve shows that model 1 had the highest power.

3.3. A Comparison of the Efficiency Maps and WLTP Class 3 Driving Cycle

Figure 8 shows the electric efficiency maps of the three models. Since model 3 did not meet the maximum torque performance requirements, this chapter mainly considers the efficiency characteristics of model 1 and model 2. It was found that due to the higher torque density of model 2, model 2 had higher efficiency in the low-speed, high-torque region where the copper loss was significant. By referring to the diagram of the magnetic flux density under a load (Figure 6), it can be seen that model 1 had a lower magnetic saturation density, resulting in lower iron loss compared to model 2. Therefore, model 1 had greater efficiency in the high-speed, low-torque region.

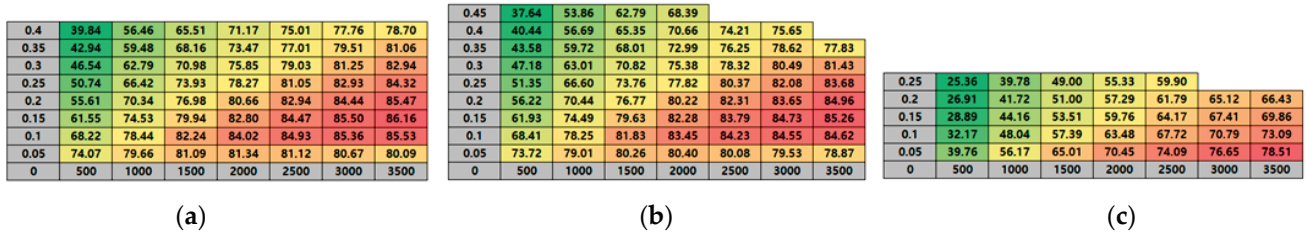


Figure 8. Efficiency maps of three models: (a) model 1; (b) model 2; (c) model 3.

To further discuss the performance of the EOP in terms of the EV traction motor system efficiency, it was necessary to comprehensively consider the operating power points of the EOP in the EV traction motor. These power points also needed to refer to the global driving cycle standard tests for electric vehicles, such as the WLTP, NEDC, and US06. It should be noted that the EOP speed needed to be determined by referring to the motor temperature (usually the end-winding temperature) and the traction motor circulating oil temperature. At the same time, power tests on the EOP needed to be conducted under different oil circulation system pressures and flow rates. Based on the test results, a three-dimensional lookup table (EOP speed/oil flow/oil temperature) was used to find the output power at each operating point during the endurance test. Finally, the efficiency of the rotary pump was added to obtain the power point of the EOP motor. Figure 9 shows the operating points of an EV oil-cooled traction motor EOP under the WLTP class 3 driving cycle, which is a specific category within the global WLTP testing program designed for high-performance light-duty vehicles, particularly EVs with a top speed exceeding 130 km/h [21–24].

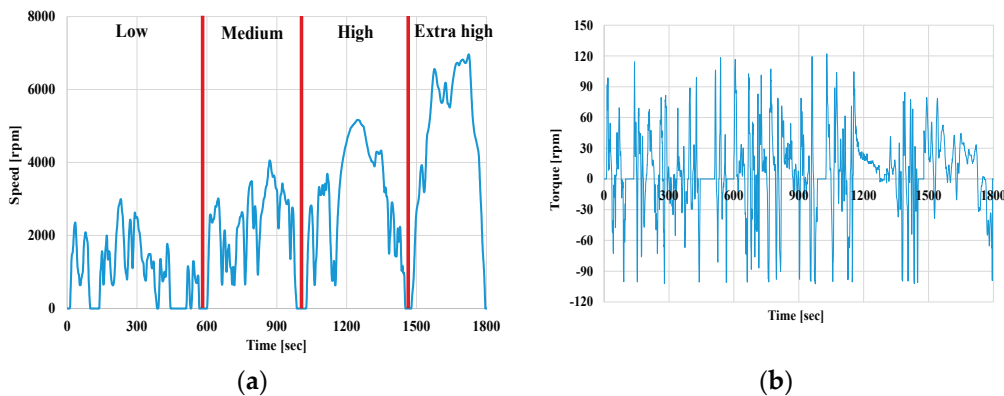


Figure 9. (a) The motor speed and (b) absolute load torque over the WLTP class 3 driving cycle, reprinted from Ref. [23].

The rotational speed of the target traction motor and the EOP motor, as well as the torque curves, are shown in Figure 10. It can be seen that during the initial cycle phase (low and medium WLTP range), the EOP motor's operating conditions were not severe. The temperature rises of the traction motor coils and the oil temperature increase in the oil

cooling system were not significant. Therefore, during the initial cycle phase, there was no need to significantly increase the oil flow rate, and the required torque of the EOP motor did not increase much. However, during the high-speed cycle phase (high and extra-high WLTP range), the motor coils heated up rapidly under high-speed operation, resulting in a significant increase in the required flow rate, which led to an increase in the EOP motor speed and torque. Next, by considering cold-start and hot-start environments, two different operating points of the EOP at 25 °C and 65 °C were extracted (the temperatures refer to the traction motor cooling inlet oil temperature; in the experiment, a fixed chiller was usually used to set a constant oil inlet temperature, which was then supplied to the traction motor). It can be seen that in a high-oil-temperature environment, the command required the EOP to operate at a high speed; therefore, the EOP operating speed was much higher. However, in a high-oil-temperature environment, the viscosity of the oil decreased, and compared to a low-oil-temperature environment, the required EOP motor torque was lower. Figure 11a shows the required operating points under the maximum torque speed of the three EOP models in WLTP class 3. It can be seen that all possible operating points of the WLTP class 3 driving cycle are within the torque–speed curve specified by model 1 and 2. However, the maximum torque margin of model 3 is insufficient (unable to meet the requirements of a below-zero oil temperature and certain extreme operating conditions).

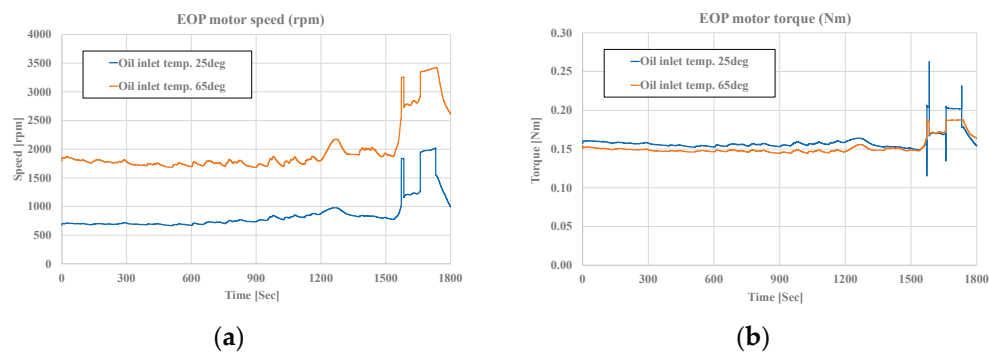


Figure 10. (a) The EOP motor speed and (b) absolute EOP motor torque over the WLTP class 3 driving cycle.

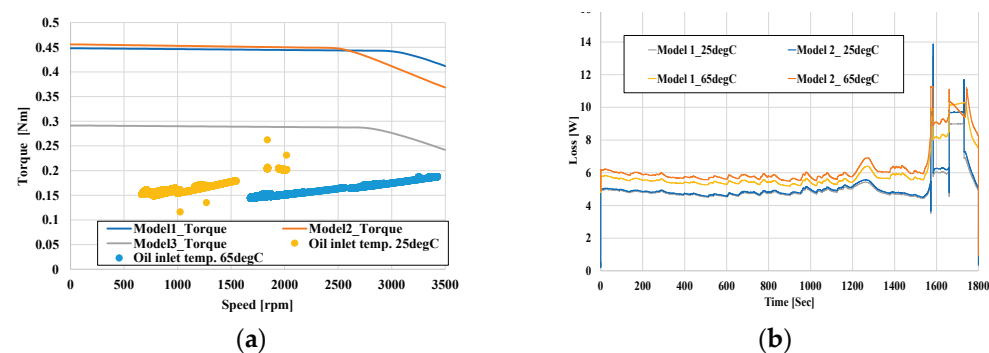


Figure 11. (a) EOP motor specification for peak torque versus speed characteristics (all models); (b) loss over WLTP class 3 for model 1 and model 2.

Finally, the motor's total loss is shown in Figure 11b. The motor's losses included iron losses, copper losses, and permanent magnet eddy current losses. These results were obtained from a steady-state FEM analysis conducted every 0.1 s. In a low-oil-temperature environment (25 °C), the losses of model 1 and model 2 exhibited similar performance during the initial cycle phase, representing urban driving conditions (low and medium WLTP range). However, during simulated suburban and high-speed driving (starting from 1300 s), the losses of model 2 were higher than those of model 1. As previously mentioned,

in the high-speed range, model 2 had higher iron losses due to a higher magnetic flux and magnetic saturation. Therefore, their energy consumption increased rapidly in the high and extra-high WLTP range. In a high-oil-temperature environment (65 °C), the losses of model 1 were lower than those of model 2 across the entire range of the WLTP. This is also because, in a high-temperature environment, the oil pump needs to rotate at a high speed across the entire WLTP range. The energy consumption in each range is confirmed in Table 3.

Table 3. The energy loss over WLTP class 3 for the EOP models.

Item	Unit	Model 1		Model 2	
		25 °C	65 °C	25 °C	65 °C
WLTP low-range loss	Wh	0.798	0.924	0.808	0.983
WLTP medium-range loss		0.529	0.602	0.536	0.639
WLTP high-range loss		0.622	0.717	0.635	0.766
WLTP extra-high-range loss		0.589	0.754	0.618	0.800

4. Results of Experiment

Through the analysis in the previous chapter, comparing model 2 and model 3, we found that model 1 had the greatest advantages in terms of the power density, efficiency, and ease of manufacturing (models 2 and 3 generally magnetized after insertion). To verify the design results, an SPM prototype was made. Figure 12 shows the stator and rotor of the SPM prototype. Figure 13a shows the experimental and simulated values of the no-load line induced voltage at a speed of 1000 r/min. The experimental value of the no-load line induced voltage was 1.47 Vrms, and the simulated value was 1.51 Vrms. Additionally, a comparison of the measured and simulated values of the cogging torque is reflected in Figure 13b. Finally, a comparison of the experimental and simulated efficiencies under the load torque is shown in Table 4. All experimental data indicated that the two values were relatively close.

Table 4. Efficiency comparison at rated power point.

Item	FEM	Experiment	Error
Base speed	3200 rpm	3194 rpm	0.18%
Torque	0.348 Nm	0.359 Nm	3.0%
Power	116.5 W	120.3 W	3.5%
Efficiency	80.2%	80.0%	0.2%

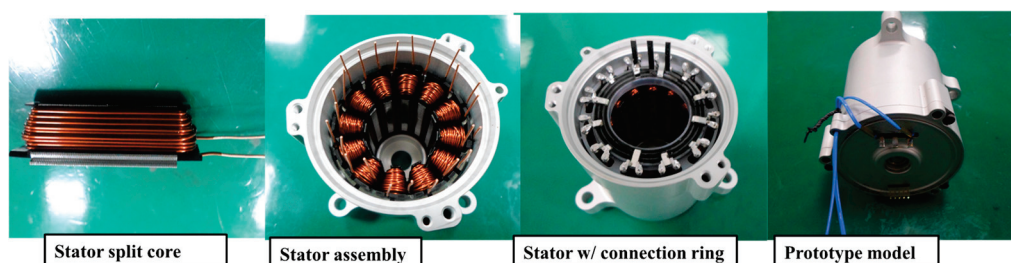


Figure 12. The prototype of the SPM with a ferrite magnet for the EOP.

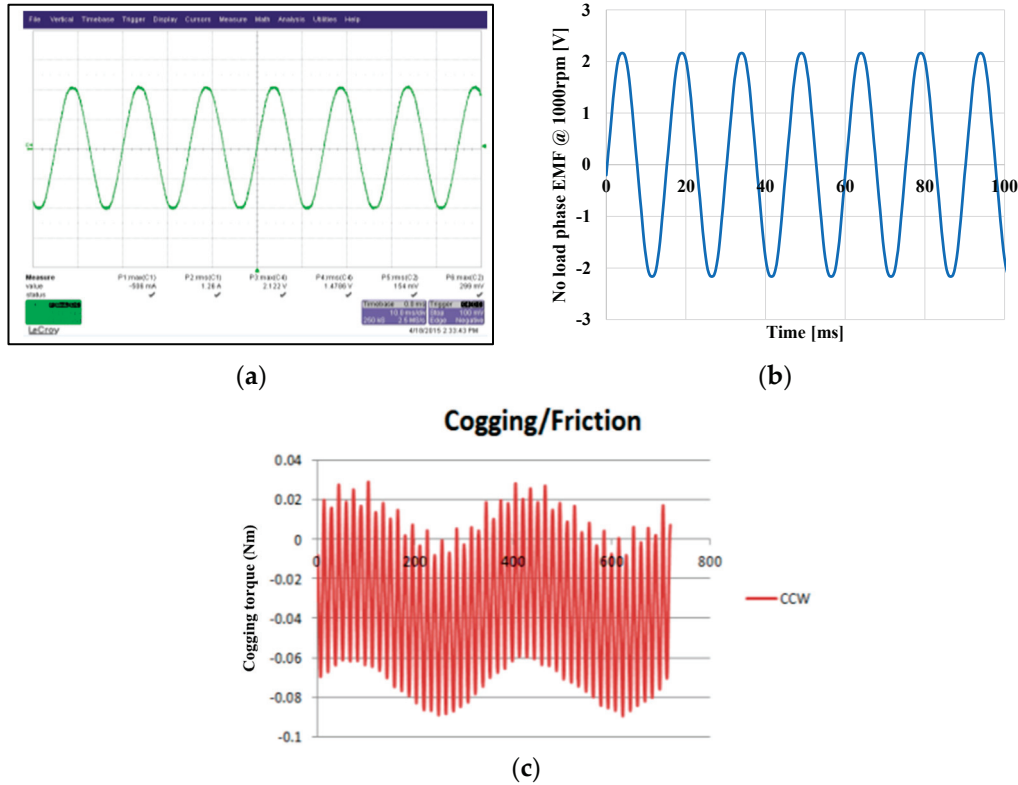


Figure 13. Experiment and simulation results of no-load line induced voltage at 1000 r/min. (a) Experiment. (b) Simulation. (c) Experiment results of cogging torque, reprinted with permission from Ref. [25]. Copyright 2020 IEEE.

5. Conclusions

This paper presents the optimal design scheme for the latest pure electric drive cooling EOP, a ferrite magnet rotor motor, which can provide high efficiency, a high torque density, and a low torque ripple in EOP applications. Combined with the cooling control scheme, the proposed Fe-PM SPM rotor achieved the highest system efficiency. Finally, the no-load and load operation performances were obtained through experimental measurements. Based on the comparison of the simulation and experimental results, the following conclusions were drawn:

- (1) The air gap magnetic density of the ferrite magnet rotor motor is very low. Therefore, when designing such a motor, it is necessary to select a design with the maximum air gap magnetic density, minimize magnetic leakage as much as possible, and concentrate the magnetic density of the magnets. Therefore, rotor structures similar to the SPM and spoke-type IPM can meet the design requirements.
- (2) The IPM structure is very unsuitable for ferrite rotors, as its construction cannot maximize the magnet area, the magnets are far from the air gap, and the structure retains ribs and bridges, which will inevitably cause magnetic leakage, thereby reducing the power density and motor efficiency.
- (3) When analyzing the system efficiency, it is necessary to consider the efficiency of the EOP motor at high operating points, considering the high cooling oil temperature. The system will require high flow rates and high EOP operating speeds. Therefore, although increasing the air gap magnetic density is particularly important, the magnetic density of the stator core also needs attention. It is necessary to improve the magnetic density of the core to reduce iron loss and enhance the high-speed efficiency of the ferrite motor.

Finally, the SPM-type motor (model 1) achieved a higher torque density by configuring more ferrite magnets, but it requires additional ferrite magnet material and a sleeve structure, which may lead to higher costs. Considering the fluctuations in magnet prices and the impact of EOP losses on the electric vehicle system, future research should delve deeper into the trade-offs between the motor manufacturing complexity, motor cost, and system performance.

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Article

Development of Integrated Chassis Control of Semi-Active Suspension with Differential Brake for Vehicle Lateral Stability [†]

Kyungtaek Lee * and Jinwoo Seol

HL Mando Global R&D, 21 Pangyo-ro 255, Bundang-gu, Seongnam-si 13486, Gyeonggi-do, Republic of Korea; jinwoo.seol@hlcompany.com

* Correspondence: kyungtaeklee@gmail.com

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Abstract: This paper describes an integrated control strategy that utilizes semi-active suspension and differential braking to enhance lateral stability while maintaining roll performance. The integrated control architecture adopts a hierarchical structure consisting of an estimator, a supervisor, a controller, and an allocator. In the estimation layer, an algorithm is proposed to robustly estimate the side slip angle and roll angle in various situations. The control mode is established by the supervision layer based on the state of the vehicle. The maneuverability mode tracks the driver's intentions, and the lateral stability mode ensures the vehicle's stability. Reference values such as yaw rate and roll angle are determined by the control mode. In the controller layer, the yaw and roll moments are generated using sliding mode control to achieve the target yaw rate and roll angle. Brake torque and suspension damping force are distributed to each wheel in the allocator layer. In particular, a damping distribution method based on the roll region index is proposed. The proposed method is compared with conventional methods, such as full stiff damping and yaw-assisted damping, through simulation and real-world evaluation. The tests demonstrate that the proposed approach enhances lateral and roll stability, particularly regarding maximum side slip and roll angle values. The roll-region-index-based distribution method reduces the maximum roll angle by about 17.4% and the maximum side slip angle by about 8.7% compared to each conventional method. Compared to conventional methods, the proposed method showed more stable driving performance by ensuring stability in both directions in extreme lane change situations.

Keywords: integrated chassis control; hierarchical architecture; lateral stability; semi-active suspension; differential brake

1. Introduction

The trend of mobility has been rapidly shifting toward autonomous driving and electrification. The electrification of not only the drivetrain but also the chassis system, which determines the vehicle's dynamic behavior, is also developing quickly. Motor-based electrification of the chassis has the advantage of accurate control response, and modularization of the system enables independent operation of each actuator. Furthermore, the development of autonomous driving enables more information to be used for chassis control. Therefore, future chassis control should optimize the performance of vehicle systems with multiple actuators by using various inputs. Conventional chassis systems generally operate independently, with one function targeting a single dynamic direction. Such an independent chassis control has difficulties in the cooperative control of multiple

targets. In addition, as the number of actuators increases, there is a limit to the allocation of control to optimize overall performance. In other words, downstream-based independent control has limitations in optimizing the vehicle's overall performance. Therefore, recent studies of integrated chassis control adopt a control mode selection method or a centralized, hierarchical control architecture that aims to improve the overall dynamic performance by coordinating multiple chassis systems [1].

In previous studies of hierarchical integrated control, much of the research was based on control mode switching. Braking and steering, which can directly affect the vehicle, were widely used to improve lateral performance, such as maneuverability and lateral stability. The authors of [2] used hierarchical structure-based control using active front steering control (AFS) and electronic stability control (ESC). This was achieved by switching between maneuverability and stability modes depending on the control mode. The authors of [3] set the nonlinear index of an AFS with direct yaw moment control according to the stability region, distributing target yaw moments to the brakes and steering.

On the other hand, the suspension control was similarly control-mode-based and mainly focused on the vehicle's ride comfort or tire grip on the ground. Some suspension control based on the control mode was configured using a rule-based method. The authors of [4] divided the control mode into six finite states and preset whether the brakes function was engaged and the gain of the suspension accordingly. In this case, the suspension uses the preset PID control gain for each mode. The authors of [5] assigned the desired moments to the suspension via a weighting coefficient in the upper controller, which is then distributed via optimal control. The weighting coefficient is pre-selected with an appropriate value through trial and error. The authors of [6] distinguished between ride comfort and stability modes based on steering angle and lateral acceleration and configured a rule-based fuzzy control logic accordingly. The above fuzzy logic is activated simultaneously with the brakes, but the suspension's control method is tuned in advance. In a recent study, suspension control is performed in control modes that target tire-to-road adhesion or ride comfort [7]. The study, considering the independent drive, presented an integrated control scheme combining an active suspension system and a brake system for a four-wheel independent-drive electric vehicle [8]. As shown above, the suspension control method has been preset for different situations and mainly controls the tire grip and roll stability. These conventional methods are considered as full hard damping methods in this study because they stiffen the suspension for attitude control.

Next, the suspension control method of influencing the vehicle's yaw moment using the load transfer of the tire's front and rear wheels was studied. The author of [9] used differential brake, suspension damping control, and active roll control to improve lateral stability and roll stability by regulating the vertical force on the tires through the suspension to influence lateral behavior [9]. The author of [10] divided the control of an MR damper into maneuverability control and attitude control modes depending on whether it is cornering or in a straight line. In this case, the maneuverability mode of the MR damper uses the tire's load transfer to the front and rear wheels. These conventional methods correspond to the yaw assist method by damping control in this study.

In a recent study on semi-suspension, especially for multiple directions, attitude control in three directions, such as yaw-roll-pitch, was optimized using weight adjustment through suspension damping control [11]. However, even in this study, assisting in one direction comes at the expense of the other's performance. In other words, within the identical control mode, one direction must be sacrificed to assist another direction. While these existing studies are based on switching control modes to achieve the proper suspension control mode for different situations, there is a trade-off between yaw assist performance and roll

performance in semi-active suspension. This issue becomes more problematic in extreme situations because both lateral and roll performance are required in severe conditions.

This paper notes that the yaw assist method, which uses front and rear load transfers, only considers models of the relationship between the tire and the ground. The real-world evaluation of the previous yaw assist method showed that even the negative control method improved the lateral stability performance under some conditions. This means that the vehicle's lateral behavior is influenced not only by the relationship between the tire and the ground but also by the change in the sprung mass as the damping softens. Based on the movement of sprung mass, this study proposes a method for improving roll and lateral performance by controlling damping according to the roll region index without switching the control mode. Especially in extreme conditions where lateral stability is required, such as sudden lane changes, the attitude of the vehicle also becomes important. In previous studies, this was solved by changing the control mode. This study shows that the roll region index improves roll performance in the same control mode without switching control modes.

The validity and effectiveness of the proposed method are verified through simulations and real-world tests. The test results show the limitations of conventional methods, such as full stiff damping and yaw assist, and confirm that the proposed method significantly improves performance in both directions.

In addition, this study considers some physical models linearly to demonstrate the method but, in the future, nonlinearities can be addressed to improve performance further. For example, the control performance can be improved in the suspension using a nonlinear dynamics model fluid inertia-based suspension model [12]. In addition, the tire model's cornering stiffness is also assumed to be linear but, in sudden lane changes in actual conditions, the tire force shows nonlinearity. In this study, a roll model assuming linear stiffness and damping is used, and a lateral and yaw model with a linear tire model is applied. However, the model error is compensated by a sliding mode control that is robust to nonlinearity. The above assumptions did not affect the performance of the proposed control method when the appropriate linear coefficients were used for the limited conditions in the real-world evaluation. However, it should be considered that nonlinearities are necessary for applying the proposed algorithm commonly under various conditions. Note that this study focuses on the hierarchical control structure and the description of the suspension control distribution method through the roll region index, which is assumed to be linear for simplicity.

Section 2 describes the overall control mode with a flow chart. Section 3 expresses how to robustly estimate the vehicle's state variables for integrated control. Sections 4 and 5 describe the implementation of control-mode-based integrated chassis control in this work. Section 6 describes the logic by which yaw assist control by damping is implemented by distributing the yaw and roll moments obtained through the controller. Then, in Section 6.2.2, the suspension damping method using the roll region index is presented. Section 7 discusses evaluation results obtained by simulation and real-world tests. Finally, Section 8 presents the conclusions, limitations of this study, and future work.

2. Overall Control Scheme

The hierarchical architecture is used for integrated control of suspension and brake, as shown in Figure 1. This structure maximizes the dynamic performance of integrated control and allows for scalability and flexibility, which are advantages of a centralized processing architecture. The integrated control structure is composed of four layers. The first layer is the estimator, responsible for estimating information about the vehicle's state. An accurate and robust vehicle state estimation is important because driving mode decisions

and control amounts are determined based on estimated values. In other words, precise state information is required for the other layers to generate the appropriate reference and control. The second layer is the supervisor, which determines the vehicle's control mode and reference motion. In this step, the control mode is determined by various parameters, and the reference value is changed according to the control mode. For example, maneuverability mode generates a reference value that aims to follow the driver's steering intentions, and lateral stability mode creates a reference that aims to increase the vehicle's lateral stability. The third layer is the controller, which determines the global vehicle input, such as the force and moment of the vehicle. In this study, the yaw moment and roll moment are determined by sliding mode control to ensure robustness against nonlinear characteristics. Lastly, the fourth layer is the control allocator. This layer distributes the appropriate amount of control to each chassis system based on optimal distribution. In addition, a distribution method using the roll region index is presented. Compared to conventional suspension control, this method improves performance in both the roll and lateral directions.

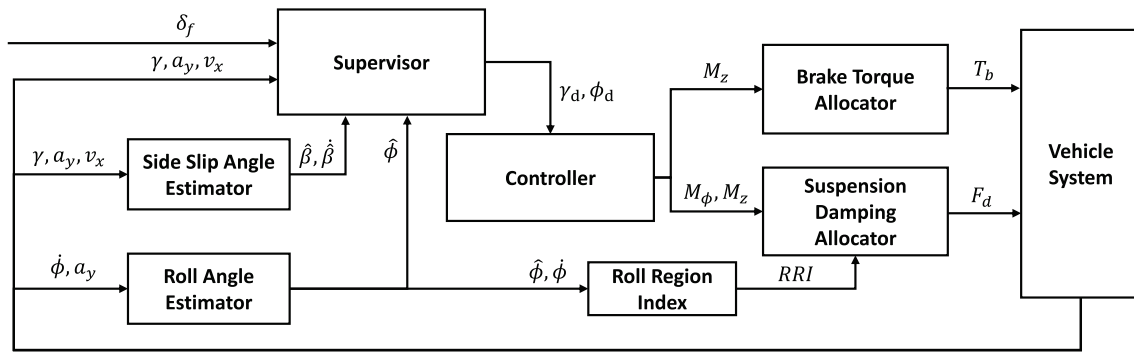


Figure 1. Overall control scheme.

3. Estimator Layer

Integrated chassis control requires an accurate estimation of the state variables, but some values are difficult or expensive to measure with commercial sensors. For example, the side slip angle is the difference in angle between the vehicle's direction of travel and its heading angle. It is used as an important factor in the vehicle's lateral stability. However, obtaining accurate side slip angles directly from commercial sensors is complex and requires additional devices, such as a global positioning system and image sensor, which increases cost. This paper needs the roll and side slip angles to control lateral and roll stability. In general, when estimating the roll angle, uncertainties in the vehicle's rotational stiffness, damping coefficient, and changes in the vehicle's center of rotation cause errors from the model to the actual outcome. In addition, the nonlinearity of tire force decreases the accuracy of the side slip angle estimation. Therefore, it is necessary to improve the precision of the modeling and design a robust estimator of uncertainties for reliable estimation. In this study, a sliding mode observer based on the sliding theory is adopted, and a Kalman filter with a kinematic model is used to improve the performance of the side slip angle observer.

3.1. Design of Roll Angle Observer

As illustrated in Figure 2b, the vehicle's roll dynamics are represented as follows:

$$I_x \ddot{\phi} + C_\phi \dot{\phi} + K_\phi \phi = m_s a_y h_s + m_s g h_s \sin \phi + M_\phi \quad (1)$$

When defined as a state vector $x = [\phi, \dot{\phi}]^T$, input vector $u = a_y$, and output vector $y = \phi$, Equation (1) can be rewritten as follows:

$$\begin{aligned}
\dot{x} &= Ax + Bu \\
y &= Cx \\
\text{where } A &= \begin{bmatrix} 0 & 1 \\ -\frac{K_\phi - m_s g h_s}{I_x} & -\frac{C_\phi}{I_x} \end{bmatrix}, B = \begin{bmatrix} 0 \\ \frac{m_s h}{I_x} \end{bmatrix}, C = [0, 1]
\end{aligned} \tag{2}$$

The Utkin observer is expressed by Equation (3).

$$\begin{aligned}
\dot{\hat{x}} &= A\hat{x} + Bu + Gv \\
\text{where } G &= \begin{bmatrix} L \\ -I \end{bmatrix}, v = \rho \operatorname{sgn}(e_y)
\end{aligned} \tag{3}$$

The system is asymptotically stable when a Lyapunov function exists that satisfies Equation (4), and the sliding surface is defined as Equation (5).

$$\begin{aligned}
V &= \frac{1}{2}s^2 \geq 0 \\
\dot{V} &= s\dot{s} < 0
\end{aligned} \tag{4}$$

$$s = e_y = \hat{y} - y \tag{5}$$

To derive the error dynamics of the output, the augmented matrix is defined as follows:

$$T = [N_c^T, C]^T \tag{6}$$

In this case, N_c^T is the null space of matrix C. If $Tx = x_a$, the augmented system is represented by Equation (6)

$$\begin{aligned}
\dot{x}_a &= [TAT^{-1}]x_a + [TB]u \\
y &= [CT^{-1}]Tx = [CT^{-1}]x_a \\
\text{where } TAT^{-1} &= \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, TB = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}, CT^{-1} = [0, I_p]
\end{aligned} \tag{7}$$

Using Equations (3) and (7), the error dynamics can be represented as follows:

$$\begin{aligned}
\dot{e}_a &= [TAT^{-1}]e_a + Gu \\
e_y &= [CT^{-1}]e_a
\end{aligned} \tag{8}$$

When $e_a = [e_1, e_2]$, Equation (8) can be written as follows:

$$\begin{aligned}
\dot{e}_a &= \begin{bmatrix} \dot{e}_1 \\ \dot{e}_y \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} e_1 \\ e_y \end{bmatrix} + \begin{bmatrix} L \\ -I \end{bmatrix} v \\
e_y &= [0 \ I_p] \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = e_2
\end{aligned} \tag{9}$$

Finally, the output error for the dynamics for the estimated output error can be written as follows:

$$\dot{e}_y = A_{21}e_1 + A_{22}e_y - v \tag{10}$$

To check for stability, substituting Equation (10) into Equation (4),

$$\begin{aligned}\dot{V} &= e_y(A_{21}e_1 + A_{22}e_y - \rho \operatorname{sgn}(e_y)) \\ &= e_y(A_{21}e_1 + A_{22}e_y) - \rho|e_y| \\ &\leq -|e_y|(\rho - |A_{21}e_1 + A_{22}e_y|)\end{aligned}\tag{11}$$

Thus, for any ρ that satisfies $\rho > |A_{21}e_1 + A_{22}e_y|$, the output error converges to zero in finite time because $\dot{V} < 0$. Finally, the observer of the roll angle is given by Equation (12).

$$\hat{\dot{x}} = A\hat{x} + Bu + Le_y + G\rho\text{sgn}(e_y) \quad (12)$$

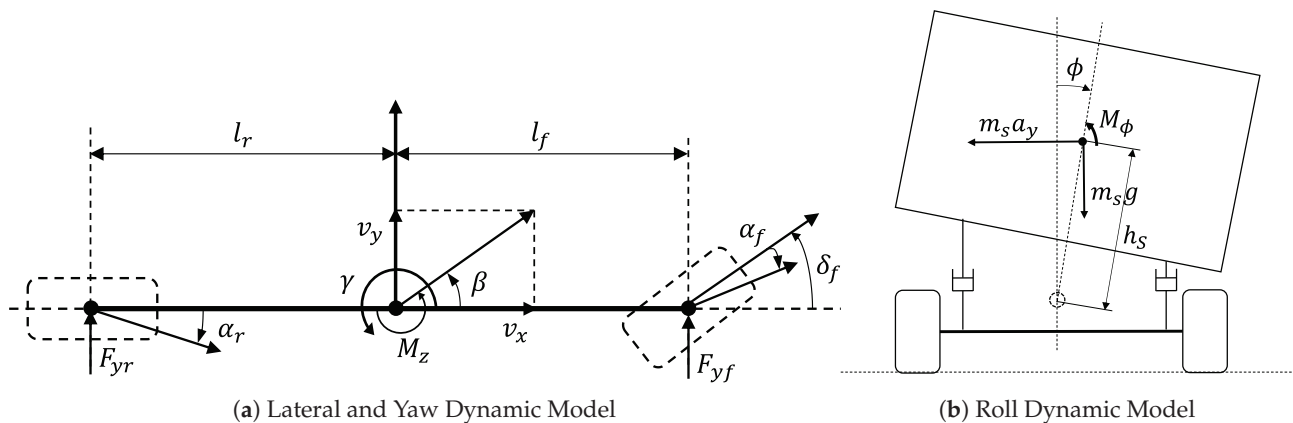


Figure 2. Dynamic model of vehicle.

3.2. Design of Side Slip Angle Observer

In previous research, side slip angle estimation can be broadly categorized into kinematics-based and dynamics-based estimation. Kinematic-based estimation can be obtained using the vehicle's heading angle and yaw angle from the global positioning system and the internal measurement unit [13,14]. However, this method has good performance at high-speed changes, but errors in integration and the low update rate degrade estimating performance. On the other hand, studies on dynamics-based estimation have used observers such as a Kalman filter and sliding mode observer to estimate the slip angle based on dynamics models. These dynamics-based estimates are advantageous for the cumulative error and update rate, and because linear tire models are typically easily available, the performance of these estimates is good in linear domains such as low speed and smooth steering. However, the estimation performance decreases as the error between the model and the actual outcome becomes larger, such as the nonlinearity of the tire and the error with simplified models. Thus, nonlinear tire models and an unscented Kalman filter were used to improve performance in nonlinear regions [15], dimensionless coefficients were introduced to account for the nonlinearity of the tire [16], a 7 DOF vehicle model and longitudinal forces were considered to reduce model error [17], and estimation performance was improved using a combined model based on frequency with a kinematic model [18]. These studies can improve performance in extreme conditions but, in real applications, additional costs are needed to tune the nonlinear model and estimate other variables by a vehicle test. In this study, in order to develop an estimator with good performance without the above additional costs, a sliding mode observer based on a linear tire model and the rate of side slip angle derived from the kinematic model are combined using a Kalman filter to obtain a modified side slip angle. As illustrated in Figure 2a, the lateral dynamics of the vehicle are expressed as follows:

$$\dot{v}_y = \frac{1}{m}(F_{yf} + F_{yr} - v_x \gamma) \quad (13)$$

$$\dot{\gamma} = \frac{1}{I_z}(l_f F_{yf} - l_r F_{yr}) \quad (14)$$

Using the lateral tire force and the tire slip angle, the equation can be expressed as follows:

$$F_{yf} = C_f \alpha_f, F_{yr} = C_r \alpha_r \quad (15)$$

$$\alpha_f = \delta_f - \frac{v_y + l_f \gamma}{v_x}, \alpha_r = -\frac{v_y - l_r \gamma}{v_x} \quad (16)$$

The side slip angle of the vehicle is presented as follows:

$$\beta = \frac{v_y}{v_x} \quad (17)$$

By summarizing expressions from Equation (13) to Equation (17), when $x = [v_y, \gamma]$, $y = k\gamma + a_y$, the state space equations can be written as follows:

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned}$$

$$\text{where } A = \begin{bmatrix} -\frac{C_f + C_r}{mv_x} & \frac{-l_f C_f + l_r C_r}{mv_x^2} - 1 \\ \frac{-l_f C_f + l_r C_r}{I_z} & \frac{l_f^2 C_f + l_r^2 C_r}{I_z v_x} \end{bmatrix}, B = \begin{bmatrix} \frac{C_f}{mv_x} \\ \frac{l_f C_f}{I_z} \end{bmatrix}, \quad (18)$$

$$C = \begin{bmatrix} -\frac{C_f + C_r}{m} & \frac{-l_f C_f + l_r C_r}{mv_x} + k \end{bmatrix}, D = \frac{C_f}{m}$$

According to the formulas from Equation (3) to Equation (11), the design of the sliding mode observer proceeds in the same way, and the observer for the side slip angle is

$$\dot{\hat{x}} = A\hat{x} + Bu + L_l e_y + G \rho \operatorname{sgn}(e_y) \quad (19)$$

3.3. Combined Model of Side Slip Angle Observer with Kinematic Model

The kinematic model and a Kalman filter are used to calibrate the estimation to improve the estimation performance of the nonlinear region of the tire. Since the kinematic model does not include the uncertainty of the tire, the side slip angle rate derived from the model has a relatively accurate value. However, when it is used as an integral, there are problems of error accumulation, and its performance is poor under noisy conditions. Therefore, using the beta rate of the kinematic model based on the sliding mode observer can construct a stable estimator that reflects rapid changes while compensating for the weaknesses of both methods. The beta rate obtained from the kinematic model is as follows:

$$\dot{\beta} = \frac{a_y}{v_x} - \gamma \quad (20)$$

The algorithm for the sliding mode observer and kinematic model using a Kalman filter is as follows. The predictive model of the side slip angle and its rate are represented in the discrete-time state space form as Equation (21).

1. Predict state model

$$\begin{bmatrix} \beta_{k+1} \\ \dot{\beta}_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_k \\ \dot{\beta}_k \end{bmatrix}$$

2. Measurement from sliding mode observer

$$z_k = \begin{bmatrix} \beta_{SMO} \\ \dot{\beta}_{SMO} \end{bmatrix}$$

3. Kalman filter

(1) Modification of side slip angle rate

$$x_{k-1} = \begin{bmatrix} \hat{\beta}_{k-1} \\ \dot{\beta}_{kin} \end{bmatrix} \quad (21)$$

(2) Prediction of the states and the covariance error

$$\hat{x}_{\bar{k}} = A\hat{x}_{k-1}$$

$$P_{\bar{k}} = AP_{k-1}A^T + Q$$

(3) Computation of the Kalman gain

$$K_k = P_{\bar{k}}H^T(HP_{\bar{k}}H^T + R)^{-1}$$

(4) Computation of estimative and covariance error

$$\hat{x}_k = \hat{x}_{\bar{k}} + K_k(z_k) - Hx_{\bar{k}}$$

$$P_k = P_{\bar{k}} - K_kHP_{\bar{k}}$$

where Q is the covariance matrix for system noise, R is the covariance matrix for the measurement noise, and H is the relationship matrix between the measurements and the state variable. With the Kalman filter, the side slip angle is updated every cycle time by the predictive state model, while the rate of change is blended with the value obtained from the kinematic model. This means that the proposed method accurately estimates the rapid change in the side slip angle by using the kinematic model, which removes the uncertainty of the model while ensuring the stability of the estimation error based on the sliding mode theory.

4. Supervisor Layer

In this layer, the control mode index is based on the vehicle state and the driver's input. The reference yaw rate is determined by the control mode, ensuring that the vehicle behaves appropriately in each mode.

4.1. Control Mode

4.1.1. Maneuverability Mode

Maneuverability mode means that the yaw rate error becomes larger than a threshold and the vehicle does not follow the intention of the driver. The maneuverability index is defined as follows:

$$I_m = \text{sgn}(\gamma) \left(\frac{\gamma_d - \gamma}{K_\gamma} \right) \quad (22)$$

where γ is the vehicle yaw rate and γ_{cr} is a yaw rate error criterion, which means the magnitude of the yaw rate error in which the entry is the control mode. If I_m exceeds 1, it means entering the maneuverability mode, if it is positive, an understeer control is performed, and if it is negative, an oversteer control is performed.

4.1.2. Lateral Stability Mode

If a side slip occurs above a certain level, the side slip angle control is performed to ensure the stability of the vehicle. In general, it is known that the driver feels unstable when the side slip angle is more than 3 degrees. As shown in Figure 3, the stable and unstable regions can be distinguished according to the side slip angle and its rate.

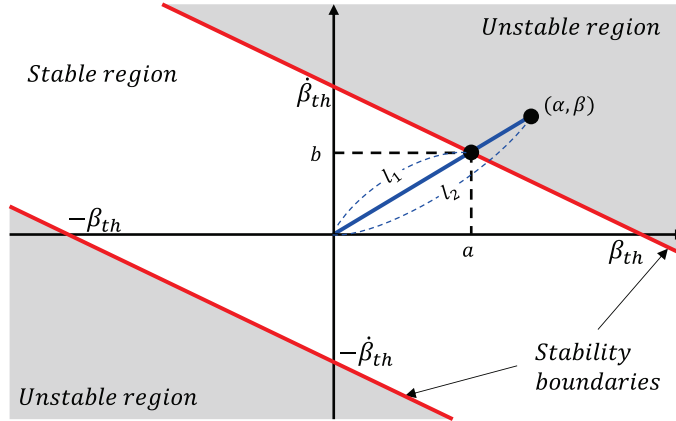


Figure 3. Lateral stability mode.

The lateral stability mode index I_β is summarized as Equation (23) and enters the lateral stability mode when the index is greater than 1.

$$I_\beta = \frac{l_2}{l_1} = \frac{\sqrt{\beta^2 + \dot{\beta}^2}}{\sqrt{a^2 + b^2}} = \frac{\dot{\beta}\beta_{th} + \beta\dot{\beta}_{th}}{\beta_{th}\dot{\beta}_{th}} \quad (23)$$

4.2. Reference Value

In maneuverability mode, depending on the driver's steering intention, the target yaw rate $\gamma_{d,M}$ as a function of the steering angle is expressed as follows:

$$\gamma_{d,M} = \frac{1}{1 - \frac{m(l_f C_f - l_r C_r) v_x^2}{2 C_f C_r (l_f + l_r)^2}} \frac{v_x}{(l_f + l_r)} \delta_f \quad (24)$$

where l_f, l_r are the distance from the center of gravity to the front/rear axle, C_f, C_r are the stiffness of the cornering of the front and rear tire, m is the mass of the vehicle, and v_x is the longitudinal velocity of the vehicle. In lateral stability mode, a reference yaw rate $\gamma_{d,\beta}$ is derived that minimizes the side slip angle as represented in Equation (25):

$$\gamma_{d,\beta} = \frac{C_f \left(\delta_f - \beta - \frac{l_f \gamma}{v_x} \right) + C_r \left(-\beta - \frac{l_r \gamma}{v_x} \right)}{m v_x} + k \beta \quad (25)$$

To obtain a smooth transition between modes, a weight factor σ is defined as shown in Figure 4.

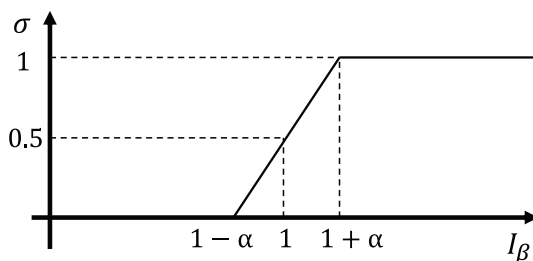


Figure 4. Weight factor for reference yaw rate.

The final desired yaw rate γ_d is shown below.

$$\gamma_d = (1 - \sigma)\gamma_{d,M} + \sigma\gamma_{d,\beta} \quad (26)$$

The desired roll angle ϕ_d for ride comfort is defined as follows:

$$\phi_d = k_\phi a_y \quad (27)$$

5. Upper Controller Layer

The upper controller determines the global control input of the vehicle, which determines the amount of control needed to obtain the desired yaw rate and the desired roll angle. The desired yaw moment and desired roll moment were determined using sliding mode control for robustness against tire cornering stiffness and vehicle state model error. The yaw dynamics of the vehicle and the uncertainty are expressed as follows:

$$\dot{\gamma} = \left(\frac{-l_f C_f + l_r C_r}{I_z} \right) \beta - \left(\frac{-l_f^2 C_f + l_r^2 C_r}{I_z v_x} \right) \gamma + \left(\frac{l_f C_f}{I_z} \right) \delta_f + \left(\frac{1}{I_z} \right) M_z + w \quad (28)$$

where I_z is the inertia of the yaw moment of the vehicle and M_z is an additional yaw moment. The sliding surface needed to track the yaw rate is defined as Equation (29):

$$s = e_\gamma = \gamma_d - \gamma \quad (29)$$

According to the Lyapunov direct theorem, the desired yaw moment needed to stabilize the system is given by Equation (30). The system is asymptotically stable if the value of gain ρ is greater than $|w|$.

$$M_z = -I_z \left(-\dot{\gamma}_d + \left(\frac{-l_f C_f + l_r C_r}{I_z} \right) \beta + \left(\frac{-l_f^2 C_f + l_r^2 C_r}{I_z v_x} \right) \gamma + \left(\frac{l_f C_f}{I_z} \right) \delta_f - \rho \operatorname{sgn}(s) \right) \quad (30)$$

The roll dynamics can be written as follows:

$$\ddot{\phi} = \frac{1}{I_x} (m_s a_y h_s - m_s g h_s \phi - C_\phi \dot{\phi} - K_\phi \phi + M_\phi) \quad (31)$$

The second-order sliding surface for the roll angle is defined below.

$$s = \dot{e}_\phi + \lambda e_\phi \quad (32)$$

The estimated stiffness and damping coefficient for the center of rotation are $\hat{C}_\phi$ and $\hat{K}_\phi$, respectively, and the desired roll moment M_ϕ is obtained as follows:

$$M_\phi = -I_x \left(\frac{-\hat{C}_\phi \dot{\phi} + \hat{K}_\phi \phi + m_s a_y h_s + m_s g h_s \phi}{I_x} + \ddot{\phi}_d - \lambda(\dot{\phi} - \dot{\phi}_d) - \rho \operatorname{sgn}(s) \right) \quad (33)$$

The system is asymptotically stable when the value of $I_x \rho$ is greater than $|\hat{C}_\phi - C_\phi| |\dot{\phi}| + |\hat{K}_\phi - K_\phi| |\phi|$.

6. Control Allocator Layer

In the control allocation layer, the global control input is distributed to each actuator, taking into account the actuator constraints. In particular, a method used to simultaneously maximize the roll and lateral performance is introduced, and an algorithm is applied to allocate the damping force of the semi-active suspension using a lower computational load.

6.1. Brake Torque Distribution

The braking torque of each wheel and the yaw moment are expressed as follows:

$$M_z = F_{b1}(-l_f \sin(\delta_f) + t_f \cos(\delta_f)) + F_{b2}(-l_f \sin(\delta_f) - t_f \cos(\delta_f)) + F_{b3}(t_r) + F_{b4}(-t_r) \quad (34)$$

where F_{bi} is the brake force of each wheel and t_f, t_r are the track width of the front and rear axle. The distribution of each wheel can be obtained by quadratic programming as follows:

$$\begin{aligned} & \text{minimize } J = x^T Q x \\ & \text{subject to } Ax = b \end{aligned}$$

The weight matrix Q is a diagonal matrix and is positive semi-definite. Then, the state variables, constraints, and weight matrix are represented as follows:

$$\begin{aligned} x &= [F_{b1}, F_{b2}, F_{b3}, F_{b4}]^T \\ A &= \begin{bmatrix} -l_f \sin \delta_f + t_f \cos \delta_f \\ -l_f \sin \delta_f - t_f \cos \delta_f \\ t_r \\ t_r \end{bmatrix}^T, \quad b = M_z \\ Q &= \text{diag} \left(\frac{\rho_1}{(\mu F_{z1})^2}, \frac{\rho_2}{(\mu F_{z2})^2}, \frac{\rho_3}{(\mu F_{z3})^2}, \frac{\rho_4}{(\mu F_{z4})^2} \right) \end{aligned} \quad (35)$$

To solve the above problem, the Hamiltonian and necessary conditions are expressed as follows:

$$H = x^T Q x + \lambda(Ax - b) \quad (36)$$

$$\frac{\sigma H}{\sigma x} = (Q + Q^T)x + \lambda A^T = 0 \quad (37)$$

$$\frac{\sigma H}{\sigma \lambda} = Ax - b = 0 \quad (38)$$

Equations (37) and (38) can be rewritten as

$$x = -\frac{1}{2}Q^{-1}A^T\lambda^T \quad (39)$$

$$\lambda^T = (-2AQ^{-1}A^T)^{-1}b \quad (40)$$

Substituting expression (40) into expression (37), the solution is given by

$$x = Q^{-1}A^T(AQ^{-1}A^T)^{-1}b \quad (41)$$

6.2. Damping Force Distribution

6.2.1. Yaw Assist by Front/Rear Damping Distribution

The mechanism for generating yaw assistance through the front and rear damping distribution is as follows. As shown in Figure 5, the lateral force of the tire is determined by the angle of slip, the friction coefficient, and the vertical force. In this context, the vertical force of each wheel can be changed by modifying the damping ratio. Depending on the left and right deviation of the tire's vertical force, the lateral force of the left and right wheels changes nonlinearly, and the sum of the lateral forces becomes smaller. This allows the vehicle to assist in preventing understeer when the front wheel is applied a larger lateral

force than the rear wheel and to improve oversteer when the rear wheel is applied a larger lateral force than the front wheel.

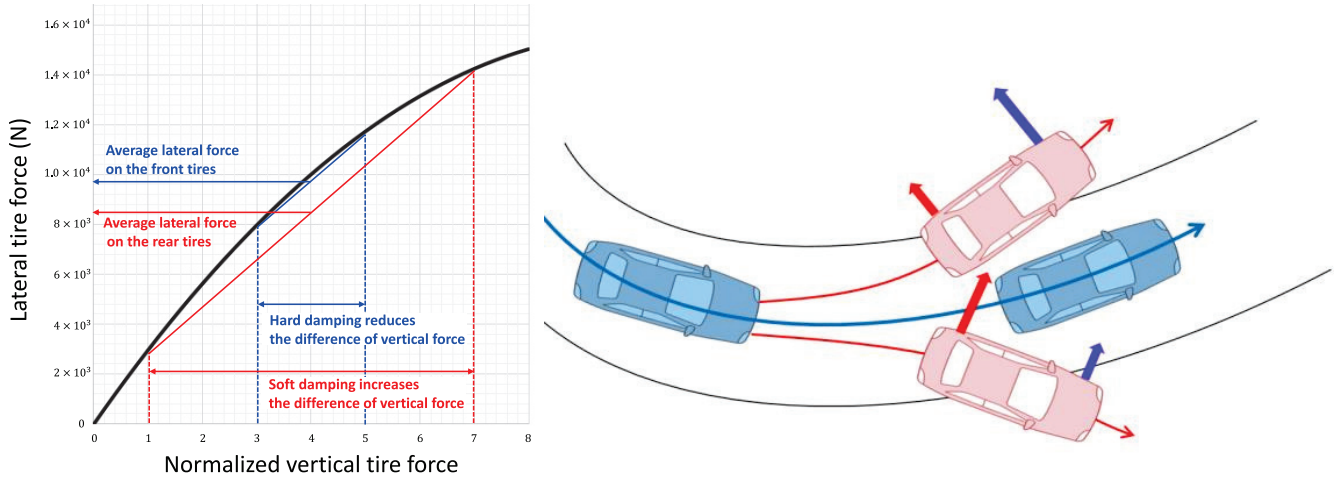


Figure 5. Relationship between lateral tire force and vertical tire force.

In this study, the roll moment of the front and rear wheels is distributed according to the direction and magnitude of the understeer and oversteer. The effect of the roll moment is to restrain the roll change of the vehicle, which means that the sum of the left and right lateral forces increases by distributing the vertical force equally to the left and right wheels. The roll moment of the front and rear wheels is distributed as follows using the yaw rate error:

$$\begin{aligned}
 M_{\phi f} &= \frac{1}{2}(1 + \epsilon)M_{\phi} \\
 M_{\phi r} &= \frac{1}{2}(1 + \epsilon)M_{\phi} \\
 \text{where } \epsilon &= \begin{cases} 1 & \text{if } ke_{\gamma} > 1 \\ ke_{\gamma} & \text{if } -1 \leq ke_{\gamma} \leq 1 \\ -1 & \text{if } ke_{\gamma} < -1 \end{cases}
 \end{aligned} \tag{42}$$

The quadratic problem with the same expression as (35) is given by

$$\begin{aligned}
 x &= [F_{d1}, F_{d2}, F_{d3}, F_{d4}]^T \\
 A &= \begin{bmatrix} -t_{fl} & 0 \\ t_{fr} & 0 \\ 0 & -t_{rl} \\ 0 & t_{rr} \end{bmatrix}^T \\
 b &= \begin{bmatrix} M_{\phi f} + t_{fl}k_1d_1 - t_{fr}k_2d_2 \\ M_{\phi r} + t_{rl}k_3d_3 - t_{rr}k_4d_4 \end{bmatrix}^T \\
 Q &= \text{diag}(1, 1, 1, 1)
 \end{aligned} \tag{43}$$

The solution is expressed in the same manner as Equations (36)–(40), as follows:

$$x = Q^{-1}A^T(AQ^{-1}A^T)^{-1}b \tag{44}$$

6.2.2. Control Utilization by Roll Region Index

The above method that yaw assists control by the front/rear suspension damping distribution improves lateral stability, but the method has two problems. The first problem

is a decrease in roll performance. When the conventional semi-active suspension control detects a turn of the vehicle, it keeps the full hard damping to minimize the roll angle. In contrast, if the front or rear wheels are softened for yaw assist control, the total roll damping coefficient of the vehicle is decreased, which causes a large roll angle in the driving. Thus, the previous yaw assist method improves lateral stability but loses roll performance. The second problem is that the effect of lateral acceleration due to changes in roll damping is neglected. As shown in the roll dynamics in Equation (31), the change in roll damping has a direct effect on the lateral acceleration. In addition, since the suspension is actually mounted along the kingpin angle, it further affects the lateral behavior more than the simplified roll dynamics model. Therefore, if the direction of change in the lateral acceleration due to roll damping is in a way that decreases lateral stability and minimizes roll behavior, and vice versa, increasing the roll behavior is advantageous for lateral stability. In this study, a suspension control method using the roll region index (RRI) is proposed to solve the above two problems. The roll region index is defined as follows:

$$RRI = k_{\phi} \operatorname{sgn}(\phi) \operatorname{sgn}(\dot{\phi}), \quad k_{\phi} = \begin{cases} 0 & \text{if } |\dot{\phi}| \leq \dot{\phi}_{th} \\ 1 & \text{if } |\dot{\phi}| > \dot{\phi}_{th} \end{cases} \quad (45)$$

where ϕ is the roll angle, $\dot{\phi}$ is the roll rate, and $\dot{\phi}_{th}$ is the roll rate threshold for transition. As shown in Figure 6, the RRI is used to determine whether the roll is increasing, decreasing, or in a transition state. Using this index, when the roll angle increases, the damping coefficient is increased to minimize the roll angle. On the other hand, when the vehicle's roll angle returns to the origin, the damping is reduced to enhance the roll change.

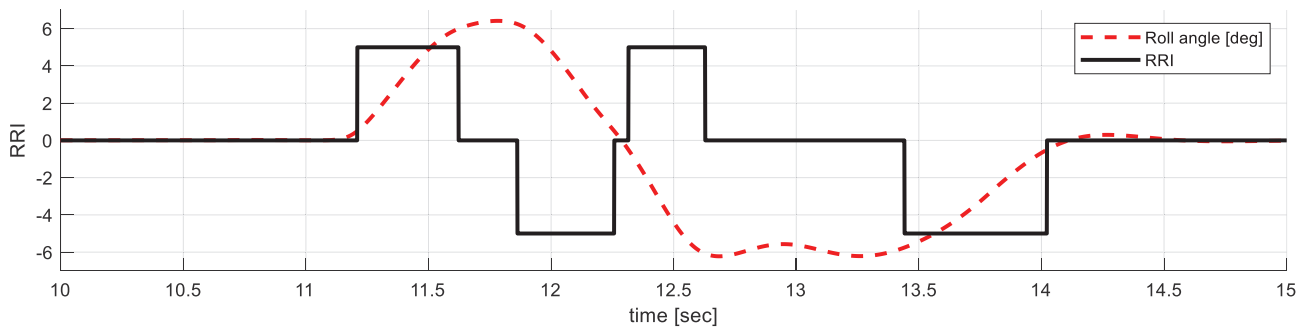


Figure 6. Roll region index.

In view of the lateral motion of the sprung mass of the vehicle, during the increased roll period, the vehicle is forced to the side by inertia, so a large damping force must be applied in the opposite direction of the roll to improve the lateral behavior of the vehicle. On the other hand, if the direction of decreasing roll angle is in the same direction as the vehicle's behavior or the driver's steering direction, reducing the damping force leads to a faster change in the lateral behavior of the sprung mass. Thus, the RRI method not only reduces the maximum value of the roll angle but also increases the response of the roll control and, through it, improves the lateral behavior, such as yaw rate response, lateral acceleration response, and maximum side slip angle.

7. Result

The proposed algorithm is evaluated in simulation and on a real-world test. Because the suspension stroke variation must be considerable enough to allow the damping system to influence the vehicle's lateral movement, a severe lane change maneuver is selected as the evaluation case. In general, these conditions require both lateral and roll stability, so the differential brake and damping control operate simultaneously to stabilize the vehicle.

Three methods are evaluated to compare vehicle control performance. The first method is independent chassis control, with brake control for lateral stability and damping control (full hard, FH) for attitude stability. In other words, each chassis system is an independent control method that controls one of the yaw or roll directions. The second method is yaw assist control by damping (YAC), which assists lateral behavior by distributing front and rear suspension damping. In short, two chassis controls are integrated to maximize performance in one direction. The YAC method supports yaw behavior by switching the damping ratio of the front and rear wheels when understeer and oversteer are repeated during a sharp lane change. The third method, the proposed method, performs attitude control and yaw assist control according to the roll region index (RRI). When the RRI is 1, FH control is performed; otherwise, YAC control is executed, that is, the two chassis systems optimize the two directions according to the conditions.

7.1. Simulation

The simulation is executed in the Carsim/MATLAB environment, and vehicle parameters are set based on Hyundai Motors' Electrified G80, which has specifications identical to those of the real-world test environment. The simulation assumes dry asphalt and uses a coefficient of friction of 0.9 for the road surface. The performance of each method was compared under the 80 km/h condition by applying the same steering angle as shown in Figure 7a,b. The test results are shown in Table 1 and Figure 7. The effect of the proposed method can be described in two aspects. The first is improvement in lateral performance. The YAC method makes a difference in lateral behavior by generating a difference in front and rear lateral force through damping distribution. As a result, as shown in Figure 7f, the proposed method and the YAC method reduce the side slip angle by 14.4% and 20.2% compared to the full hard method, respectively, improving the lateral stability of the vehicle. Furthermore, as shown in Figure 7c,d, the maximum value of the yaw rate is not significantly different, but the yaw rate response is improved by about 10~20 ms. In this case, the driver feels that the vehicle more quickly follows the driver's intention, resulting in improved maneuverability. The second is improvement in roll performance. As shown in Figure 7e, the proposed method prioritizes attitude control according to the RRI when the roll increases and keeps the damping hard, which prevents the increasing roll. As a result, the maximum roll angle of the proposed method is about 5.09 degrees, which is 20.2% better than 6.38 degrees when the YAC method is applied, and it is almost as good as the performance when fully hard, with a difference of 5.8%. In addition, when the roll angle decreases, the total damping is softened by the yaw assist control, which makes the roll movement respond more quickly to the driver's intention. In other words, the period where the steering phase and roll phase are reversed is decreased, so the vehicle's heading direction and vehicle roll direction are aligned, and the driving feel is improved.

Table 1. Simulation result.

Control Method	Max. Roll Angle [deg]	Max. Side Slip Angle [deg]
Full hard damping	4.80 (−24.8%)	6.19 (max. value)
Yaw assist by damping	6.38 (max. value)	5.15 (−20.2%)
Proposed method	5.09 (−20.2%)	5.41 (−14.4%)

(%) is the ratio to the maximum value.

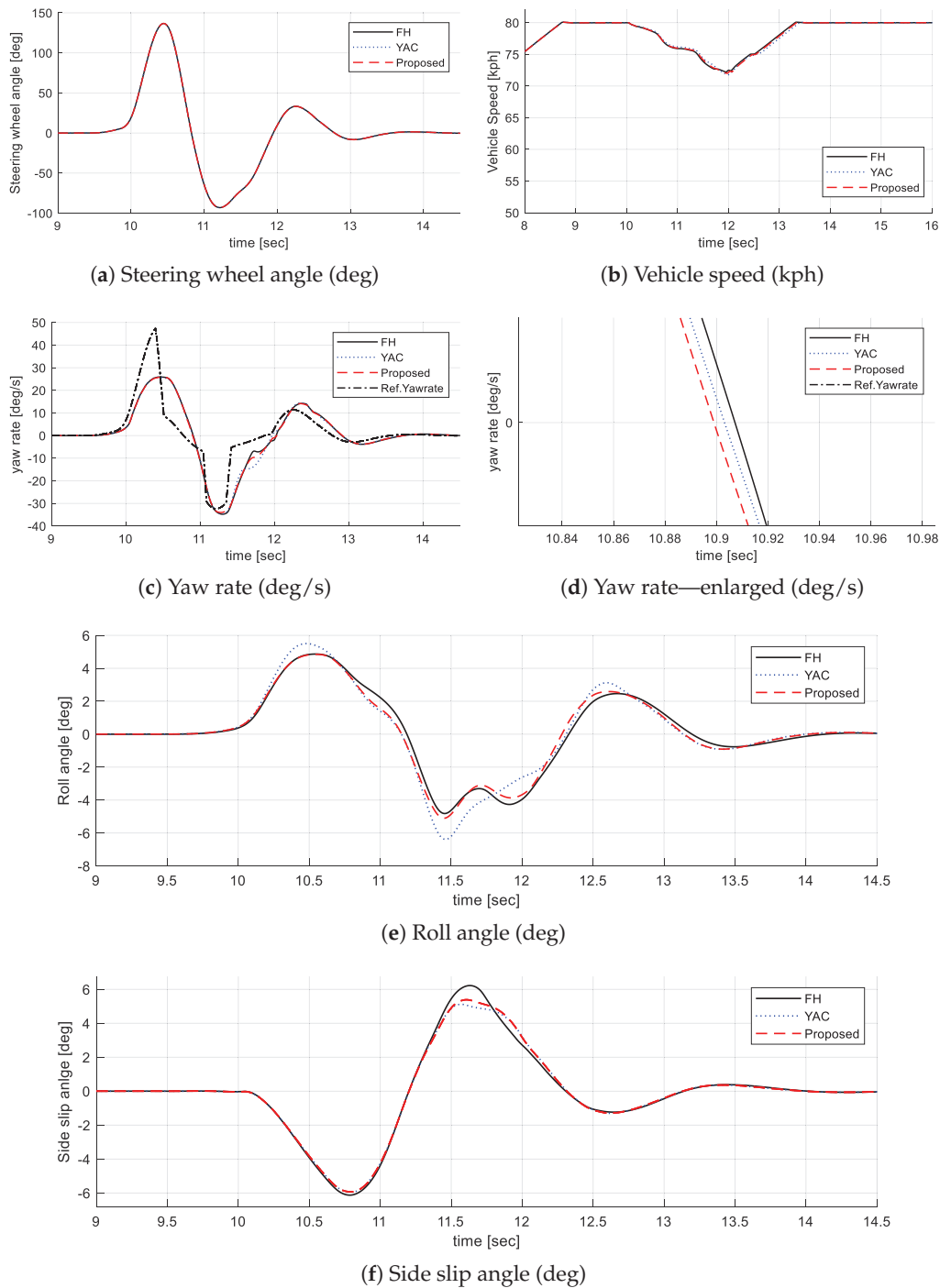


Figure 7. Simulation result.

7.2. Vehicle Test

7.2.1. Evaluation of Estimator

The test maneuver for estimator validation is selected as lane changes ranging from about 50 to 100 kph, with side slip angles measured from about 1 to 10 degrees. In practice, it is known that drivers feel nervous when the side slip angle is greater than about 3 degrees, and the range from 0 to 10 degrees includes almost all conditions that can occur in a driving situation. The performance of the estimator is verified by comparing it with the measured values of the RT3000. The sliding mode observer using the linear model is selected as a comparison group to check the performance of the combined model proposed in Section 3.3.

The evaluation result showed that, in most cases, the estimation error is within 1.0 degrees of the measured value with the RT3000, as shown in Table 2. Regarding the error with RT3000 measurements, the maximum error of the linear SMO was 2.9 degrees on average, while the proposed method improved the performance by about 72%, with a maximum error of 0.8 degrees on average. The average error of the total period is 0.42 degrees for the linear SMO and 0.18 degrees for the proposed method, which is an improvement of about 58%, showing the better performance of the proposed method. Figure 8 shows that the proposed method outperforms the linear SMO method in all cases. For linear SMO, the performance of the estimator was highly dependent on how the cornering stiffness constant is determined. As shown in Figure 8, the linear SMO has similar maximum values for conditions where the maximum side slip angle is around 5 to 6 degrees but tends to overestimate the true measurement in the 0 to 5 degrees range and underestimate the true measurement above 7 degrees. In other words, the linear SMO is ineffective for estimating a variety of conditions. However, the proposed method estimates the maximum side slip angle similarly under all conditions by using the side slip angle rate obtained from the kinematic model. In addition, the proposed method has a shorter time lag with the actual measurement than the conventional SMO, which significantly reduces the error at the same time.

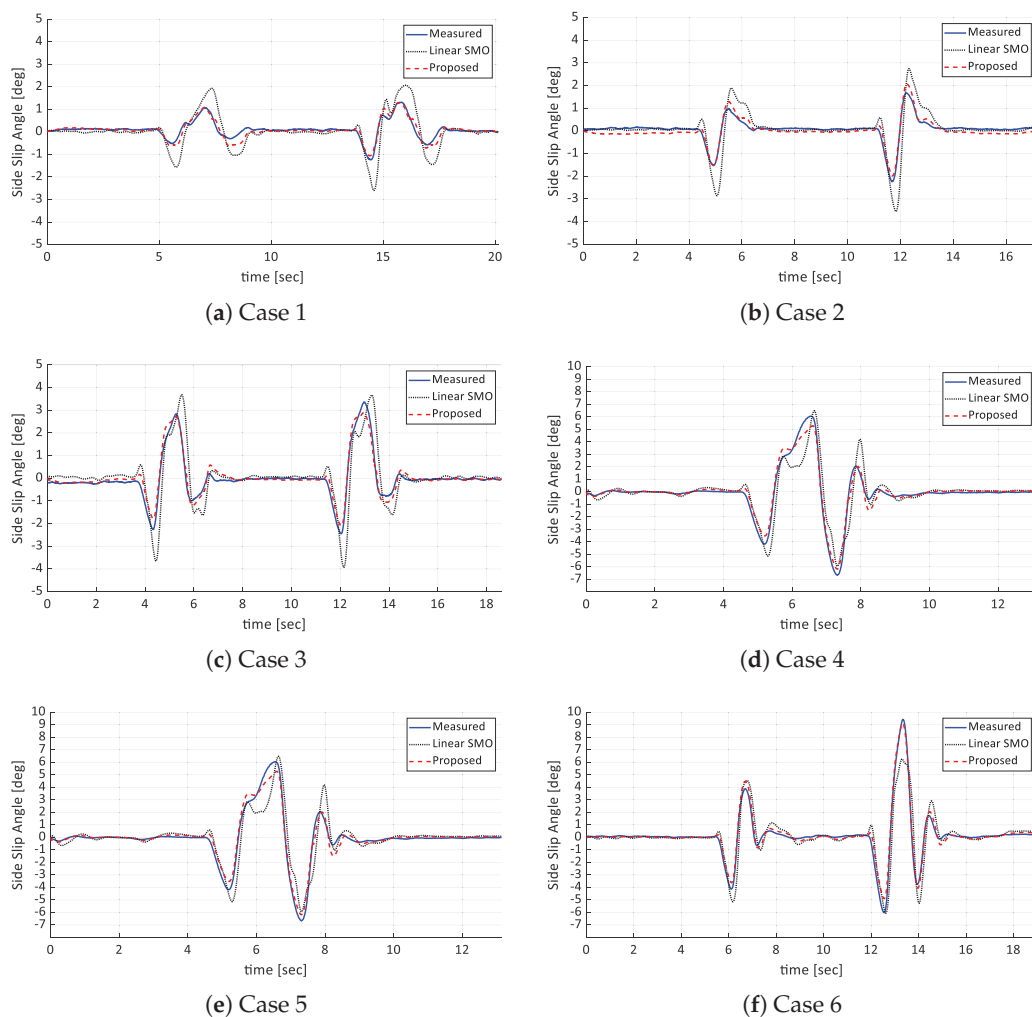


Figure 8. Test result of estimator.

Table 2. Test result of estimator.

Test Case	Speed/Max. Steering Angle [km/h]/[deg]	Max. Side Slip Angle (Measured) [deg]	Max./Mean. Error of Linear SMO [deg]	Max./Mean. Error of Proposal [deg]
Case 1	50/79.5	1.32	1.98/0.327	0.51/0.097
Case 2	60/94.3	2.24	2.63/0.264	0.26/0.148
Case 3	65/107.6	3.37	2.93/0.417	0.66/0.140
Case 4	70/106.0	6.67	3.09/0.528	0.97/0.225
Case 5	80/104.8	7.07	2.90/0.365	0.82/0.219
Case 6	80/123.5	9.43	3.51/0.485	1.21/0.204

7.2.2. Validation of Integrated Chassis Control

The test configuration is shown below. The test vehicle is an electrified G80 of Hyundai Motors, as shown in Figure 9. The vehicle has an electronic damping control suspension and brakes for chassis control. It is also equipped with an HL Mando steer-by-wire system. The road wheel actuator of the steer-by-wire system has a separate driver's and tire's steering wheel, allowing for independent tire wheel steering control. This allows us to pass the rack position corresponding to a predefined steering profile to the road wheel actuator, as shown in Figure 10a, and to use the trigger to start the steering profile at 80 km/h, as shown in Figure 10b, to achieve the same input. The integrated control logic was implemented using a rapid control prototype machine, the AUTOBOX II from dSPACE, Paderborn, Germany. Each actuator ECU was given control instructions via CAN communication. The driving environment was performed on dry asphalt under high- μ conditions. The tire specifications were 275/40/R19 for the front tires and 245/45/R19 for the rear tires. Each method was repeated five times to analyze reliable data, and the average value is shown.

**Figure 9.** Test vehicle with steer-by-wire.

The validation results of real-world tests show improvements in roll and lateral performance, similar to the simulations. In terms of roll performance, as shown in Figure 10c, the maximum roll angle of the proposed method is 4.5 degrees, which is an improvement of approximately 7.3% and 17.4%, respectively, compared to the maximum roll angle of the FH method (4.8 degrees) and YAC method (5.4 degrees). In addition, the proposed method reduces the roll response by about 40–50 ms. The proposed method improves roll performance with a smaller maximum roll angle and a faster phase, similar to the result of simulations. This change in phase affects not only the roll but also the lateral behavior. As shown in Figure 10d, the lateral acceleration of the proposed method responds about 20 ms faster than the FH method, which also affects the side slip angle in Figure 10e, which is the integrated value. The results of the side slip angle show that the maximum value of the proposed method is 5.0 degrees, which is 8.7% and 3.6% better than the FH and YAC methods, respectively. In addition, the phase is reduced by about 30~40 ms. As shown in Figure 10f, the YAC method helps the yaw rate to rapidly track the reference yaw rate. Overall, only YAC control has the smallest error and, in some sections where the direction changes, such as 10.2 s and 10.7 s, the proposed method shows better performance.

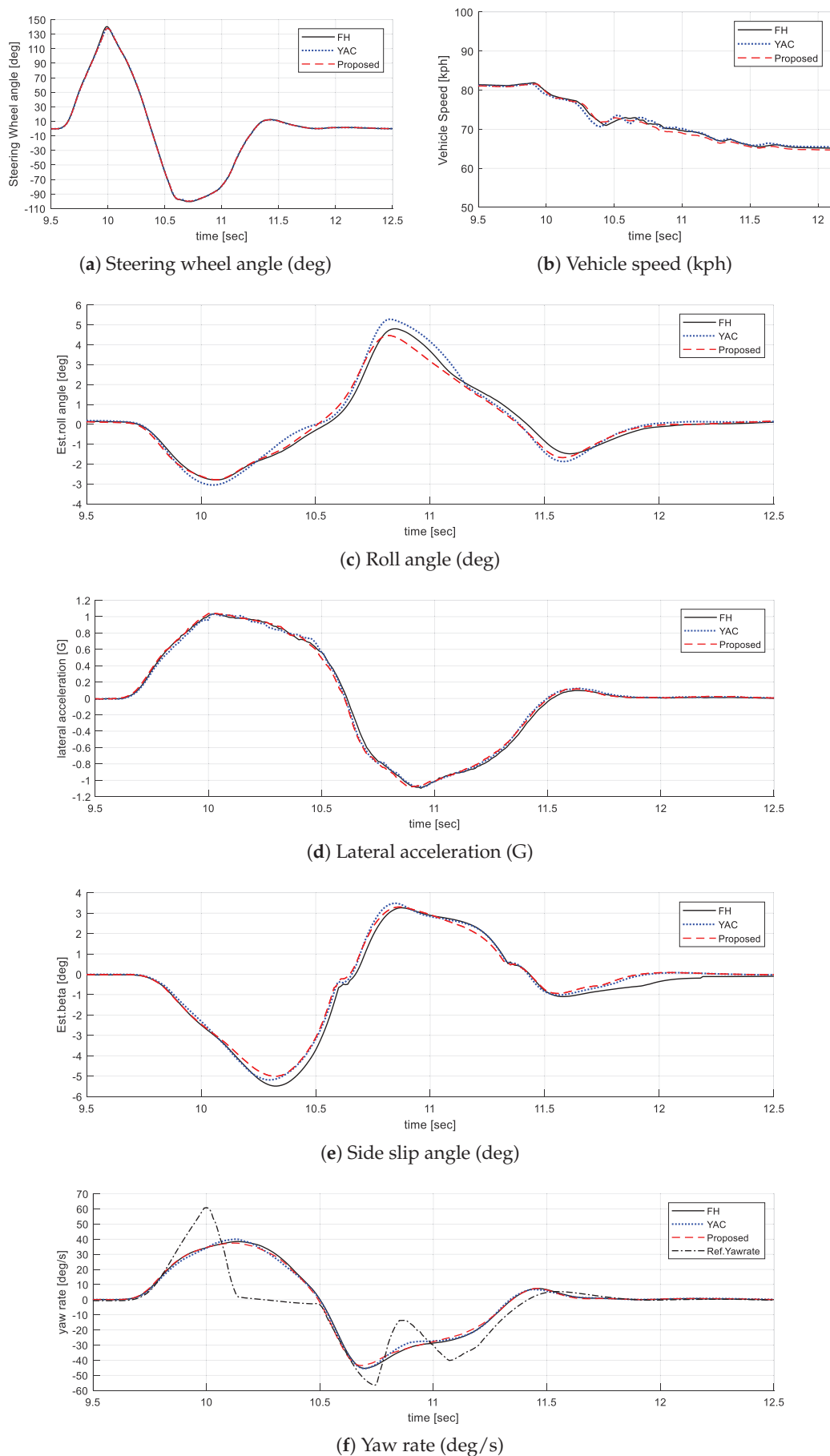


Figure 10. Vehicle test result.

This phenomenon is expected to result from the change in lateral behavior starting from a more stable state than vehicle attitude control. Consequently, by controlling attitude and yaw assist through classification of the roll region, both the maximum roll angle and maximum side slip angle are reduced. The response times of the roll angle, lateral acceleration, side slip angle, and yaw rate all improve, enhancing the vehicle's response to the driver's intentions.

8. Conclusions

This article presented an integrated chassis control of lateral and roll dynamics based on differential brake and suspension damping control using a hierarchical structure. The robust estimation algorithm of side slip angle is proposed in the estimation layer to determine the vehicle's lateral stability. The supervision layer determines the control mode based on the vehicle's state variables and generates control target values accordingly. Sliding mode control theory is applied to ensure robust control performance for nonlinearities in the vehicle model. The distribution layer distributes the yaw and roll moments to the brakes and suspension based on optimal distribution. Suspension control logic using the roll region index is proposed to satisfy roll and lateral performance simultaneously. The main contributions of this study are as follows.

- Previous hierarchical structure-based studies have performed suspension control under different conditions by switching the control mode, e.g., when roll stability is required, damping control is performed by reducing the roll angle. When lateral control is required, damping control assists the yaw moment by causing the front and rear wheel load transfer. However, since the limitation of the yaw assist method is that it only considers the relationship between the tire and the ground, this study proposes a method to maintain stiff damping when the movement of the sprung mass degrades the lateral stability.
- Two cases are selected for comparison with conventional suspension. The fully hard method does not improve lateral performance because it only considers attitude control by stiff damping, and the yaw assist control by damping method improves lateral performance but it has the disadvantage of decreasing roll performance. The proposed method can improve the overall performance of roll and lateral motion by controlling according to the roll region index. In a real-world evaluation, assuming a sharp lane change at 80 kph, the maximum roll angle was improved by about 17.4% compared to the yaw assist method, and the side slip angle was improved by about 8.7% compared to full hard damping.
- In a severe situation, it is important to have stability in both directions, not only lateral or roll stability. The proposed algorithm has the advantage of simultaneously improving both roll and lateral performance, making it more suitable for sudden situations.

Author Contributions: Conceptualization, K.L.; methodology, K.L.; software, J.S. and K.L.; validation, J.S. and K.L.; formal analysis, J.S. and K.L.; investigation, J.S. and K.L.; resources, J.S. and K.L.; data curation, J.S.; writing—original draft preparation, K.L.; writing—review and editing, K.L.; visualization, J.S. and K.L.; supervision, K.L.; project administration, K.L.; funding acquisition, K.L. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Kyungtaek Lee and Jinwoo Seol are employees of HL Mando. The paper reflects the views of the researchers and not the company.

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Article

Linear Continuous-Time Regression and Dequantizer for Lithium-Ion Battery Cells with Compromised Measurement Quality

Zoltan Mark Pinter ^{1,*}, Mattia Marinelli ¹, M. Scott Trimboli ² and Gregory L. Plett ²

¹ Department of Wind and Energy Systems, Technical University of Denmark, Frederiksborgvej 399, 4000 Roskilde, Denmark; matm@dtu.dk

² Department of Electrical and Computer Engineering, University of Colorado Colorado Springs, 1420 Austin Bluffs Pkwy, Colorado Springs, CO 80918, USA; mtrimbol@uccs.edu (M.S.T.); gplett@uccs.edu (G.L.P.)

* Correspondence: pinzo@dtu.dk

Abstract: Battery parameter identification is a key challenge for battery management systems, as parameterizing lithium-ion batteries is resource-intensive. Electrical circuit models (ECMs) provide an alternative, but their parameters change with physical conditions and battery age, necessitating regular parameter identification. This paper presents two modular algorithms to improve data quality and enable fast, robust parameter identification. First, the dequantizer algorithm restores the time series generating the noisy, quantized data using the inverse normal distribution function. Then, the Linear Continuous-Time Regression (LCTR) algorithm extracts exponential parameters from first-order or overdamped second-order systems, deducing ECM parameters and guaranteeing optimality with respect to RMSE. The parameters have low sensitivity to measurement noise since they are continuous-time. Sensitivity analyses confirm the algorithms' suitability for battery management across various Gaussian measurement noise, accuracy, time constants and state-of-charge (SoC), using evaluation metrics like root-mean-square-error (RMSE) (<2 mV), relative time constant errors, and steady-state error. If the coarseness of rounding is not extreme, the steady-state is restored within a fraction of a millivolt. While a slight overestimation in the lower time constants occurs for overdamped systems, the algorithms outperform the conventional benchmark for first-order systems. Their robustness is further validated in real-life applications, highlighting their potential to enhance commercial battery management systems.

Keywords: battery management system; parameter identification; quantization; Gaussian noise; continuous-time

1. Introduction

Battery systems play a crucial role in the shift towards green energy by storing and rapidly transferring electrical energy. While lithium-ion batteries offer high efficiency and performance, their sensitivity to various physical variables and battery chemistry parameters is a challenge. Understanding these nonlinear sensitivities is vital for both performance and safety [1]. Although physics-based bottom-up models can be employed, they are often costly, time-consuming, and energy-intensive for parameter identification [2]. Additionally, the parameters change over time with battery aging, rendering initial identifications less accurate.

The Thévenin equivalent, or equivalent circuit model (ECM), serves as a primary alternative to physics-based models [3] (see Figure 1). It captures input–output battery behavior to the extent the user requires and data quality allows. However, this is an imposed interpretation, hence when the physical variables change, the ECM parameters change with them [4]. Including more variables like state of charge (SoC), temperature, frequency, current, hysteresis state, or pressure results in the curse of dimensionality for parameter lookup tables [5]. This necessitates neglecting certain factors or resorting to online identification of parameters, which requires high-quality measurements of current and terminal voltage as inputs and outputs, respectively.

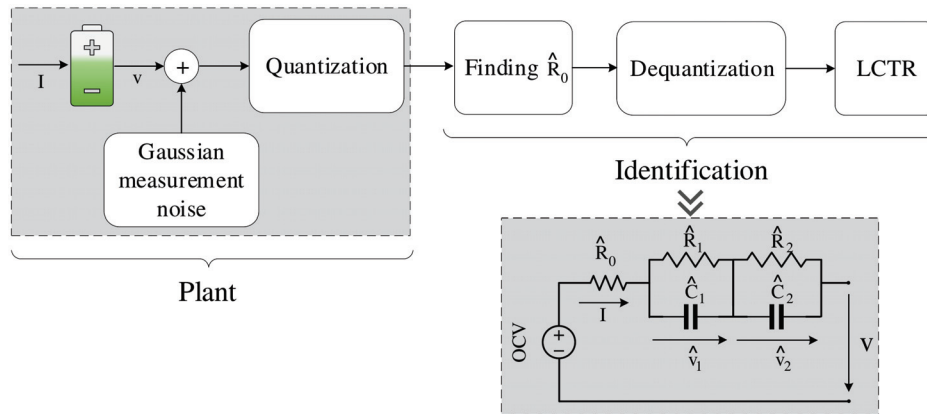


Figure 1. (Top): Data generation (meaning the assumptions for the identification and the simulation), and ECM parameter identification. (Bottom): the Thévenin equivalent (or ECM, see [2]) of a second-order model. Estimation is denoted by $\hat{\square}$, where $\square$ is the variable of interest. Open circuit voltage (OCV) is found from a lookup table based on the SoC. The SoC is calculated by Coulomb-counting $\Delta \text{SoC} = \frac{100\%}{Q} \int I dt$, where Q is capacity and I is current.

Parameter identification methods fall into two categories: offline and online algorithms. Offline algorithms process data in batches to find a posterior, while online algorithms incorporate earlier identifications into their prior for updates [6]. This makes the latter computationally more efficient. Identification algorithms can determine either time or frequency domain parameters. They include regression techniques like linear regression, Gaussian processes, support vector machines, neural networks, and ensembles considered as machine learning methods due to their data-driven nature [7]. Input–output methods can identify transfer function, state-space and polynomial model parameters. Such methods produce autoregressive models with exogenous output (ARX, or ARMAX if stochastic). Models can be both linear and nonlinear and are easily computed via online algorithms. For cases where nonlinearities can be separated from the linear model, Hammerstein–Wiener models can be applied [8].

Nonlinear identification methods are notoriously sensitive to initial parameter guesses. Furthermore, they are iterative and time- and memory-intensive. One commonly used linear method, ARX models, becomes particularly sensitive to noise, leading to the overfitting of irrelevant patterns. In order to provide a robust alternative, this paper extends the linear continuous-time regression presented in [9,10] by fitting it to the battery parameter identification problem.

Some challenges that all identification algorithms face are sensitivities to noise, quantization, sampling rate, or the window of the investigated data batch. Assessing lower-cost device feasibility requires understanding the trade-offs in data quality due to sensor limitations. High data quality requires better measurement devices, though this can be impractical or costly. Alternatively, the quality can be improved by software solutions. The issue arises in various fields. In radar applications [11], for example, addressing

spectrum corruption from angular quantization during blind phase searches involves low-pass filtering, enhancing phase noise tolerance. Analog-digital conversion [12] tackles sigma-delta quantization error with an optimization algorithm, showing polynomial decay in estimation error with increased sample numbers. Image reconstruction in image processing [13] utilizes generalized expectation maximization for noisy, quantized, and sparse measurements. Seismology [14] finds noise and rounding burden the slope of the Gutenberg–Richter magnitude distribution, revealing biased probability distribution modeling. Compressed sensing studies like [15,16] explore the impact of coarsely quantized, sparse, and noisy data, indicating L1 regularized maximum likelihood’s superiority over L1 regularized least squares. In ARMA or output error (OE) models, parameter bound estimates for quantized data are examined in [17], with such measurements enhancing the innovation signal in [18]. An Unscented Kalman filter is adapted in [19] to handle rounding and Gaussian (normal) measurement noise, noting that high standard deviation (denoted as std. or σ) has a whitening effect on the combined noise. The Monte Carlo simulation reveals potential sample misplacement due to Gaussian noise in the combined PDF. To achieve parameters with low sensitivity to measurement noise, this approach identifies continuous-time parameters rather than relying on the commonly used linear discrete-time regression.

In our application, the identification of step response functions are studied, where we note two main problems introduced by quantization: (1) the steady-state estimate is biased, (2) the information about the transient is distorted with colored noise. Despite the code’s microcontroller-friendly compactness, an offline algorithm is designed to confirm specific assumptions in the investigated data batch. These assumptions include the following: (1) sufficient charge transfer at the series start for accurate ECM capacitor current estimation, (2) knowledge of SoC at the end of charge transfer due to strong parameter dependency, and (3) a sufficiently long battery cell rest period to capture parameters. The battery cell needs to rest during the identification period since the change in SoC introduces nonlinearities to the investigated time series, and the proposed algorithm assumes constant input. Given the intended accuracy of the application, parameter dependency on current and temperature is neglected.

Contribution. We desire to efficiently determine the ECM parameters of lithium-ion battery cells throughout their lifetime, despite white Gaussian sensor noise and quantization corrupting the terminal voltage measurements. This work proposes two combined, but modular algorithms to address these challenges and investigate their parameter sensitivities. The key contributions (depicted in Figure 1) are as follows:

- A dequantizing algorithm that recovers information lost due to quantization or large noise magnitudes, hence restoring terminal voltage. It utilizes the inverse normal distribution function to reconstruct time series data from quantized measurements corrupted by Gaussian measurement noise.
- The filtered data are processed by the novel Linear Continuous-Time Regression (LCTR) algorithm, capable of deducing gains, time constants, and bias for first-order or overdamped second-order systems.
- Investigation of the combined algorithms’ sensitivity to quantization noise, measurement noise, steady-state, and time constants. Evaluation statistics include root-mean-square-error (RMSE), time-constant errors, and steady-state errors.

The proposed LCTR algorithm aims at providing a fast alternative to nonlinear algorithms, while also ensuring optimality with respect to RMSE. Additionally, we presume that continuous-time parameters have low sensitivity to measurement noise compared to linear regression with discrete-time models.

This paper is structured as follows: Section 2.1 gives an overview of the parameter identification algorithm, then Section 2.2 elaborates on the dequantization and Section 2.3 on the LCTR. The results are described in Section 3 and concluded in Section 4.

2. Methodology

2.1. Overview of the Identification Algorithm

The investigated time series (both simulated and deployed) is 3600 s in length. The battery cell (with $Q = 100$ Ah capacity) starts from rest at 85% SoC, is discharged at 30 A from 500 s to 1000 s, and then rests until 3600 s. Time is denoted by t and is a discrete variable when used with an index $\square(t_k)$. The sampling time is 1 s. There are five main steps for deducing the parameters of the lithium-ion cell, namely:

I. Finding switching times. Observations indicate that the dynamics behind the R_0 step reach steady-state by 1 ms. This means that R_0 is overestimated at the 1 s sample period, since after 1 s the voltages over the ECM RC branches are already on the rise. This creates a bias in the estimates of the ECM resistances. To address this, the first sample before a current jump of at least the current threshold 5 A is taken as switching time. There is 1 switch-on and 1 switch-off in each time series.

II. Dequantizing. When applied, the dequantization algorithm operates on the time series data after the switch-off time and estimates the underlying data generating the measurement samples. The first estimate then becomes the first measurement. The last 100 samples are discarded as the receding sample window deteriorates the statistics.

III. Finding R_0 . The difference between the first sample after switching $v(t_{\text{off}} + 1)$ and the mean of 10 samples before switching $\bar{v}_{\text{off}-10:t_{\text{off}}}$ is divided by the instantaneous jump in the current I to find R_0 . The current after switching is zero and is averaged for 500 samples before the jump to reduce the effect of measurement outliers.

$$\hat{R}_0 = \frac{v(t_{\text{off}} + 1 \text{ s}) - \bar{v}_{t_{\text{off}}-10:t_{\text{off}}}}{\bar{I}_{t_{\text{off}}-500:t_{\text{off}}}}, \quad \begin{aligned} \mathbf{v}_{t_{\text{off}}-10:t_{\text{off}}} &= [v(t_{\text{off}} - 10 \text{ s}) \quad \dots \quad v(t_{\text{off}})]^T \\ \mathbf{I}_{t_{\text{off}}-500:t_{\text{off}}} &= [I(t_{\text{off}} - 500 \text{ s}) \quad \dots \quad I(t_{\text{off}})]^T \end{aligned} \quad (1)$$

IV. Linear Continuous-Time Regression. The algorithm is used to find the initial values b_i of one or two exponentials, the coefficients a_i of their exponents, and their bias. The index of an exponential is denoted by i . Since the regression has multiple objectives, it is corrupted by colored noise. Hence, the initial values are fixed by stretching them to fit between the first measurement after switching and the mean of the last 100 points of the dequantized time series, i.e.,

$$b'_i = \frac{v(t_{\text{off}} + 1 \text{ s}) - \bar{v}_{\text{pf}, t_{3400}:t_{3500}}}{\sum_i b_i}, \quad i \in \{1, 2\}, \quad (2)$$

$$\bar{v}_{\text{pf}, t_{3400}:t_{3500}} = [v(t_{3400}) \quad \dots \quad v(t_{3500})]^T.$$

V. Deducing RC branch parameters. The time constants are the reciprocals of the coefficients of the exponents. The currents through the resistances of the RC branches $\hat{i}_{Ri, t_{\text{off}}}$ are calculated from the differential equation of the RC branch assuming that the exponents are exact and constant before switching off. At last, the RC resistances are obtained from the voltage before switching off and the current through the resistance,

$$\hat{\tau}_i = \frac{1}{a_i}, \quad (3)$$

$$\hat{R}_i = \frac{\hat{v}_{i, t_{\text{off}}}}{\hat{i}_{Ri, t_{\text{off}}}}, \quad \text{where } \hat{v}_{i, t_{\text{off}}} = -b_i \quad \text{and} \quad \hat{i}_{Ri, t_{\text{off}}} = \left(1 - e^{-(t_{\text{off}} - t_{\text{on}})a_i}\right) \bar{I}_{t_{\text{off}}-100:t_{\text{off}}}. \quad (4)$$

Equations (3) and (4) find the time constants τ_i and the resistances R_i within the Thévenin equivalent in Figure 1, whose parameters are related to the response time and the magnitude of the diffusion voltage, respectively. These parameters will be identified by the LCTR algorithm.

2.2. Dequantizing Algorithm to Alleviate Corrupted Measurements

The dequantizing algorithm aims to recover information lost due to Gaussian measurement noise and quantization. It addresses the rise in the current step response with smoothing and the slower dynamics by leveraging the inverse normal distribution function and the Gaussian assumption. Figure 2a shows how the mean is encoded in the samples. Estimation quality depends on the sampling rate, with limited benefits beyond a level. This sampling rate is typically 1 Hz due to BMS limitations; however, increasing it up to 100 Hz–1 kHz can provide better R_0 estimations [20]. The quantization algorithm assumes that a sufficient amount of data is collected for each time instant to estimate the mean, and the electrochemical dynamics are negligible within the investigated time window.

The ratio of samples from the quantization regions uses the inverse normal distribution function to determine the mean value, from which the data are generated. Therefore the data samples and the threshold in the *center* or *right* of Figure 2a are utilized to find the distribution on the *left*. The average estimation error in Figure 2b depends on the location of the mean between the $lR - R/2$ denoted by 0 and lR by 1, where R is the accuracy bit, and $l \in \mathbb{Z}$. The expected value of the error is zero at lR . It rises linearly in the vicinity since the number of samples at another value of l is negligible. Close to $lR - R/2$, there are more samples at different l values to describe the distribution. As described in [19], the increasing standard deviation whitens the estimation error. This latter effect is stronger for the green curves with a larger standard deviation.

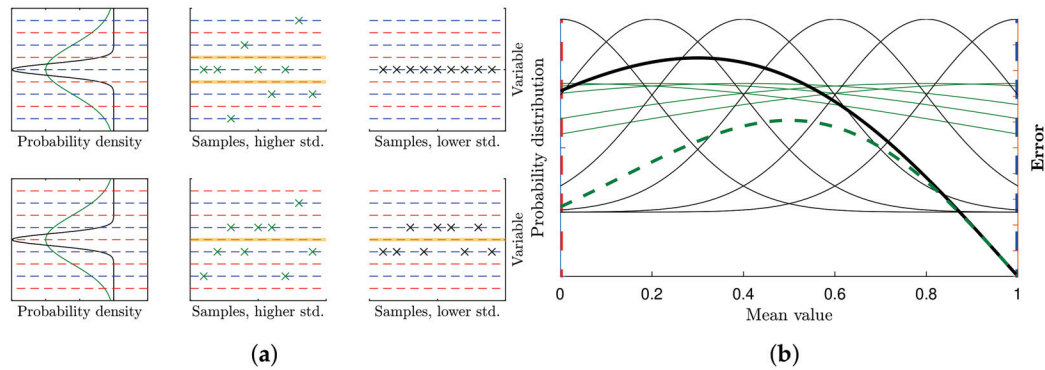


Figure 2. Features of the dequantizing algorithm. (a) Choosing threshold (orange) for the inverse normal distribution. Rounded values are dashed blue. (top): odd number of values, (bottom): even number of values. (Left): Gaussian distribution, (center): large std. (green), (right): low std. (black). (b) Estimation error dependence on the mean's position between the rounded value (1) and the average of neighboring rounded values (0). Green: large std. Black: low std.

The estimated mean is calculated at each sampling point based on the sample data batch $\mathbf{y}_s(t)$. The time window w is,

$$w = \max \left\{ 200, \left\lceil 200 \sqrt{\max \left\{ \frac{2mV}{\sigma}, \frac{\sigma}{2mV} \right\}} \right\rceil \right\} \quad (5)$$

$$\mathbf{y}_s(t) = [y(t_{k-w}) \ \dots \ y(t_{k+w})]^T, \quad \text{hence} \quad \|\mathbf{y}_s(t)\| = 2w + 1.$$

The minimum window size is 200 s; it increases proportional to the square of the lack or excess of noise power, since either the estimation error is not whitened sufficiently, or the

signal-to-noise-ratio (SNR) is too low. The length of the batch is $\|\mathbf{y}_s(t)\|$. The sampling occurs within a symmetric window around the time instant in question, meaning that it is receding at the edges, decreasing both sample length and estimation quality.

The range of the sample $r(t)$ counted in accuracy bits R is found via Equation (6). Too large an R leads to $r(t) = 0$, hence the quantized data are the sole source of information, giving $\mu(t)$ as the mean. Nonzero and even / odd $r(t)$ in Figure 2a depicts the mechanism to find the threshold for the data separation. The thresholds $T_i(t)$ indicate where data are naturally separated by the rounding (red); otherwise, the estimation becomes biased. In order to alleviate the sampling bias, the inverse normal distribution is evaluated symmetrically from two opposite points of the distribution function.

$$r(t) = \frac{\max \mathbf{y}_s(t) - \min \mathbf{y}_s(t)}{R} \quad (6)$$

$$\begin{aligned} &\text{if } r(t) = 0 && \mu(t) = \bar{\mathbf{y}}_s(t) \\ &\text{if } r(t) \in \mathbb{Z}^+ \text{ is even} && \begin{cases} T_1(t) = \frac{\min \mathbf{y}_s(t) + \max \mathbf{y}_s(t)}{2} - \frac{R}{2} \\ T_2(t) = \frac{\min \mathbf{y}_s(t) + \max \mathbf{y}_s(t)}{2} + \frac{R}{2} \end{cases} \\ &\text{if } r(t) \in \mathbb{Z}^+ \text{ is odd} && \begin{cases} T_1(t) = T_2(t) = \frac{\min \mathbf{y}_s(t) + \max \mathbf{y}_s(t)}{2} \end{cases} \end{aligned}$$

The sample realization $\mathbf{y}_s(t)$ of the random variable $Y(t)$ is classified according to how large a proportion of the data points is less than or equal to the threshold $T_i(t)$. This estimated probability $\hat{\text{Pr}}(Y(t) \leq T_i(t))$ is expressed in Equation (7). The estimated deviation from the threshold value $\hat{y}_i(t)$ maximizes the likelihood function $\mathcal{L}(\hat{y}(t)|\mathbf{y}_s(t))_i$.

$$\begin{aligned} \hat{\text{Pr}}(Y(t) \leq T_i(t)) &= \frac{\sum_{j=k-w}^{k+w} q(t_j)}{\|\mathbf{y}_s(t)\|} \quad i \in \{1, 2\}, \quad q(t_j) = \begin{cases} 1 & \text{if } y(t_j) \leq T_i(t) \\ 0 & \text{if } y(t_j) > T_i(t) \end{cases} \quad (7) \\ \hat{y}_i(t) &= \mathcal{N}^{-1}(\hat{\text{Pr}}(Y(t) \leq T_i(t)) | \mu = 0, \sigma) \end{aligned}$$

The mean of the sample can then be calculated from the threshold and the deviation as,

$$\begin{aligned} \hat{\mu}_i(t) &= T_i(t) - \hat{y}_i(t) \quad i \in \{1, 2\}, \\ \hat{\mu}(t) &= \frac{\hat{\mu}_1(t) + \hat{\mu}_2(t)}{2}, \quad \text{if } r(t) \in \mathbb{Z}^+. \end{aligned} \quad (8)$$

At the beginning of the time series, dynamics affect the sample. During this transient region, better results can be obtained if the following smoothing function is used:

$$y_{\text{smooth}}(t) = \frac{\sum_{i=k-w/4}^{k+w/4} y(t)}{\frac{w}{2} + 1}. \quad (9)$$

At the edges smoothing is conducted with a receding window, similar to the statistics of the inverse normal distribution. The weighting function $W_{dq}(t)$ in Equation (10) is used to merge the results of Equations (8) and (9). It consists of a linearly spaced vector with its elements raised to the power c , where c is proportional to the noise power. This enhances

noise power to uncover the mean. Finally, the dequantized signal y_{dq} is obtained from the weighted samples $y_{dq}(t)$.

$$W_{dq}(t) = \frac{\left(\left[\|\mathbf{y}\|_s(t) : -1 : 1\right]^T\right)^c}{\|\mathbf{y}\|_s(t)}, \quad \text{where } c = 4 \frac{\sigma}{2mV}, \quad (10)$$

$$y_{dq}(t) = W_{dq}(t)y_{smooth}(t) + (1 - W_{dq}(t))\mu(t).$$

2.3. Linear Continuous-Time Regression

The challenge with fitting a sum of exponentials to measured data is that it is inherently a nonlinear regression problem. The literature suggests either nonlinear optimization or considers special cases and converts the problem to an approximate linear regression problem to be solved in a closed form. However, most of these methods do not generalize easily to ECM parameter identification. The method below (introduced in [10]) provides a solution to cope with this challenge.

The problem. We desire to take a set of time points $\{t_1, \dots, t_N\}$ together with a set of data points $\{y_1, \dots, y_N\}$ and fit them to the model in Equation (11). Parameter m denotes the number of exponential terms in the identification problem. The problem requires that we find the constants $b = \{b_0, b_1, \dots, b_m\}$ and $a = \{a_1, a_2, \dots, a_m\}$ so as to minimize the root-mean-squared error (RMSE) as defined in Equation (12).

$$\hat{y}(t) = b_0 + \sum_{i=1}^m b_i e^{-a_i t} = b_0 + b_1 e^{-a_1 t} + b_2 e^{-a_2 t} + \dots \quad (11)$$

$$\text{RMSE} = \frac{1}{N} \sum_{i=1}^N (y(t_i) - \hat{y}(t_i))^2. \quad (12)$$

2.3.1. Single Exponential with and Without Bias

In Equation (13), we begin with the simplest exponential form that also allows a steady-state bias. Its time derivative is calculated in Equation (14). Using Equation (13) and Equation (14), we then find a form without the exponential function explicitly, as stated in Equation (15).

$$\hat{y}(t) = b_0 + b_1 e^{-a_1 t}. \quad (13)$$

$$\dot{\hat{y}}(t) = -b_1 a_1 e^{-a_1 t}. \quad (14)$$

$$\dot{\hat{y}}(t) = -a_1 \hat{y}(t) + b_0 a_1. \quad (15)$$

The initial value of Equation (13) is

$$\hat{y}(0) = b_0 + b_1. \quad (16)$$

The next step is to integrate both sides of the expression,

$$\int_0^t \dot{\hat{y}}(\tau) d\tau = -a_1 \int_0^t \hat{y}(\tau) d\tau + \int_0^t b_0 a_1 d\tau$$

$$\hat{y}(t) = (b_0 + b_1) + b_0 a_1 t - a_1 \int_0^t \hat{y}(\tau) d\tau. \quad (17)$$

The rightmost term is approximated in two ways: (i) by replacing $\hat{y}(t)$ with the measured data $y(t)$, and (ii) by replacing the integration with a trapezoidal approximation.

We can then write the last line of Equation (17) as Equation (18), where $I_t = \int_0^t t dt$ is the approximate integral between time 0 and t .

$$\begin{aligned}\hat{y}(t) &= (b_0 + b_1) + b_0 a_1 t - a_1 I_t, \quad \text{rewritten as} \\ \hat{y}(t) &= A + Bt - CI_1(t).\end{aligned}\tag{18}$$

This form is now linear in the parameters and the values of A , B , and C can be found by standard linear regression,

$$\underbrace{\begin{bmatrix} y_0 \\ y_1 \\ \vdots \end{bmatrix}}_{\mathbf{Y}} = \underbrace{\begin{bmatrix} 1, & t_0, & -I_1(t_0) \\ 1, & t_1, & -I_1(t_1) \\ \vdots & \vdots & \vdots \end{bmatrix}}_{\mathbf{M}} \underbrace{\begin{bmatrix} A \\ B \\ C \end{bmatrix}}_{\mathbf{X}}\tag{19}$$

The least squares solution is computed as in Equation (20), where † denotes the matrix pseudo-inverse.

$$\mathbf{X} = \mathbf{M}^\dagger \mathbf{Y}\tag{20}$$

Once we have computed $\mathbf{X}$, and therefore, A , B , and C , we can find the coefficients we desire as,

$$a_1 = C, \quad b_0 = B/a_1 \quad \text{and} \quad b_1 = A - b_0.\tag{21}$$

If, for some reason, we happen to be confident that $a_0 = 0$, then we can simplify the method. We form

$$\underbrace{\begin{bmatrix} y_0 \\ y_1 \\ \vdots \end{bmatrix}}_{\mathbf{Y}} = \underbrace{\begin{bmatrix} 1, & -I_1(t_0) \\ 1, & -I_1(t_1) \\ \vdots & \vdots \end{bmatrix}}_{\mathbf{M}} \underbrace{\begin{bmatrix} A \\ B \end{bmatrix}}_{\mathbf{X}}\tag{22}$$

and compute the least-squares solution $\mathbf{X} = \mathbf{M}^\dagger \mathbf{Y}$. Once we have computed $\mathbf{X}$, and therefore, A , and B , we can find the coefficients we desire as $a_1 = B$ and $b_1 = A$.

2.3.2. Double Exponential with and Without Bias

The method presented in this work generalizes nicely to higher-order exponential fits. We next consider a double-exponential form with a steady-state bias in Equation (23), with its first and second time derivatives shown in Equation (24). We can express the second-order derivatives from these equations as shown in Equation (25).

$$\hat{y}(t) = b_0 + b_1 e^{-a_1 t} + b_2 e^{-a_2 t}.\tag{23}$$

$$\begin{aligned}\dot{\hat{y}} &= -b_1 a_1 e^{-a_1 t} - b_2 a_2 e^{-a_2 t} \\ \ddot{\hat{y}}(t) &= b_1 a_1^2 e^{-a_1 t} + b_2 a_2^2 e^{-a_2 t}.\end{aligned}\tag{24}$$

$$\ddot{\hat{y}}(t) = -(a_1 + a_2)\dot{\hat{y}}(t) - a_1 a_2 \hat{y}(t) + b_0 a_1 a_2.\tag{25}$$

The initial values for the model are as follows:

$$\begin{aligned}\hat{y}(0) &= b_0 + b_1 + b_2 \\ \dot{\hat{y}}(0) &= -b_1 a_1 - b_2 a_2.\end{aligned}\tag{26}$$

Again, we integrate both sides of Equation (25) (we integrate twice here; we will do so one step at a time for clarity),

$$\begin{aligned}
\int_0^t \ddot{y}(\tau) d\tau &= -(a_1 + a_2) \int_0^t \dot{y}(\tau) d\tau - a_1 a_2 \int_0^t \dot{y}(\tau) d\tau + \int_0^t b_0 a_1 a_2 d\tau \\
\dot{y}(t) - \dot{y}(0) &= -(a_1 + a_2)(\dot{y}(t) - \dot{y}(0)) - a_1 a_2 \int_0^t \dot{y}(\tau) d\tau + b_0 a_1 a_2 t \\
\dot{y}(t) &= -(a_1 + a_2)\dot{y}(t) - a_1 a_2 \int_0^t \dot{y}(\tau) d\tau + b_0 a_1 a_2 t + (b_1 a_2 + b_2 a_1 + b_0(a_1 + a_2)).
\end{aligned} \tag{27}$$

We now integrate again to write,

$$\begin{aligned}
\int_0^t \dot{y}(\tau) d\tau &= -(a_1 + a_2) \int_0^t \dot{y}(\tau) d\tau - a_1 a_2 \int_0^t \int_0^t \dot{y}(\tau) d\tau d\zeta + b_0 a_1 a_2 \int_0^t \tau d\tau \\
&\quad + \int_0^t (b_1 a_2 + b_2 a_1 + b_0(a_1 + a_2)) d\tau \\
\hat{y}(t) &= -(a_1 + a_2) \int_0^t \dot{y}(\tau) d\tau - a_1 a_2 \int_0^t \int_0^t \dot{y}(\tau) d\tau d\zeta + b_0 a_1 a_2 t^2 / 2 \\
&\quad + (b_1 a_2 + b_2 a_1 + b_0(a_1 + a_2))t + (b_0 + b_1 + b_2).
\end{aligned} \tag{28}$$

The two integrals are again approximated by replacing $\dot{y}(t)$ with the measured data $y(t)$, and by replacing the integration with a trapezoidal approximation. Then, we can write,

$$\begin{aligned}
\hat{y}(t) &= -(a_1 + a_2)I_1(t) - a_1 a_2 I_2(t) + b_0 a_1 a_2 t^2 / 2 \\
&\quad + (b_1 a_2 + b_2 a_1 + b_0(a_1 + a_2))t + (b_0 + b_1 + b_2), \quad \text{rewritten as} \\
\hat{y}(t) &= A + Bt + Ct^2 - DI_1(t) - EI_2(t).
\end{aligned} \tag{29}$$

As before, this form is now linear in the parameters and the values of A , B , and C can be found via standard linear regression,

$$\underbrace{\begin{bmatrix} y_0 \\ y_1 \\ \vdots \end{bmatrix}}_{\mathbf{Y}} = \underbrace{\begin{bmatrix} 1, & t_0, & t_0^2, & -I_1(t_0), & -I_2(t_0) \\ 1, & t_1, & t_1^2, & -I_1(t_1), & -I_2(t_1) \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}}_{\mathbf{M}} \underbrace{\begin{bmatrix} A \\ B \\ C \\ D \\ E \end{bmatrix}}_{\mathbf{X}} \tag{30}$$

by computing the least-squares solution $\mathbf{X} = \mathbf{M}^\dagger \mathbf{Y}$. To determine the a and b sets of coefficients from this solution, consider the polynomial $(x - a_1)(x - a_2) = 0$. It can be seen that a_1 and a_2 are roots of the first expression in Equation (31), which can be found using the quadratic equation. We can solve for b_0 similarly, using Equation (29). Then, we can assemble a system of equations and solve for b_1 and b_2 as stated in Equation (32).

$$x^2 - Dx + E = 0 \quad \text{and} \quad b_0 = 2C/E. \tag{31}$$

$$\begin{bmatrix} A - b_0 \\ B - b_0 D \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ a_2 & a_1 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \tag{32}$$

If, for some reason, we happen to be confident that $a_0 = 0$, then we can simplify the method. We form

$$\underbrace{\begin{bmatrix} y_0 \\ y_1 \\ \vdots \end{bmatrix}}_{\mathbf{Y}} = \underbrace{\begin{bmatrix} 1, & t_0, & -I_1(t_0), & -I_2(t_0) \\ 1, & t_1, & -I_1(t_1), & -I_2(t_1) \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}}_{\mathbf{M}} \underbrace{\begin{bmatrix} A \\ B \\ C \\ D \end{bmatrix}}_{\mathbf{X}} \quad (33)$$

and compute the least-squares solution $\mathbf{X} = \mathbf{M}^\dagger \mathbf{Y}$. Once we have computed $\mathbf{X}$ we can then solve for a_1 and a_2 as roots of the polynomial $x^2 - Cx + D = 0$, which can be found using the quadratic equation. Then, we solve the system of equations Equation (34) to find b_1 and b_2 .

$$\begin{bmatrix} A \\ B \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ a_2 & a_1 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \quad (34)$$

2.3.3. The LCTR Algorithm

Special modifications were made to improve LCTR performance. The modified outputs are noted by apostrophe.

Weighted least squares and normalization. The least square solution of Equation (20) is modified to the weighted least squares solution (for both orders) in Equation (35). Normalization was applied to improve matrix conditioning; here $\max |\mathbf{M}_{:,j}|$ denotes the maximum absolute value of column j . The vector $\mathbf{X}$ consists of the matrix columns X_j .

$$X_j = \frac{(\mathbf{M}'^T \mathbf{W} \mathbf{M}')^{-1} \mathbf{M}'^T \mathbf{W} \mathbf{y}}{\max |\mathbf{M}_{:,j}|}, \quad \text{where } \mathbf{M}'_{ij} = \frac{\mathbf{M}_{ij}}{\max |\mathbf{M}_{:,j}|} \quad \forall \{i, j\} \quad (35)$$

Differential constraint for the second-order case. Reduced data quality can often lead to one of the time constants being incorrectly identified as negative. In order to enforce stable parameters, differential constraints were introduced in Equation (36) for the last 1000 data points, equating the differential of the estimated output with zero. Note that $\mathbf{X}$ is constant, hence $\dot{\mathbf{X}} = \mathbf{0}$. The augmented matrices are $\mathbf{M}'$ and $\mathbf{Y}'$. The weight function for the differential constraint $\mathbf{W}$ in Figure 3 increases in a quadratic manner after the sample point 2500, since subsequent data points are expected to change their values less than the ones prior.

$$\begin{aligned} \mathbf{Y} &= \mathbf{M}\mathbf{X}, \\ \dot{\mathbf{Y}}_{t_{2600}:t_{3600}} &= \mathbf{0} = \dot{\mathbf{M}}_{t_{2600}:t_{3600}} \mathbf{X}, \\ \text{where } \begin{cases} \mathbf{Y}_{t_{2600}:t_{3600}} &= [\mathbf{Y}(t_{2600}) \quad \dots \quad \mathbf{Y}(t_{3600})]^T, \\ \mathbf{M}_{t_{2600}:t_{3600}} &= [\mathbf{M}(t_{2600}, i) \quad \dots \quad \mathbf{M}(t_{3600}, i)]^T \quad \forall i, \end{cases} \quad (36) \\ \mathbf{Y}' &= \begin{bmatrix} \mathbf{Y} \\ \mathbf{0} \end{bmatrix}, \quad \mathbf{M}' = \begin{bmatrix} \mathbf{M} \\ \dot{\mathbf{M}} \end{bmatrix}. \end{aligned}$$

Transient weighting. Figure 3 also shows that weighting on data points at the rise times of the transients is greater than that at the end of the data series. This ensures that the more informative dynamics at the beginning dominate the fitting so that the right time constants are found. Due to the nature of least squares, the longer the data series, the less exact the rise periods are fitted. Furthermore, since regression techniques assume white noise [7], the noise coloring due to using larger time windows (see Equation (5)) reduces estimation quality. This was taken into consideration when choosing window sizes.

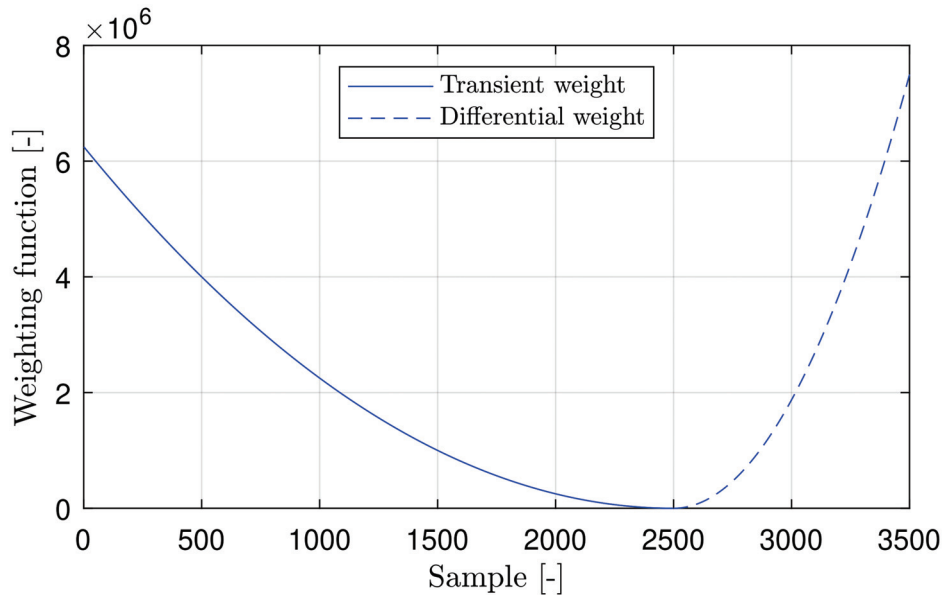


Figure 3. The LCTR weighting function. The first 2500 samples set a preference to model early data points, the last 1000 samples weight the steady-state differential.

2.4. Matlab Implementations

The Matlab code of the dequantizer:

```
function y_dq = dequantize(y_off,sig,R)
    % Window and smoothing
    w = max([200,...
        round(200*sqrt(max([2e-3/sig sig/2e-3])))]);
    y_smooth = smooth(y_off,w/2)'; mu = y_smooth;
    for it = 2:length(y_off)-1
        wp = min([w, it-1, length(y_off)-it]);
        % Sample and range
        s = y_off(it-wp:it+wp);
        r = round((max(s)-min(s))/R);
        % Threshold
        if ~r
            mu(it) = s(1);
        elseif ~mod(r,2)
            th = (max(s)+min(s))/2-R/2*([1, -1]);
        else
            th = (max(s)+min(s))/2*ones(1,2);
        end
        % Probability and mean
        p = sum(s<=th)/length(s);
        mu(it) = mean(th-norminv(p,0,sig));
    end
    % Weighting and the dequantized function
    leny = length(y_off);
    W = (linspace(1,leny)/leny).^4*(sig/2e-3);
    y_dq = (y_smooth.*W + mu.*(1-W))';
```

The Matlab code for second-order fit:

```
function [ahat,bhat] = fitTwoExponentialsWithBias(t,y)
    % Trapezoidal integration
    F = cumtrapz(t,y); G = cumtrapz(t,F);
    % Regressor
```

```

M1 = [ones(size(t(:))), t(:), (t(:)).^2, -F(:), -G(:)];
% Differential constraint
n_diff = 1000;
yp = [y; zeros(n_diff,1)];
M1p = [M1; diff(M1(end-n_diff:end,:))];
% Weight function and normalizing
W = diag([length(t)*3e-3*(1:n_diff).^2,...
          linspace(length(t),1,length(t)).^2]);
M1max = max(eps,max(abs(M1p))); M1pn = M1p./M1max;
% Weighted least squares
X = (M1pn'*W*M1pn)\M1pn'*W*yp./M1max';
% Parameters
ahat = roots([1 -X(4) X(5)]); b0hat = 2*X(3)/X(5);
M2 = [1 1; ahat(2) ahat(1)];
bhat = M2\[X(1)-b0hat; X(2)-b0hat*X(4)];
bhat = [bhat; b0hat];

```

3. Results

3.1. Sensitivity Analysis Overview

A sensitivity analysis was performed to assess the performance and robustness of the algorithms with respect to Gaussian measurement noise σ , resolution R , state of charge (SoC, analogous to open-circuit voltage), and time constants τ_i . Evaluation metrics included RMSE (see Equation (12)), relative time constant errors ($\tilde{\tau}_i/\tau_i$, where $\tilde{\tau}_i$ denotes estimation error), and steady-state errors. Steady-state errors are approximated as the error at the last time instant of the window. Table 1 displays nominal and extreme parameter values. Nominal values are used when not distributed.

Table 1. Nominal, extreme values and number of parameter test points for second order systems (Figure 1). The test points are distributed logarithmically, except for SoC, which is linear. The base of the logarithm is 2 for σ and R and 1.5 for τ_1 and τ_2 .

	σ	R	τ_1	τ_2	R_0	R_1	R_2	SoC(t_0)
Nominal value	2 mV	0.31 mV	22 s	647 s	0.63 m Ω	0.47 m Ω	0.24 m Ω	80%
Minimum value	0.25 mV	0.63 mV	4.3 s	128 s	-	-	-	10%
Maximum value	16 mV	10 mV	111 s	3275 s	-	-	-	100%
Number of test points	7	6	9	9	1	1	1	91

3.2. Visualization of Parameter Identification

First, visualizations of the dequantizing and the LCTR time series are shown for minimal and maximal resolution and Gaussian noise, using a second-order model. Next, RMSE improvement with the dequantizer is shown; the dequantizer is used hereafter in what follows. Then, relative time constant error sensitivity to time constants is shown in order to explore how the combined locations of the two time constants challenge the program. Tests on the first-order system show that a reduced number of parameters are easier to find. A comparison of RMSE improvement and relative time constant errors with those of a benchmark algorithm follows. Steady-state errors are plotted against accuracy and state-of-charge to highlight biased estimation due to coarse rounding. Finally, a real-life scenario test is presented. Matlab experiments show that the dequantizer takes 20 ms, and the LCTR takes 40 ms for second-order and 20 ms for first-order systems.

Figure 4 shows the performance of the LCTR for low/high values of Gaussian noise and resolution. The first row shows that the dequantizer's smoothing effect slightly distorts the data; by using overlapping sample batches, it adds a correlation between data points. However, as soon as the data quality decreases and the data statistics begin to convey

more than the individual points, it becomes useful. When the data are coarsely quantized, the steady-state is missed by the estimation. The LCTR estimates unstable time constants for the dataset with high Gaussian noise without dequantization. It also overestimates low time constants for large Gaussian noise standard deviation.

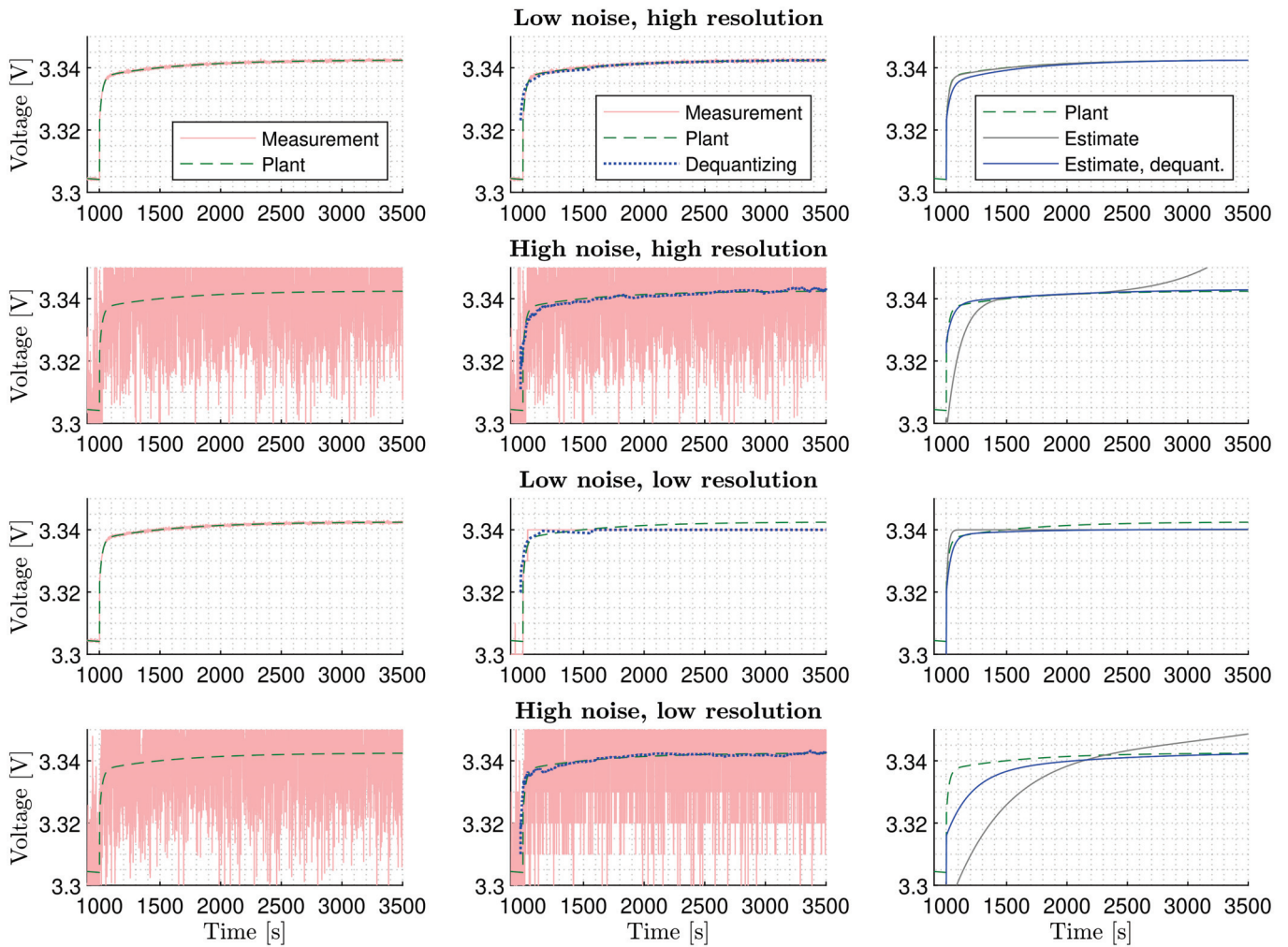


Figure 4. Dependency of estimation quality on Gaussian noise and resolution for an overdamped second-order system.

Figure 5 displays RMSE variations based on accuracy and Gaussian noise standard deviation, comparing unfiltered and dequantized cases. The red regions on the right indicate challenges posed by the Gaussian noise, particularly evident at a low resolution, but notably mitigated by dequantization. Yet, at low Gaussian noise, dequantization's impact on RMSE is not substantial due to the coloring effect of quantization, where the dequantizer lacks sufficient information to recover the steady-state. Given the improvements, subsequent usage of the dequantizer is implied.

Figure 6 depicts relative time constant errors $(\hat{\tau}_i - \tau_i)/\tau_i$ for varying time constant values. The estimation of τ_1 deteriorates with lower values since limited samples are used to describe the rise. It also worsens when τ_2 is lower or τ_1 is higher, indicating challenges when the two time constants are close together, which leads the LCTR to mix information about the exponentials. The relative error of τ_2 increases with larger values, likely due to the incomplete convergence captured in the 2500 s time window.

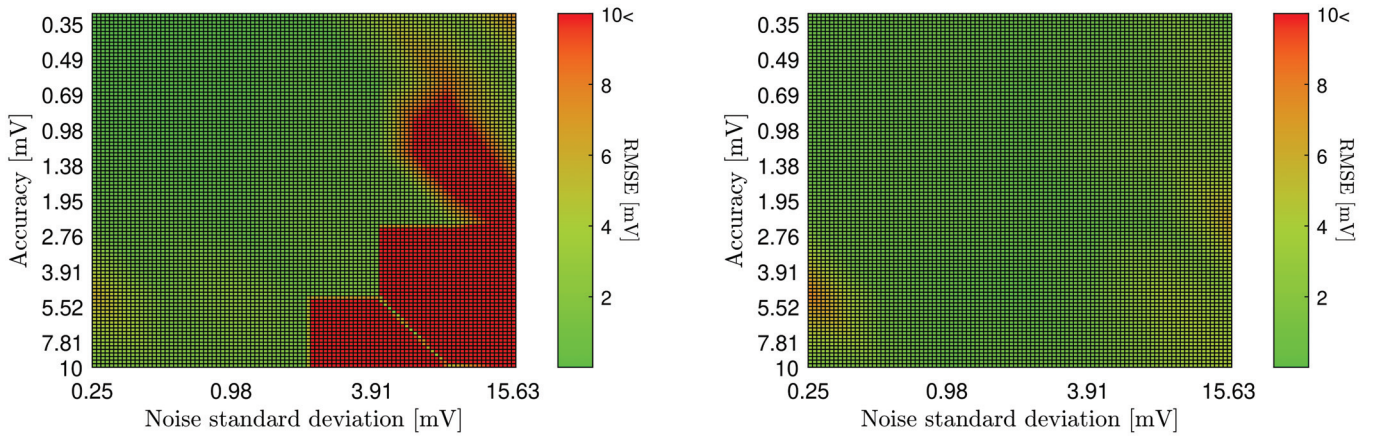


Figure 5. RMSE for the unfiltered (**left**) and the dequantized (**right**) estimation for an overdamped second-order system.

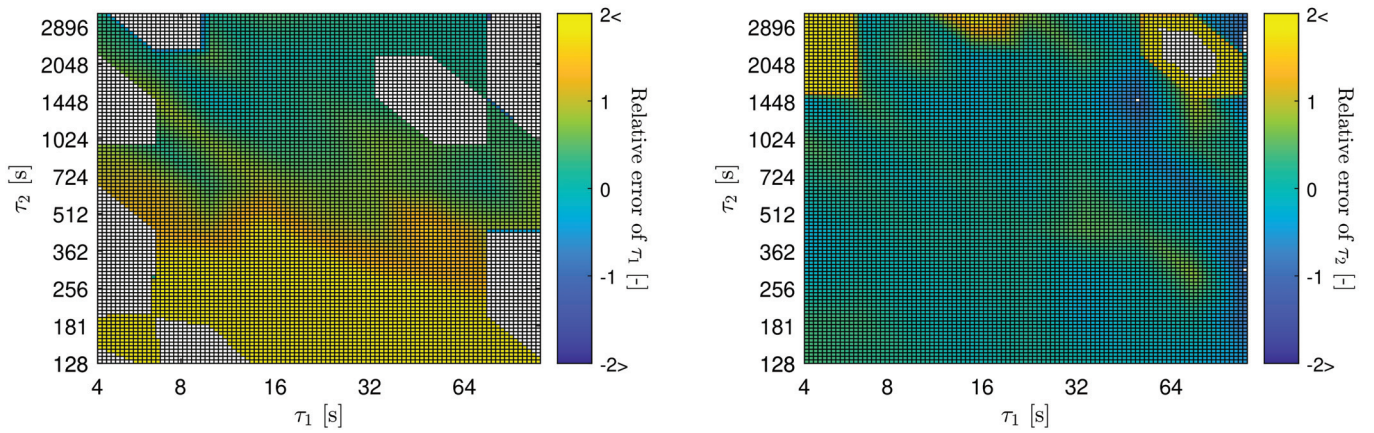


Figure 6. Relative error of τ_1 (**left**) and τ_2 (**right**). White areas denote estimations below 10% or above 10 times of the true value.

3.3. Parameter Sensitivities for the First-Order Model

The *benchmark algorithm* refers to the analytical method used to find the parameters of a first-order model. If the sampling rate is high enough, the data are deterministic, and the end of the time series is near the steady-state, then it gives nearly exact estimations. The mean of the last 100 samples is taken as the estimated steady-state. The estimated initial value is the difference between the initial data point and the steady-state. The time constant is the time when the $1 - e^{-t/\tau} = 1 - e^{-1} = 63\%$ of the initial value is attained by the curve. This algorithm takes 7 ms.

Tests on the first-order model assumed the geometric mean of τ_1 and τ_2 , i.e., 119.2 s, as the time constant. Figure 7 left shows the LCTR RMSE improvement compared to the benchmark for first-order systems. It is larger in regions with a high Gaussian noise standard deviation due to the inherent robustness of the LCTR. However, it worsens in the coarsely rounded region with low noise. Figure 7 right shows the steady-state error of the LCTR plotted against accuracy and SoC (similar results for the benchmark). The OCV is a strictly monotonic function of the SoC, and it equates to the steady-state; hence the rounding error shows periodicity over SoC as displayed in Figure 2b. The dequantizer reduces the steady-state error to a fraction of a mV in most of the region, except where the data are coarsely rounded.

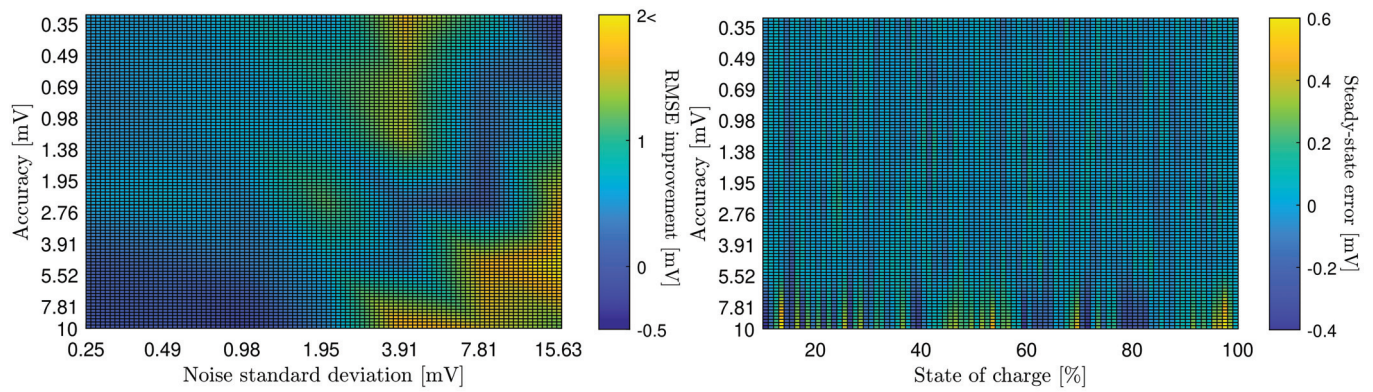


Figure 7. (left) Difference in RMSE in mV for benchmark and the LCTR. Yellow means larger error for the benchmark, dark blue means larger error for the LCTR. The investigated system is a first-order system. (right) Steady-state error in mV depicted for LCTR (similar results found for the benchmark).

3.4. Field Test Results

Figure 8 shows one of a series of measurements that were made to test a LiFePO_4 cell [21]. The battery cell was charged for 15 min then rested for 40 min with data captured at 10 mV accuracy. The dequantizer algorithm restored the data sufficiently for the LCTR to process it. In doing so, the LCTR found $R_0 = 0.9 \text{ m}\Omega$, $R_1 = 1.1 \text{ m}\Omega$, $R_2 = 1.5 \text{ m}\Omega$, $\tau_1 = 225 \text{ s}$ and $\tau_2 = 859 \text{ s}$ for this particular cell. Based on the data and general experience with LiFePO_4 chemistry (see such a cell from another manufacturer in [2]), all the parameters are realistic, except for τ_1 , which is normally expected to be around one minute.

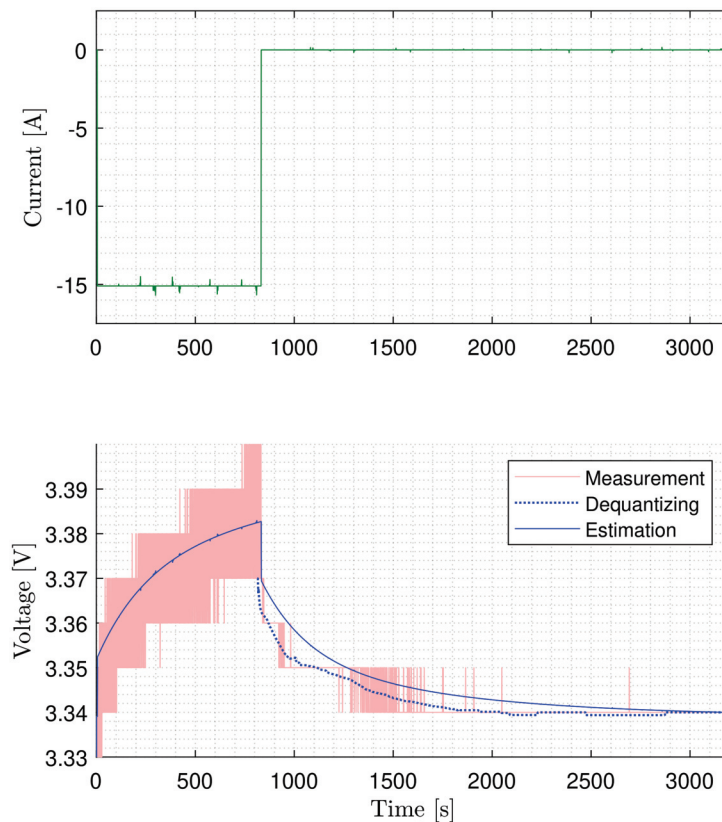


Figure 8. Results of the first-order algorithm on a field test with a lithium-ion phosphate cell. (top) current time series, (bottom) measurement, dequantized and estimated voltage time series. The spikes in the voltage occur because the model uses the noisy current measurement as an input.

4. Conclusions

This work addresses the parameter estimation of single and double exponential functions with application to lithium-ion battery cells, under compromised data quality conditions. Its main contributions are as follows: (i) the dequantizer algorithm, (ii) Liner Continuous-Time Regression (LCTR), and (iii) corresponding sensitivity analysis. The dequantizer is able to recover the shape of the underlying data in the presence of Gaussian noise, although it introduces some correlation due to overlapping sample windows and fails to find the steady-state at extremely coarse resolution. The LCTR demonstrates robustness after data processing by the dequantizer and outperforms an analytical benchmark algorithm, which is a typical commercial application. The RMSE is normally below 2 mV and the steady-state error is within a fraction of a millivolt if rounding is not extremely coarse. The lower time constant of second-order systems may be overestimated under higher noise levels. In summary, the algorithm is fast, robust and analytically sound to estimate the battery parameters throughout their lifespan.

There are several avenues of improvement for future work. The dequantizer used a maximum of two thresholds. Dividing the data along all possible thresholds can further improve recovery. The author observed that higher sampling rates improve the lower time constant's estimate, warranting a sensitivity analysis. Addressing missing or intermittent data could also be included in such an analysis. Lastly, converting the least squares algorithm to a recursive formulation could potentially reduce memory usage and improve algorithm speed.

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Article

Development of Deep Learning-Based Algorithm for Extracting Abnormal Deceleration Patterns [†]

Youngho Jun ¹, Minha Kim ², Kangjun Lee ³ and Simon S. Woo ^{3,*}

¹ Vehicle Control Solutions Center, Hyundai-KEFICO, Gunpo 15849, Republic of Korea; youngho.jun@hyundai-kefico.com

² Department of Artificial Intelligence, Sungkyunkwan University, Seoul 03063, Republic of Korea; sunshine01@g.skku.edu

³ Department of Computer Science & Engineering, Sungkyunkwan University, Seoul 03063, Republic of Korea; gkd1677@g.skku.edu

* Correspondence: swoo@g.skku.edu; Tel.: +82-31-299-4799

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Abstract: A smart regenerative braking system for EVs can reduce unnecessary brake operations by assisting in the braking of a vehicle according to the driving situation, road slope, and driver's preference. Since the strength of regenerative braking is generally determined based on calibration data determined during the vehicle development process, some drivers could encounter inconveniences when the regenerative braking is activated differently from their driving habits. In order to solve this problem, various deep learning-based algorithms have been developed to provide driving stability by learning the driving data. Among those artificial intelligence algorithms, anomaly detection algorithms can successfully separate the deceleration data in abnormal driving situations, and the resulting refined deceleration data can be used to train the regression model to achieve better driving stability. This study evaluates the performance of a personalized driving assistance system by applying driver characteristic data, obtained through an anomaly detection algorithm, to vehicle control.

Keywords: time series; anomaly detection; electric vehicle; personalized data

1. Introduction

The smart regenerative braking system for electric vehicles can provide driving convenience for drivers and avoid unnecessary brake operations by automatically controlling regenerative braking in response to driving environments. Additionally, the driver can select the preferred level of braking force and timing in user options, which are categorized as soft, medium, and strong. However, some drivers could encounter inconveniences when the regenerative braking is activated differently from their driving habits because the strength and timing of regenerative braking are controlled based on calibration data predetermined during vehicle development.

Various efforts have been made to alleviate driving discomfort resulting from automated brake control, and recent initiatives have involved diverse research endeavours leveraging artificial intelligence [1–4]. Applying anomaly detection algorithms to various artificial intelligence algorithms enables the identifying and refining of abnormal driving scenarios, such as the unexpected merging of the leading vehicle, drowsy driving, and abrupt braking. Subsequently, the vehicle can be controlled to enhance driving stability

with an intelligent driver assistance system trained on refined data acquired through an anomaly detection algorithm.

Among various studies aimed at refining abnormal driving data, one study utilizes DBSCAN-DTW (density-based spatial clustering of applications with noise-dynamic time warping) to cluster driving data, excluding data that fail to form clusters as outliers [5]. However, the DBSCAN algorithm forms clusters based on the density of the data, leading to a significant impact on cluster results based on the quantity of data. Therefore, hyperparameters such as ϵ and $\min_samples$ substantially influence the clustering outcomes, making it challenging to generalize the clustering algorithm. Thus, in this study, deep learning-based algorithms are developed to perform anomaly detection based on the features of the data without being influenced by hyperparameters.

Subsequently, the anomaly detection algorithm is utilized to refine data from abnormal driving scenarios and driver characteristic data are applied to vehicle control systems. Furthermore, the regenerative braking system incorporating personalized data is assessed to determine whether it controls braking intensity in a manner similar to that of actual driver behaviour, thereby improving driving consistency and reducing discomfort.

2. Background

2.1. Smart Regenerative Braking System

The smart regenerative braking system is a driver convenience feature that assists in braking the vehicle based on driving conditions, road incline, and the driver's deceleration tendency, even without the driver pressing the brake pedal. The fundamental control of the smart regenerative braking system blends the Constant Time Gap Policy (1) and the Uniformly Accelerated Motion Equation (2) according to the distance and relative speed of the vehicle ahead. The Constant Time-Gap Policy [6–10], aimed at improving string stability, offers the advantage of preventing congestion in trailing vehicles compared to the use of constant spacing. Additionally, the Uniformly Accelerated Motion Equation is a formula that calculates target deceleration based on the equation of uniformly accelerated motion.

$$a_{CTG} = -\frac{1}{h}(\dot{\epsilon} + \lambda\delta) \quad (1)$$

$$a_{UAM} = \frac{v_{front}^2 - v_{ego}^2}{2\epsilon} \quad (2)$$

Here, ϵ represents the distance to the vehicle ahead, λ is the control parameter, h is the target time gap, δ is the distance error, v_{front} is the speed of the vehicle ahead, and v_{ego} is the speed of the ego vehicle.

In addition, by adjusting the intervention timing and braking intensity of smart regenerative braking, it is possible to improve the driving discomfort experienced by the driver due to automatic control. However, since the intensity of regenerative braking is determined based on predefined data during the vehicle development process, some users may feel uneasy while driving due to the regenerative braking activating too late or too strongly. This study proposes a smart regenerative braking system that learns the driver's driving data and controls the vehicle in a manner identical to the driver's usual habits, providing a sense of driving stability.

2.2. Dataset Description

The real driving data used to measure the model's utility are summarized in Table 1. These data were collected during actual drives from Yongsan in Seoul to Gunpo in Gyeonggi Province in South Korea. Among these, data instances where the driver's foot was off the accelerator pedal were considered to indicate a lack of intention to accelerate and a desire

to reduce speed; thus, only these instances were acquired through preprocessing. Each dataset consists of 11 features, and the labelling was manually conducted by an expert to classify solely the stable deceleration data. During this process, states showing a similar pattern of the driver pressing the brake pedal where the longitudinal deceleration values increased in the negative direction and then converged to zero were defined as the driver's braking habits and labelled accordingly. Additionally, unlabeled driving datasets were also used to qualitatively assess the anomaly detection model's potential for generalization.

Table 1. Dataset statistics.

Vehicle Types	Drivers	Dataset Size	Anomaly Ratio
IONIQ5	Driver 1	55	0.67
IONIQ5	Driver 2	35	0.60
G80EV	Driver 2	29	0.63
G80EV	Driver 3	23	0.56

3. Unsupervised Anomaly Detection

3.1. Motivations

In time series anomaly detection, benchmark datasets typically feature fewer anomalies than normal data, challenging the effectiveness of traditional supervised learning algorithms and leading to a focus on unsupervised learning for anomaly detection. These algorithms, using normal data, train models for tasks such as prediction or reconstruction, enabling them to recognize normal data patterns. However, when these models encounter unseen anomalous data, they exhibit significant performance drops, indicating anomalies.

For developing smart regenerative braking systems, accurately extracting drivers' deceleration patterns is key. Our study assumes that patterns where a leading vehicle's deceleration is followed by the trailing vehicle are the most representative. While general clustering algorithms can identify these patterns without extensive labelling, their hyperparameter sensitivity complicates real-world application.

To address this issue, we advocate for an anomaly detection approach. By defining data that reflect a driver's deceleration style as 'normal', we train anomaly detection models to identify and exclude 'anomalous' profiles during deployment. This method streamlines data filtering and reduces hyperparameter tuning needs, though it requires some labelled data and advanced generalization techniques for diverse drivers and vehicles.

3.2. Anomaly Detection Algorithms

We explore the use of EncDec-AD [11] and Transformer [12] models in identifying unique deceleration patterns. Our evaluation extends to the models' generalizability across various driving conditions, vehicle types, and driver behaviours, highlighting their potential for real-world applications.

3.2.1. EncDec-AD

In Figure 1, The EncDec-AD model is a Long Short Term Memory (LSTM) network-based Encoder–Decoder scheme for anomaly detection that is designed to learn to reconstruct 'normal' time series behaviour and uses reconstruction errors to detect anomalies. This approach is robust and can detect anomalies from predictable, unpredictable, periodic, aperiodic, and quasi-periodic time series. It is particularly useful in scenarios where anomalous data are not available or are sparse, making it difficult to learn a classification model over the normal and anomalous sequences. This is especially true for machines that undergo periodic maintenance and therefore are serviced before anomalies show up in the sensor readings.

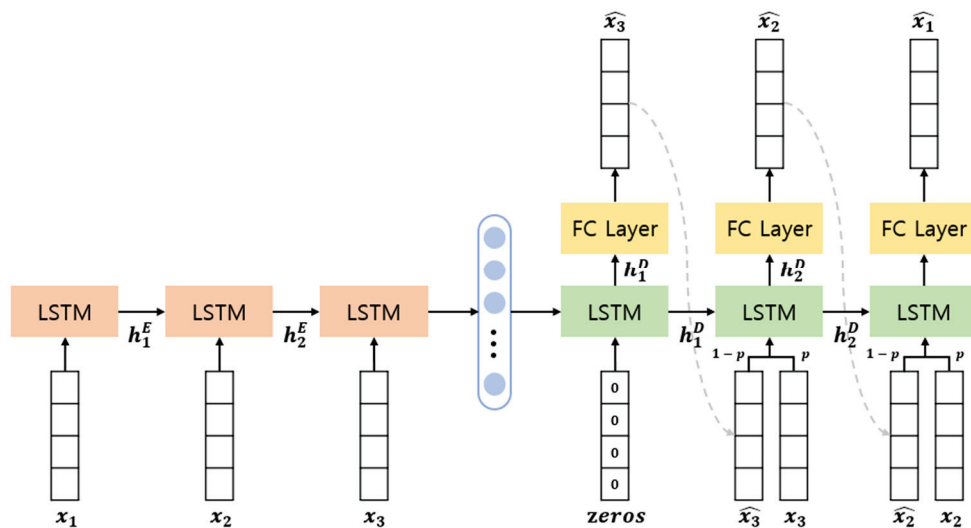


Figure 1. Architecture of EncDec-AD.

The model works by first training the LSTM Encoder–Decoder to reconstruct the normal time series. The LSTM encoder learns a fixed-length vector representation of the input time series, called the feature vector, and the LSTM decoder uses this representation to reconstruct the time series in reverse order. Here, a special technique called teacher forcing is applied which uses the original data as the input to the decoder with a certain probability (p) during training. The reconstruction errors are then used to obtain the likelihood of a point in a test time series being anomalous. A higher anomaly score indicates a higher likelihood of the point being anomalous.

The EncDec-AD model is shown to be effective in detecting anomalies in various scenarios, including different datasets with characteristics such as periodicity, predictability, and dimensionality. It has been tested on datasets from diverse domains, demonstrating its ability to detect anomalies from short time series (length as small as 30) as well as long time series (length as large as 500).

3.2.2. Transformer

In Figure 2, The Transformer model offers an alternative approach to sequence modelling by replacing traditional recurrent and convolutional neural networks with an architecture based solely on attention mechanisms. This design enables the model to directly compute relationships between all timestamps in the input and output sequences, irrespective of their positional distances. The architecture comprises an encoder and a decoder, each consisting of six identical layers that incorporate multi-head attention mechanisms and position-wise fully connected feed-forward networks. This configuration allows the model to dynamically allocate attention, effectively capturing long-range dependencies within sequences.

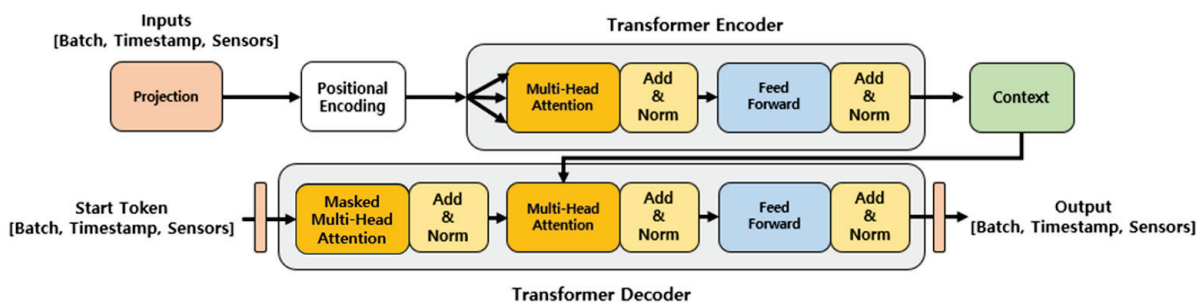


Figure 2. Architecture of a Transformer.

In this work, we utilize the Transformer model as a time series predictor within a prediction-based unsupervised anomaly detection framework. Given the past w timestamps (where w represents the window size), the Transformer predicts values for the subsequent h timestamps (where h denotes the horizon length). Unlike LSTM models the Transformer processes the entire sequence in parallel, which can cause the positional information of individual values within the sequence to be lost. To address this, sinusoidal positional encoding is added to the input data, enabling the model to account for the order of values in the sequence. The transformed input is then passed into the Transformer encoder, starting with the multi-head attention layer. This layer employs a “Scaled Dot-Product Attention” mechanism, which calculates the output as weighted sums of the inputs, with weights being determined based on the compatibility between queries and keys. This mechanism allows the model to flexibly adjust its focus across the sequence, facilitating parallel data processing compared to LSTM, thereby reducing training time and enhancing the efficiency of sequence modelling tasks. The multi-head attention layer performs scaled dot-product attention computations in parallel for a number of heads specified as a hyperparameter, collecting information from diverse perspectives. Subsequently, the outputs pass through a feed-forward network, and the encoder generates the context vector, which serves as the representation of the input sequence over the w timestamps.

During training, the Transformer decoder employs the teacher forcing technique, similar to the EncDec-AD architecture, to facilitate learning. Specifically, the target output sequence is used as part of the decoder input, starting with a special start token. The masked multi-head attention layer within the Transformer decoder restricts the scaled dot-product attention operation to only consider positions preceding the current one. This masking ensures that the model generates predictions in an autoregressive manner, preventing any information leakage from future timestamps. Following this, the multi-head attention layer in the decoder does not use self-attention but instead uses the encoder’s context vector as keys and values. This operation enables the decoder to leverage the encoded representation of the input sequence while predicting the output sequence. Finally, the decoder’s output passes through a projection layer to generate predictions for the subsequent h timestamps. Through this process, the Transformer decoder predicts the probability distribution of the next token in the sequence based on the entire input sequence.

In the inference phase, since teacher forcing is not applied, the decoder receives only the start token, which is initialized as a zero vector. Using an iterative decoding process, the decoder is repeatedly invoked, with each predicted output token being fed back as input to generate the output sequence incrementally. Ultimately, the predicted output sequence is compared with the ground truth to compute the prediction error, which is subsequently refined into an anomaly score. This score quantifies the level of anomaly for the given timestamps.

3.3. Experimental Results

We conducted various experiments and visualizations to compare and analyze whether the EncDec-AD or Transformer model more effectively detects abnormal deceleration driving profiles and generalizes to unseen vehicles and drivers. For quantitative anomaly detection evaluation, we utilized precision, recall, and the F1-score metric, which is one of the most commonly used evaluation metrics for anomaly detection tasks in machine learning. Unlike accuracy, which can be misleading due to the inherent class imbalance nature of anomaly detection problems, where normal samples significantly outnumber anomalies, the F1-score provides a more reliable evaluation by harmonically averaging precision and recall. We placed an additional emphasis on recall due to the task’s characteristics by also employing an $f\beta$ -score with $\beta = 2$. The formula for the $f\beta$ -score is as

shown in Equation (3). The threshold for the anomaly score was set to the value that yields the highest f1 score in the test data.

$$F_{\beta} = (1 + \beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}} \quad (3)$$

The results of all experiments are based on the values obtained using the feature set combination that shows the highest detection performance out of a total of 11 features. For EncDec-AD, the dimensions of the LSTM hidden layers and the number of layers were chosen from {5,10} and {1,2,3}, respectively. For the Transformer, the dimensions of the hidden layers, the number of heads, and the number of layers were chosen from {4,6}, {2,3}, and {1,2}, respectively. The final hyperparameter configurations were determined through a grid search.

The results of the quantitative comparison between the two models for each vehicle type, IONIQ5 and G80EV, are documented in Table 2. Across all experiments, and regardless of the model or vehicle type, it was observed that anomaly detection techniques for extracting abnormal deceleration driving patterns performed significantly well. This demonstrates that learning through deep learning reduces dependency on hyperparameters and can yield stable, high performance, serving as evidence that the approach shifting the problem's paradigm to anomaly detection is justified. As seen in Table 2, for IONIQ5 data, the Transformer showed quantitatively better performance. However, for G80EV data, the limited amount of labelled data presents challenges in comparing the performances of the two models. Therefore, a qualitative analysis through a substantial amount of unlabelled data is necessary to select the model most suitable for actual deployment.

Table 2. Quantitative results for EncDec-AD and Transformer Dataset statistics.

Dataset	IONIQ5		G80EV	
Model	EncDec-AD	Transformer	EncDec-AD	Transformer
Precision	0.9686	0.9336	1.0000	0.9767
Recall	0.7708	0.8792	1.0000	1.0000
F1-score	0.8585	0.9056	1.0000	0.9882
F β -score	0.8037	0.8896	1.0000	0.9952

3.4. Generalizability Analysis

From an anomaly detection viewpoint, the method for extracting abnormal deceleration patterns, unsuitable for training smart regenerative braking systems, demonstrates a lower dependence on hyperparameters and superior performance over traditional clustering-based methods, enhancing its practicality. However, a notable limitation is the requirement of a specific amount of labelled data to facilitate effective training. Despite being an unsupervised learning technique which typically does not necessitate labelled data for training it still requires a dataset of high-purity normal estimates. Moreover, labelled data are essential for periodic evaluation of the model's performance. Given these challenges and the real-world difficulty in obtaining high-quality labelled data, the success of deploying anomaly detection-based filtering largely hinges on the model's ability to generalize. Should a model trained on a limited selection of vehicle types and drivers demonstrate robust generalization across a broad spectrum of vehicle types and drivers, it would affirm the practical viability of the anomaly detection-based method.

3.4.1. Experiment Settings

The experimental setup for evaluating the generalization performance of the anomaly detection model across different vehicle types and drivers is constructed by combining

the datasets in Table 1, as shown in Table 3. Scenario 1 and 2 involves using one anomaly detection model per vehicle type to assess whether a pre-trained model can generalize across all drivers. In contrast, Scenario 3 examines whether a single pre-trained universal anomaly detection model can uniformly generalize across vehicle types.

Table 3. Qualitative evaluation in generalizability experimentation settings.

Scenario	Train Dataset	Test Dataset
Scenario 1	IONIQ5 + G80EV normal dataset	IONIQ5—Driver 1 IONIQ5—Driver 2
Scenario 2	IONIQ5 + G80EV normal dataset	G80EV—Driver 2 G80EV—Driver 3
Scenario 3	IONIQ5 + G80EV normal dataset	IONIQ5—Driver 2 G80EV—Driver 2

Figure 3 illustrates the deceleration profile during a vehicle braking scenario. The braking process is divided into four stages: Coasting, Deceleration, Adjustment, and Termination. We analyzed the braking initiation point (Ⓐ deceleration start point) and braking intensity (Ⓑ deceleration rate) during the deceleration phase, where the driver's braking tendencies are most pronounced with scatterplots. Additionally, a quantitative evaluation was conducted to assess whether the data refined by the anomaly detection algorithm could effectively classify representative data reflecting the driver's braking tendencies. The results and analysis for each scenario are discussed in the following Section 3.4.2.

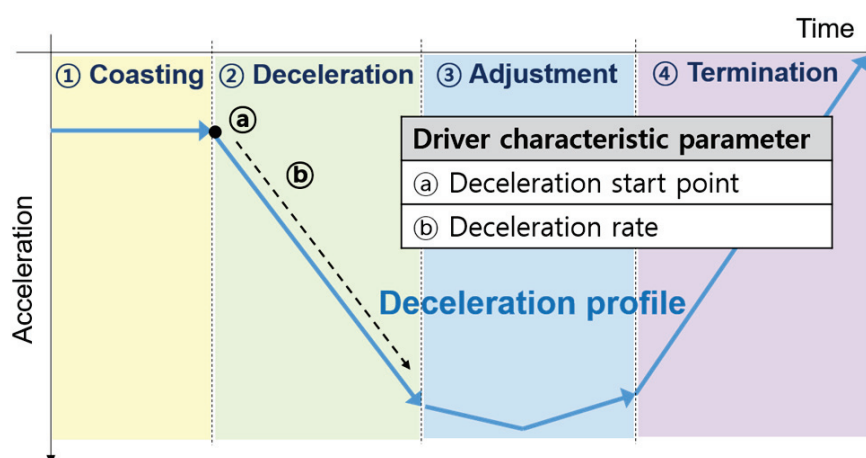


Figure 3. Deceleration profile and driver characteristic parameters (vehicle braking conditions).

3.4.2. Analysis for Scenario 1 and Scenario 2

For qualitative evaluation, we analyzed scatterplots representing gradient deceleration and vehicle speed according to distance for both normal and abnormal data. It is common for normal data to exhibit an upward trend in both scatterplots, so we examined whether the yellow dots used in training and the green dots identified as normal during inference displayed a distinct upward trend. Furthermore, a well-generalized anomaly detection model is expected to have a clearer decision boundary and identify points deviating from the pattern as outliers, marked with a red 'x'. All qualitative evaluations were conducted with the consultation of domain experts.

Figures 4 and 5 illustrate the results of Scenario 1 in Table 3, presenting the outcomes of outlier removal applied to driving data collected from Driver 1 and Driver 2 using the IONIQ5. Both results indicate, consistent with pre-trained data, that braking intensity increases as the distance to the preceding vehicle decreases (with an increase in the gradient

of deceleration in the negative direction). Furthermore, when employing the Transformer model, the boundaries between normal and abnormal data are more distinctly separated, suggesting that the Transformer model might have detected anomalies more conservatively to cover a wider range of normality. The IONIQ5 data showed significant differences in data distribution across drivers. At the same vehicle speed, Driver 1 demonstrated a characteristic tendency to commence braking at shorter distances from the preceding vehicle. Thus, it can be observed that the processed data inherently reflect the distinct driving characteristics of individual drivers.

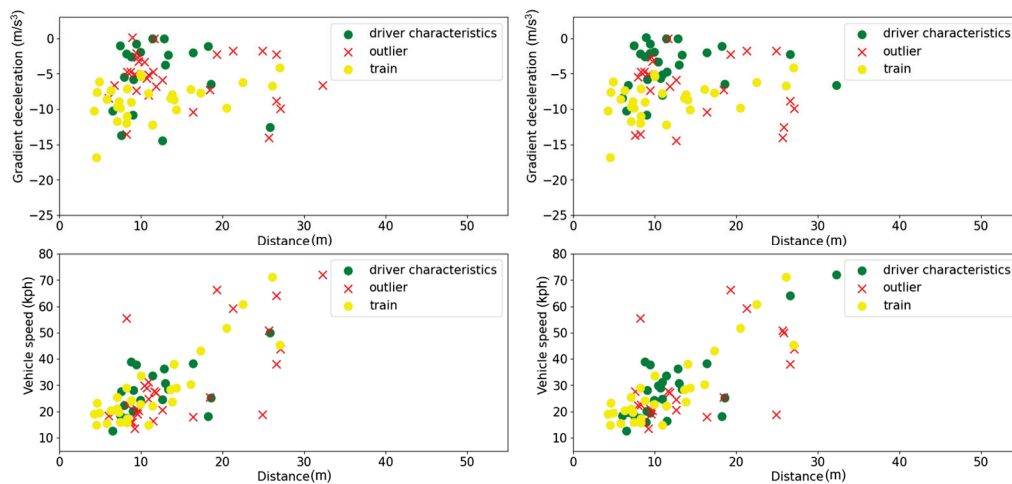


Figure 4. IONIQ5 results for Driver 1 (left: EncDec-AD; right: Transformer).

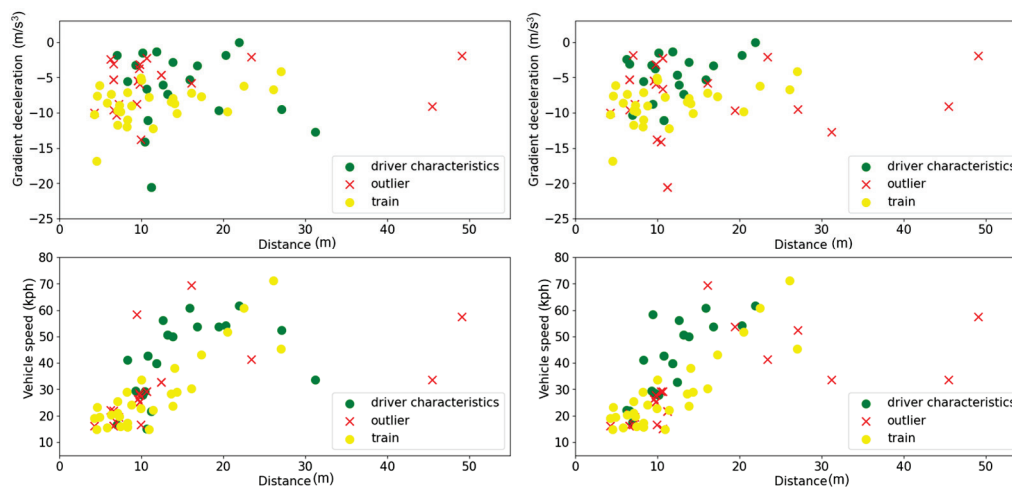


Figure 5. IONIQ5 results for Driver 2 (Left: EncDec-AD, Right: Transformer).

Figures 6 and 7 present the results of Scenario 2 in Table 3, applying the same anomaly detection algorithm to the data collected from Driver 2 and Driver 3 using the G80EV. An examination of the driving data distribution for Driver 3 reveals a clearer distinction between anomalous and normal data. The application of the anomaly detection algorithm to this dataset exhibits a pronounced effect, effectively categorizing most data points deviating from the pre-trained dataset as anomalous.

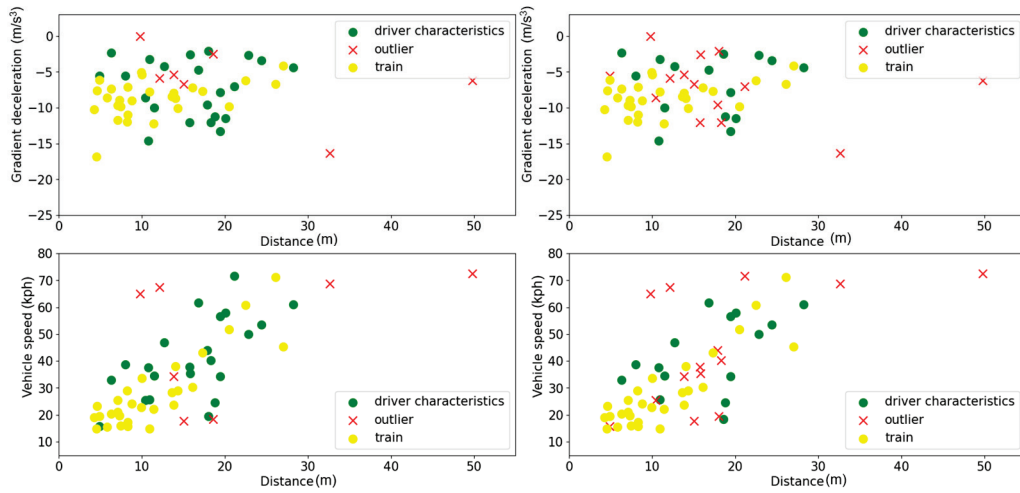


Figure 6. G80 results for Driver 2 (Left: EncDec-AD, Right: Transformer).

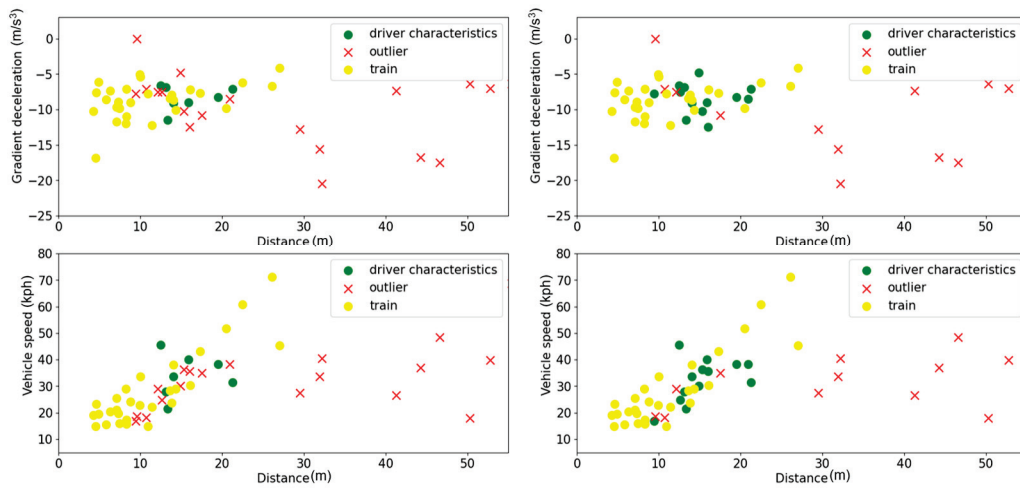


Figure 7. G80 results for Driver 3 (Left: EncDec-AD, Right: Transformer).

3.4.3. Analysis for Scenario 3

Figures 5 and 6 show the results of the same driver operating two vehicles, the G80EV and IONIQ5, providing a basis for a comparative analysis to evaluate Scenario 3, as outlined in Table 3. The results of Scenario 3 indicate that the models demonstrated a certain degree of generalization success, consistent with the findings from Scenarios 1 and 2. It was confirmed that anomalous driving data falling outside the domain of the pre-trained dataset could be consistently classified, regardless of changes in the vehicle. However, due to the change in the vehicle being driven, the tendencies in the driver's characteristic data appear differently. Ultimately, the evaluation of all scenarios makes it clear that generalized results can be achieved using the same anomaly detection model, regardless of the vehicle or driver.

4. Vehicle Testing and Assessment

4.1. Vehicle Testing Environments

In Section 4, the refined data generated through the anomaly detection model were applied to actual vehicle control to examine whether the driving discomfort experienced during the operation of the smart regenerative braking system could be alleviated.

As shown in Figure 4, the data from Driver 1 operating the IONIQ5 were refined using an anomaly detection model. The refined data express the relationship between the

distance to the preceding vehicle and braking intensity as a second-order equation using polynomial regression. Additionally, the vehicle speed and inter-vehicle distance at the moment of braking were represented as a first-order equation. Based on these equations, software was implemented to perform smart regenerative braking control, allowing for the evaluation of whether personalized data could reduce driving discomfort. The evaluation was conducted by comparing the actual driving data of the driver with the personalized smart regenerative braking driving data.

4.2. Assessment of Testing Results

Figure 8 presents the results of applying personalized data to smart regenerative braking control and comparing it with actual driving data. In the section where the relative distance to the preceding vehicle is approximately 20 m and the driving speed is about 40 kph, the comparison shows braking intensities of -5.74 m/s^3 and -4.78 m/s^3 , respectively, indicating similar levels. This demonstrates that the smart regenerative braking control with the personalized data operates with braking forces comparable to those observed during actual driving. These results confirm the validity of the personalized data refined through the anomaly detection algorithm.

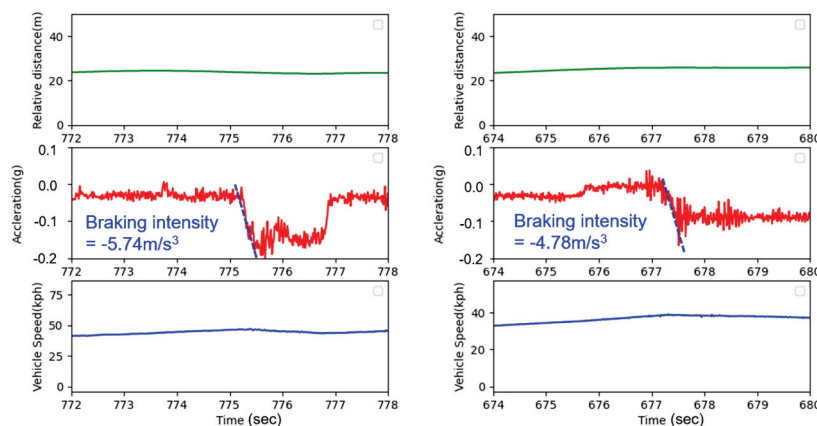


Figure 8. The evaluation results of the validity of the personalized data (left: actual driving data; right: personalized smart regenerative braking driving data).

5. Conclusions

Our research investigates an anomaly detection method for selectively extracting the deceleration patterns that best represent a driver's driving characteristics from raw driving data. To account for the complex nature of multivariate data, deep learning-based anomaly detection methods such as EncDec-AD and Transformers were utilized, demonstrating their potential for generalization. A quantitative and qualitative comparison of the two approaches revealed that the Transformer model, by detecting anomalies more conservatively to encompass a broader range of normalcy, is more suitable for this study. Furthermore, data refined through the anomaly detection model was applied to a smart regenerative braking system, and real-world vehicle tests confirmed the capability of achieving braking performances similar to that of actual drivers. These advancements serve as a critical technology for flexible and driver-friendly smart regenerative systems, reducing driving discomfort and enhancing driving safety.

Future work will focus on extending the proposed anomaly detection approach to account for dynamic driving environments, integrating additional sensor data for enhanced context awareness and exploring personalized adaptation mechanisms to further optimize braking performance based on individual driving behaviours. Additionally, large-scale de-

ployment and long-term testing will be conducted to evaluate the robustness and reliability of the system under diverse driving scenarios.

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Article

Static Output-Feedback Path-Tracking Controller Tolerant to Steering Actuator Faults for Distributed Driven Electric Vehicles

Miguel Meléndez-Useros *, Fernando Viadero-Monasterio, Manuel Jiménez-Salas
and María Jesús López-Boada

Mechanical Engineering Department, Advanced Vehicle Dynamics and Mechatronic Systems (VEDYMEC),
Universidad Carlos III de Madrid, Avenida de la Universidad, 30 (edificio Sabatini), Leganés,
28911 Madrid, Spain; fviadero@ing.uc3m.es (F.V.-M.); manuejim@ing.uc3m.es (M.J.-S.);
mjboada@ing.uc3m.es (M.J.L.-B.)

* Correspondence: mmelende@ing.uc3m.es

Abstract: The steering system plays a critical role in the vehicle's handling and directly influences its lateral dynamics. Faults or abnormal behavior in this system can affect performance, cause vehicle instability, and even lead to accidents. Therefore, considering these potential events is essential for designing robust controllers for autonomous vehicles. For this reason, in this work, a fault-tolerant path-tracking Static Output-Feedback controller is designed to handle steering actuator faults in autonomous vehicle steering systems. The controller adopts a Linear Parameter Varying approach to effectively handle nonlinearities associated with varying vehicle speeds and tire behavior. Furthermore, it only uses information from sensors, avoiding estimation stages. This controller can operate in two modes: a no-fault mode where only the steering is controlled to follow the reference path and a fault mode where the controller manages both the steering and torque vectoring. In fault mode, torque vectoring compensates for faults in the steering actuator. The design of the controller is completed considering gain faults in the steering system. The simulation results show that the proposed controller successfully maintains vehicle stability and significantly reduces tracking errors during high-risk maneuvers, achieving reductions of up to 50.65% in lateral error and 47.26% in heading error under worst-case fault scenarios.

Keywords: fault-tolerant control; path-tracking; static output-feedback control; steering actuator fault; torque vectoring control; vehicle safety

1. Introduction

Automated vehicles (AVs) have emerged as a transformative technology with the potential to revolutionize transport systems worldwide. These vehicles promise numerous benefits, including improved safety, increased mobility, and greater efficiency in transport networks. The convergence of AV technology with electric vehicles (EVs) and the rise of distributed energy systems have further accelerated this transition. Electric powertrains offer benefits such as lower emissions, reduced noise, and simpler mechanical designs that support more sustainable transport solutions [1,2]. EVs include several types, such as Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicles (FCEVs), each with unique characteristics and control requirements [3].

One of the critical tasks in automated driving is path-tracking, which involves guiding the vehicle along a predetermined path while maintaining stability and passenger comfort. Some of the most widely used methods include simple geometry-based techniques such as the pure pursuit controller and the Stanley controller [4], as well as classical control

methods such as Proportional–Integral–Derivative (PID) control [4,5]. These controllers are popular for their ease of implementation. Although effective at lower speeds, these methods are unsuitable for high-speed applications where the nonlinear dynamic behavior of the vehicle can lead to tracking errors or instability. Consequently, model-based approaches that better capture vehicle dynamics are preferred in these cases [6]. More modern approaches such as Linear Quadratic Regulator (LQR) control have been introduced to improve path-following control and stability by minimizing a cost function that balances tracking accuracy and control efforts [7,8]. More recently, Model Predictive Control (MPC) has emerged as a powerful control technique for path-tracking. MPC uses predictive models to optimize future control actions over a receding horizon, providing enhanced path-tracking performance, particularly in challenging driving scenarios [9–11]. However, this method is computationally demanding and requires knowledge of all vehicle states, which are often difficult to measure directly or require additional state observers [12]. Ensuring the stability of the system is crucial, and Lyapunov-based stability methods are commonly used to ensure the stability of the system [13,14].

To further increase robustness to disturbances and model uncertainties, robust control techniques have been applied regarding the path-tracking problem. In [15–17], Sliding Mode Control (SMC) is used to ensure stability in the context of parameter variations and external disturbances in the design of path-tracking controllers. Another commonly used approach, $\mathcal{H}_\infty$ control, provides robustness by minimizing the worst-case gain between input disturbances and system outputs, effectively enhancing the system's ability to handle uncertainties [18–20]. Robust Model Predictive Control (RMPC) combines the predictive capabilities of MPC with a robust design, ensuring that the controller remains effective even in the presence of significant model mismatches or disturbances [21–23].

Vehicle components are susceptible to faults that degrade performance and compromise stability, potentially leading to unsafe driving situations. Such effects can be mitigated by the early detection of these anomalies using model-based [24] and data-driven techniques [25,26]. Beyond detection, fault-tolerant control (FTC) incorporates fault handling into the controller design, enabling the system to adjust inputs and provide a robust dynamic response even when faults occur [27,28].

In the literature, path-tracking fault-tolerant control has been extensively studied to improve the robustness of automated vehicles against actuator faults. FTC control has been used to deal with faults in both steering actuators and wheel motors [29,30]. In [31], a second-order Kalman filter is used to estimate the steering actuator fault so that this estimation can then be used in a fault-tolerant path-tracking Sliding Mode Controller (SMC). In [32], an LQR controller is designed to deal with faults in the steering system, working in conjunction with an SMC to achieve the desired yaw rate, while [33] uses a fault-tolerant controller based on SMC, incorporating fault diagnosis based on the use of neural networks. The work presented in [34] compensates for stuck steering faults by using a differential steering approach for compensation. In [35], an interval observer is presented to recalculate the control input and mitigate the effects of steering actuator faults, similar to the work in [36], where a robust SMC is used in combination with an MPC.

Many of the aforementioned approaches rely on information that is typically not available in commercial vehicles or require additional stages to estimate faults or vehicle states, making real-world implementation difficult. The purpose of this work is to overcome these challenges and enhance the practicality of controller designs for commercial vehicles by introducing a flexible Static Output-Feedback (SOF) controller that adapts to both fault-free and fault conditions using only information available from on-board sensors. The proposed controller operates in two modes: a fault-free mode that controls the vehicle using only the front steering angle and a fault-tolerant mode that uses torque vectoring (TV) to

compensate for actuator faults. This dual-mode operation ensures that vehicle stability and path-tracking performance are maintained even under fault conditions, thereby minimizing tracking degradation, along with steering control. The main contributions of this work are as follows:

- A Multi-Input–Multi-Output (MIMO) SOF controller is developed for a path-tracking system, enabling operation in both fault-tolerant and fault-free modes. This novel approach enables the system to operate in a dual mode: under normal conditions, it relies only on the steering input actuator, and, in the event of a steering system fault, torque vectoring is activated to assist the vehicle and effectively compensate for the steering actuator faults.
- Vehicle uncertainties and nonlinearities caused by varying vehicle speeds are considered in the controller design using an LPV approach. This ensures that the system remains robust and stable under a wide range of operating conditions.
- The driving automation system presented in this work only requires on-board sensors that can be found in series-production vehicles to compute the control inputs. By eliminating the need for expensive sensors for the estimation of vehicle states such as sideslip angle, the practical implementation of the method is guaranteed.

The rest of the article is organized as follows: in Section 2, the problem formulation is introduced, along with the formulation of the vehicle model considered for the controller design. Section 3 presents the controller design methodology. Section 4 discusses the results obtained via simulation. Section 5 concludes the paper.

2. Problem Formulation

2.1. Vehicle Model

The lateral dynamic behavior of the vehicle can be expressed as [37]

$$\begin{aligned} m(\dot{v}_y + rv_x) &= (F_{x,fl} + F_{x,fr})\sin(\delta) + (F_{y,fl} + F_{y,fr})\cos(\delta) + F_{y,r} - F_{y,rl} + F_{y,rr} \\ I_z \dot{r} &= l_f(F_{y,fl} + F_{y,fr})\cos(\delta) - l_r(F_{y,rl} - F_{y,rr}) + \frac{t_w}{2}(F_{y,fl} - F_{y,fr})\sin(\delta) + \Delta M_z \end{aligned} \quad (1)$$

where v_x , v_y , and r are the vehicle's longitudinal velocity, lateral velocity, and yaw rate. The vehicle parameters are described in Table 1. δ stands for the front steering angle and ΔM_z for the yaw moment generated by the action of braking/driving on the individual controller wheels:

$$\Delta M_z = (F_{x,rr} - F_{x,rl})\frac{t_w}{2} + F_{x,fl}(l_f\sin(\delta) - \frac{t_w}{2}\cos(\delta)) + F_{x,fr}(l_f\sin(\delta) + \frac{t_w}{2}\cos(\delta)) \quad (2)$$

where $F_{x,ij}$ denotes the longitudinal driving/braking forces and $F_{y,ij}$ the lateral tire forces, for $i \in f, r$, front and rear axes and for $j \in l, r$, left and right sides of the vehicle. The values of these forces depend on several factors, including vertical load, tire pressure, and road conditions. Despite nonlinear tire–road models existing that represent tire behavior, such as the Pacejka magic formula, the Burckhardt model, or the Dugoff model [38–40], in this work, a simplified linear model [41,42] is considered to simplify the tire behavior as follows:

$$\begin{aligned} F_{y,f} &= 2C_f\alpha_f \\ F_{y,r} &= 2C_r\alpha_r \end{aligned} \quad (3)$$

where $\alpha_f = \delta - \frac{v_y - l_f v_r}{v_x}$ and $\alpha_r = \frac{r l_r - v_y}{v_x}$ are the front and rear tire slip angles, respectively. C_f and C_r are the front and rear tire cornering stiffness, respectively. These parameters are

functions of the vertical load and tire–road interaction. As direct measurement in real-time is not possible, they can be assumed to be bounded as

$$\begin{aligned} C_f &\in [C_{f,min}, C_{f,max}] \\ C_r &\in [C_{r,min}, C_{r,max}] \end{aligned} \quad (4)$$

This enables the nonlinearities of the tire model to be taken into account, especially at high slip angles (Figure 1).

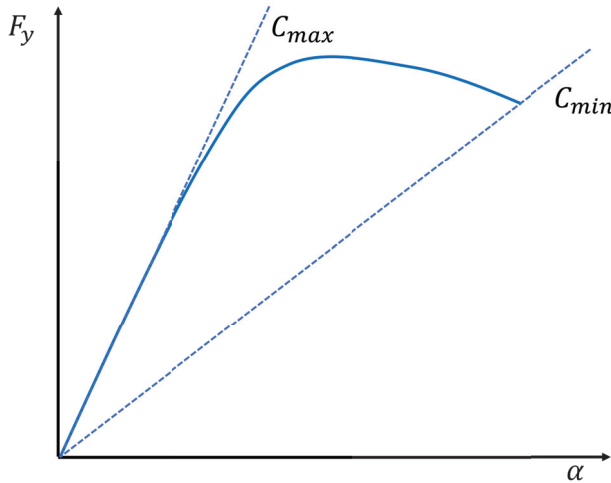


Figure 1. Cornering stiffnesses limits for tire lateral force.

Table 1. Vehicle model parameters.

Symbol	Description	Value	Units
$C_{f,min}/C_{f,max}$	Cornering stiffness of the front tire	80,750/109,250	N/rad
$C_{r,min}/C_{r,max}$	Cornering stiffness of the rear tire	72,250/97,750	N/rad
l_f	Distance from CoG to front axis	1.49	m
l_r	Distance from CoG to rear axis	1.81	m
R	Wheel radius	0.465	m
t_w	Track width	1.9	m
m	Vehicle total mass	1700	kg
I_z	Moment of inertia about the yaw axis	3246.6	kgm ²
a	Look-ahead bias parameter	7	m
b	Look-ahead gain parameter	0.5	s

By combining Equations (1) and (3), the lateral vehicle dynamics can be described as

$$\begin{aligned} \dot{v}_y &= -\frac{2C_f + 2C_r}{mv_x}v_y + \left(\frac{l_r C_r - l_f C_f}{mv_x} - v_x\right)r + \frac{C_f}{m}\delta \\ \dot{r} &= \frac{l_r C_r - l_f C_f}{I_z v_x}v_y - \frac{l_r^2 C_r + l_f^2 C_f}{I_z v_x}r + \frac{l_f C_f}{I_z}\delta + \frac{1}{I_z}\Delta M_z \end{aligned} \quad (5)$$

2.2. Path-Tracking Model

Consider the path defined by its reference positions and reference heading angle $\begin{bmatrix} x_r & y_r & \psi_r \end{bmatrix}$, as represented in Figure 2. To track the reference path, the lateral error e_y and the heading error e_ψ must be minimized:

$$\begin{aligned} e_y &= (y_v - y_r)\cos(\psi_r) - (x_v - x_r)\sin(\psi_r) \\ e_\psi &= \psi - \psi_r \end{aligned} \quad (6)$$

ψ being the heading angle of the vehicle. The path-tracking error dynamics are [43]

$$\begin{aligned}\dot{e}_y &= v_y + l_a(v_x)r + v_x e_\phi \\ \dot{e}_\psi &= r - v_x C_R\end{aligned}\quad (7)$$

where C_R denotes the path curvature and is assumed as unknown in this work; $l_a(v_x)$ is the look-ahead distance, which has been defined as a function of the vehicle's speed as in [44]

$$l_a(v_x) = a + bv_x \quad (8)$$

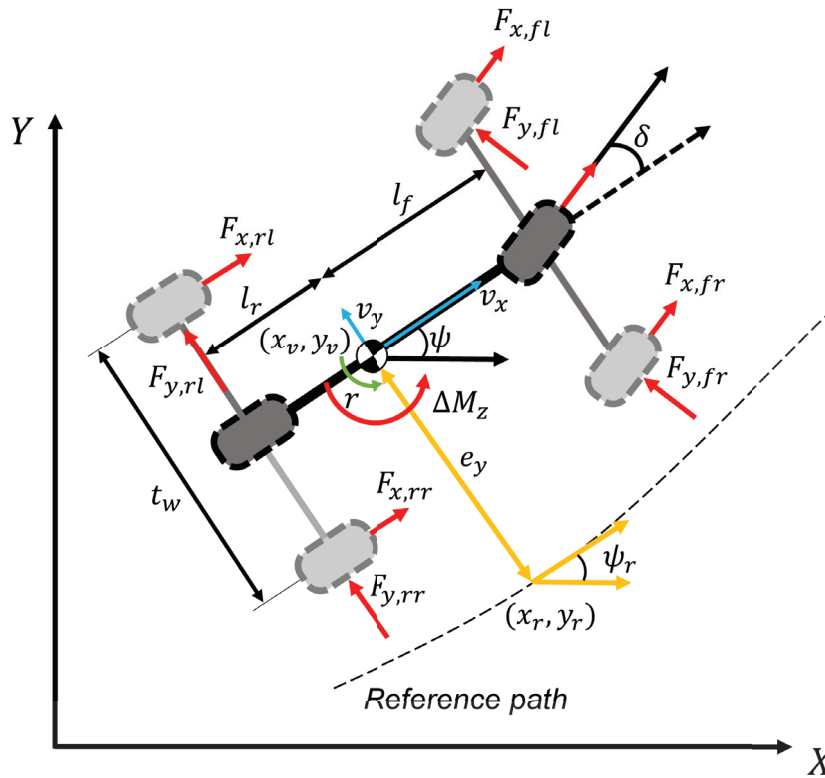


Figure 2. Vehicle path-tracking model.

2.3. Combined Lateral Dynamics and Path-Tracking Model

A model that captures both the vehicle lateral dynamics and the path-tracking behavior is obtained by combining (5) and (7) such that

$$\dot{x} = A_c(t)x(t) + B_c u(t) + E_c d(t) \quad (9)$$

where $x(t) = [v_y \ r \ e_y \ e_\psi]^\top$ is the vehicle state vector, $u(t) = [\delta \ \Delta M_z]^\top$ is the control input, and $d(t) = -v_x C_R$ is the system disturbance. The state-space matrices are

$$A_c(t) = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ 1 & l_a(v_x) & 0 & v_x \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad B_c(t) = \begin{bmatrix} b_1 & 0 \\ b_2 & b_3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad E_c(t) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad (10)$$

with

$$\begin{aligned} a_{11} &= -\frac{2C_f + 2C_r}{mv_x}, & a_{12} &= -v_x + \frac{l_r C_r - l_f C_f}{mv_x} \\ a_{21} &= \frac{l_r C_r - l_f C_f}{I_z v_x}, & a_{22} &= -\frac{l_r^2 C_r + l_f^2 C_f}{I_z v_x} \\ b_1 &= \frac{C_f}{m}, & b_2 &= \frac{l_f C_f}{I_z} \\ b_3 &= \frac{1}{I_z} \end{aligned} \quad (11)$$

Matrices $A_c(t)$ and $B_c(t)$ from (9) depend on the stiffness of the front and rear tires and the longitudinal velocity of the vehicle through the terms C_f , C_r , v_x , and $1/v_x$, with $\underline{v}_x \leq v_x \leq \bar{v}_x$. To overcome this problem, a polytope model method is used to handle the range of varying parameters. As a result, the time-varying parameters can be expressed as a linear combination of $2^4 = 16$ vertices. The terms v_x and $1/v_x$ are not completely independent; a change in the variable can occur to reduce the conservatism of the problem:

$$\frac{1}{v_x} = \frac{1}{v_1} + \frac{1}{v_2} \mu \quad (12)$$

where μ is a bounded parameter that satisfies $-1 \leq \mu \leq 1$. If we use Taylor's approximation [43] and $v_1 = \frac{2\bar{v}_x \underline{v}_x}{\underline{v}_x + \bar{v}_x}$ and $v_2 = \frac{2\bar{v}_x \underline{v}_x}{\underline{v}_x - \bar{v}_x}$, we can obtain

$$v_x \simeq v_1 \left(1 - \frac{v_1}{v_2} \mu \right) \quad (13)$$

In this way, the number of polytope vertices is reduced to $2^3 = 8$ vertices:

$$\mu = \sum_{i=1}^2 \alpha_{1i} \rho_{1i}, \quad C_f = \sum_{i=1}^2 \alpha_{2i} \rho_{2i}, \quad C_r = \sum_{i=1}^2 \alpha_{3i} \rho_{3i} \quad (14)$$

with

$$\alpha_{11} = \frac{\bar{\mu} - \mu}{\bar{\mu} - \underline{\mu}}, \quad \alpha_{21} = \frac{\bar{C}_f - C_f}{\bar{C}_f - \underline{C}_f}, \quad \alpha_{31} = \frac{\bar{C}_r - C_r}{\bar{C}_r - \underline{C}_r}, \quad \alpha_{i2} = 1 - \alpha_{i1} \quad (15)$$

and

$$\rho_{11} = \underline{\mu}, \quad \rho_{12} = \bar{\mu}, \quad \rho_{21} = \underline{C}_f, \quad \rho_{22} = \bar{C}_f, \quad \rho_{31} = \underline{C}_r, \quad \rho_{32} = \bar{C}_r \quad (16)$$

Then, the nonlinear system in (9) can be rewritten as

$$\dot{x}(t) = \sum_{i=1}^8 \zeta_i [A_{c,i} x(t) + B_{1c,i} u(t) + E_c d(t)] \quad (17)$$

where $\zeta_i > 0$ represents the weights of the polytope vertices and

$$\begin{aligned} \sum_{i=1}^8 \zeta_i &= 1, & \zeta'_{ijk} &= \alpha_i \alpha_j \alpha_k, \\ \zeta_1 &= \zeta'_{111}, & \zeta_2 &= \zeta'_{112}, & \zeta_8 &= \zeta'_{222} \end{aligned} \quad (18)$$

To facilitate design and implementation, the system in (17) is converted into its discrete analogue via Euler's discretization:

$$\dot{x}(t) \simeq \frac{x(k+1) - x(k)}{T_s} \quad (19)$$

T_s being the sampling time. The discrete-time state-space model of the system in question is

$$x(k+1) = \sum_{i=1}^8 \zeta_i [A_i(k)x(k) + B_i u(k) + E d(k)] \quad (20)$$

with

$$A = I + T_s A_c, \quad B = T_s B_c, \quad E = T_s E_c \quad (21)$$

Using on-board vehicle sensors, the vehicle's yaw rate can be measured using the vehicle's Inertial Measurement Unit (IMU), while lateral and heading errors are acquired using a LiDAR sensor or a video camera. Therefore, the vector of measured variables $y(k) = [r \quad e_y \quad e_\psi]^T$ is obtained as follows:

$$y(k) = C_y x(k), \quad C_y = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (22)$$

In order to achieve good tracking performance, the lateral tracking error and heading tracking error must be minimized. Additionally, lateral velocity should remain as low as possible in order not to compromise driving safety. These key performance indicators are contained in the output vector $z(k) = [v_y \quad e_y \quad e_\psi]^T$, which is expressed as

$$z(k) = C_z x(k), \quad C_z = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (23)$$

2.4. Active Steering System Actuator Fault

In this work, the fault in the ASS is modeled as a loss of effectiveness fault, which is very common in the literature [45,46]:

$$\delta_f = \varepsilon \delta \quad (24)$$

where ε stands for the loss of effectiveness factor $0 \leq \varepsilon \leq 1$ and δ_f is the final steering angle in the front wheels. To compensate for this fault, a yaw torque is generated when a steering actuator fault is detected. Under this consideration, system (20) is rewritten as

$$x(k+1) = \sum_{i=1}^8 \zeta_i [A_i(k)x(k) + \varepsilon B_{1,i} u_1(k) + B_{2,i} u_2(k) \sigma(k) + E d(k)] \quad (25)$$

where $u_1 = \delta$, $u_2 = \Delta M_z$, $B_1 = B(:,1)$, $B_2 = B(:,2)$, and $\sigma \in \{0,1\}$ is a switching variable that indicates whether the steering actuator is faulty or not and is used to activate the torque-vectoring control:

$$\sigma(k) = \begin{cases} 0 & \text{fault-free steering actuator, } \varepsilon = 1 \\ 1 & \text{fault in the steering actuator, } \varepsilon \neq 1 \end{cases} \quad (26)$$

2.5. Torque Allocation

In order to distribute the torque to the four wheels of the vehicle, the yaw moment ΔM_z provided by the upper-level controller is distributed as [47]

$$\begin{aligned}\Delta T_{fl} &= -\frac{R}{4L_{fl}}\Delta M_z\lambda_l \\ \Delta T_{fr} &= \frac{R}{4L_{fr}}\Delta M_z(1-\lambda_l) \\ \Delta T_{rl} &= -\frac{R}{4L_{rl}}\Delta M_z\lambda_r \\ \Delta T_{rr} &= \frac{R}{4L_{rr}}\Delta M_z(1-\lambda_r)\end{aligned}\quad (27)$$

with

$$\begin{aligned}L_{fl} &= \frac{t_w}{2}\cos(\delta) - l_f\sin(\delta) \\ L_{fr} &= \frac{t_w}{2}\cos(\delta) + l_f\sin(\delta)\end{aligned}\quad (28)$$

$$L_{rl} = L_{rr} = \frac{t_w}{2}\quad (29)$$

where ΔT_{ij} represents the torque increment added to the current torque of the wheel motor ij to avoid compromising the longitudinal dynamics, and λ_l and λ_r represent the trade-off between the torque in the left and right sides of the vehicle, respectively. In this work, these parameters are set to 0.5 to provide an even distribution between both sides of the vehicle.

3. Fault-Tolerant Controller Design

This section derives the fault-tolerant path-tracking controller that compensates for the steering actuator faults using TV. The control architecture is shown in Figure 3.

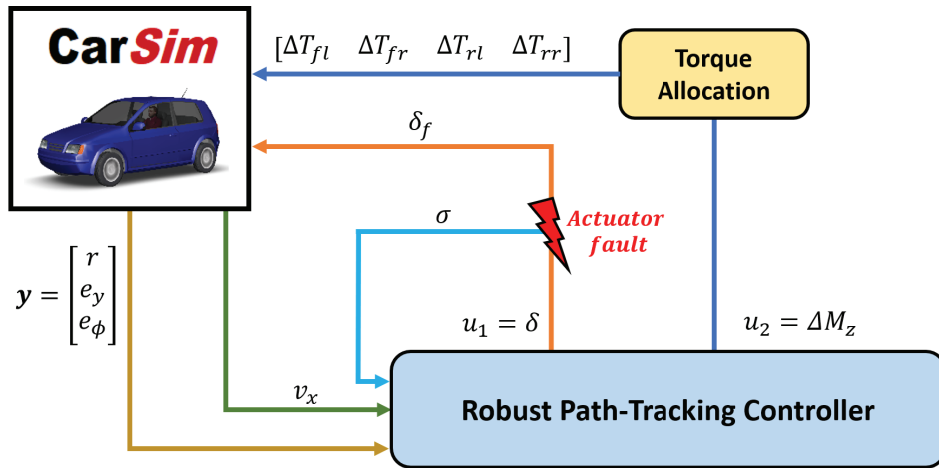


Figure 3. Control scheme of the proposed fault-tolerant controller.

The controller has to maintain the stability of the vehicle and track the reference path in both fault-free and faulty conditions of the steering actuator. Furthermore, the controller may only use the information provided by commercial vehicles [48]. For this purpose, the following control laws are proposed:

$$\begin{aligned}u_1(k) &= K_1 y(k) \\ u_2(k) &= K_2 y(k)\end{aligned}\quad (30)$$

where $K_1 = \sum_{i=1}^2 \theta_i K_{1,i}$ and $K_2 = \sum_{i=1}^2 \theta_i K_{2,i}$ are the gain control matrices to be found. Matrices K_1 and K_2 are computed online using μ , as is the only polytopic parameter available, which is considered to be known as it depends on the longitudinal velocity of the vehicle (12):

$$\begin{aligned}\theta_1 &= \frac{\bar{\mu} - \mu}{\bar{\mu} - \underline{\mu}} \\ \theta_2 &= 1 - \theta_1\end{aligned}\quad (31)$$

Combining the control laws from (30) and state-space equation from (25), we can write the closed-loop dynamics as

$$x(k+1) = \sum_{i=1}^8 \zeta_i \left[A_i x(k) + \varepsilon B_{1,i} \left(\sum_{j=1}^2 \theta_j K_{1,j} C_y y(k) \right) + \sigma(k) B_2 \left(\sum_{j=1}^2 \theta_j K_{2,j} C_y y(k) \right) + E d(k) \right] \quad (32)$$

Theorem 1. Given a definite positive symmetric matrix $Q_j = Q_j^\top \succ 0$, the system of (32) is asymptotically stable with an $\mathcal{H}_\infty$ performance index less than γ and for an actuator fault gain $\varepsilon \in [0, 1]$ if the following LMIs hold:

$$\begin{aligned}& \begin{bmatrix} -Q_j & * & * & * \\ 0 & -\gamma^2 I & * & * \\ A_i Q_j + B_{1,i} K_{1,j} C_y Q_j & E & -Q_j & * \\ C_z Q_j & 0 & 0 & -I \end{bmatrix} \prec 0, \\& \begin{bmatrix} -Q_j & * & * & * \\ 0 & -\gamma^2 I & * & * \\ A_i Q_j + \varepsilon B_{1,i} K_{1,j} C_y Q_j + B_{2,i} K_{2,j} C_y Q_j & E & -Q_j & * \\ C_z Q_j & 0 & 0 & -I \end{bmatrix} \prec 0\end{aligned}\quad (33)$$

Proof. Let us define a Lyapunov function

$$\mathcal{V}(k) = \sum_{j=1}^2 \varrho_j x^\top(k) P_j x(k) \quad (34)$$

with $P_j = P_j^\top \succ 0$. It is assumed that the parameter ϱ does not change significantly between successive instants since it depends on the longitudinal velocity, which is assumed to vary slowly. For the system in (32) to be stable, the following condition must be satisfied:

$$\mathcal{V}(k+1) - \mathcal{V}(k) < 0 \quad (35)$$

In order to minimize the influence of the external disturbance over the chosen controlled outputs, H_∞ approach is used:

$$z(k)^T z(k) < \gamma^2 d(k)^T d(k) \quad (36)$$

γ being the upper bound of the worst-case gain from disturbance d to controlled outputs z . For control design, combining $\mathcal{H}_\infty$ performance in (36) and Lyapunov stability criterion in (35) yields

$$\mathcal{V}(k+1) - \mathcal{V}(k) - \gamma^2 d^\top(k) d(k) + x^\top(k) C_z^\top C_z x(k) < 0 \quad (37)$$

According to the steering, the actuator fault indicator $\sigma(k)$ (37) can be expressed in LMI form for both non-faulty $\sigma(k) = 0$ and faulty $\sigma(k) = 1$ cases as

$$\begin{bmatrix} -P_j + C_z^\top C_z + \Theta_{ij}^\top P_j \Theta_{ij} & \star \\ E^\top P_j & -\gamma^2 I + E^\top P_j E \end{bmatrix} \prec 0$$

$$\begin{bmatrix} -P_j + C_z^\top C_z + \Gamma_{ij}^\top P_j \Gamma_{ij} & \star \\ E^\top P_j & -\gamma^2 I + E^\top P_j E \end{bmatrix} \prec 0 \quad (38)$$

with $\Theta_{ij} = A_i + B_{1,i}K_{1,j}C_y$ and $\Gamma_{ij} = A_i + \varepsilon B_{1,i}K_{1,j}C_y + B_{2,i}K_{2,j}C_y$. Using Schur complement, LMIs in (38) are rewritten as

$$\begin{bmatrix} -P_j & \star & \star & \star \\ 0 & -\gamma^2 I & \star & \star \\ P_j(A_i + B_{1,i}K_{1,j}C_y) & P_j E & -P_j & \star \\ C_z & 0 & 0 & -I \end{bmatrix} \prec 0$$

$$\begin{bmatrix} -P_j & \star & \star & \star \\ 0 & -\gamma^2 I & \star & \star \\ P_j(A_i + \varepsilon B_{1,i}K_{1,j}C_y + B_{2,i}K_{2,j}C_y) & P_j E & -P_j & \star \\ C_z & 0 & 0 & -I \end{bmatrix} \prec 0 \quad (39)$$

Now, if we apply a congruent transformation by multiplying by $\text{diag}[P_j^{-1}, I, P_j^{-1}, I]$ on the left and by its transpose on the right, the LMIs in (39) become

$$\begin{bmatrix} -P_j^{-1} & \star & \star & \star \\ 0 & -\gamma^2 I & \star & \star \\ (A_i P_j^{-1} + B_{1,i}K_{1,j}C_y P_j^{-1}) & E & -P_j^{-1} & \star \\ C_z P_j^{-1} & 0 & 0 & -I \end{bmatrix} \prec 0$$

$$\begin{bmatrix} -P_j^{-1} & \star & \star & \star \\ 0 & -\gamma^2 I & \star & \star \\ (A_i P_j^{-1} + \varepsilon B_{1,i}K_{1,j}C_y P_j^{-1} + B_{2,i}K_{2,j}C_y P_j^{-1}) & E & -P_j^{-1} & \star \\ C_z P_j^{-1} & 0 & 0 & -I \end{bmatrix} \prec 0 \quad (40)$$

By defining a matrix $Q_j = P_j^{-1}$, the LMIs (40) are equivalent to the LMIs in (33). $\square$

The controller gains are determined by solving the following optimization problem:

$$\begin{aligned} \min \quad & \gamma^2 \\ \text{s.t.} \quad & Q_j = Q_j^\top \succ 0, \quad (33) \end{aligned} \quad (41)$$

The LMI in (33) to be solved is a bi-linear problem as variable Q_j is coupled to $K_{1,j}$ and $K_{2,j}$; an iterative procedure is used to find a feasible solution [44]. A full description of this method is presented in Algorithm 1.

Algorithm 1 Iterative procedure for solving bi-linear LMI problem.**Input:**

Vehicle parameters from Table 1.

Output:

Controller gain matrices from (30)

```

1: Set  $C_y = I$  and  $\tilde{K}_{1,j}^{sf} = K_{1,j}Q_j$ ,  $\tilde{K}_{2,j}^{sf} = K_{2,j}Q_j$ .
2: Solve (41).
3: Obtain  $K_{1,j}^{sf}$  and  $K_{2,j}^{sf}$ ,  $j \in 1, 2$ , with the optimal value  $\gamma_{min} = \gamma^{(0)}$ .
4: Set  $C_y$  as in (22) and set  $K_{1,j}^{(0)} = K_{1,j}^{sf}(:, 2:4)$  and  $K_{2,j}^{(0)} = K_{2,j}^{sf}(2:4)$ .
5: for  $k = 1 : k^{max}$  do
6:   Given  $K_{1,j}^{(k)}$  and  $K_{2,j}^{(k)}$ , solve LMIs from (41) to obtain  $Q_j^{(k)}$ 
7:   Given  $Q_j^{(k)}$ , solve LMIs from (41) to obtain  $K_{1,j}^{(k+1)}$ ,  $K_{2,j}^{(k+1)}$  and  $\gamma^{(k)}$ 
8:   if  $\frac{|\gamma^{(k)} - \gamma^{(k-1)}|}{\gamma^{(k)}} < \epsilon$  then
9:     stop
10:  end if
11: end for

```

4. Results and Discussion

In this section, the proposed fault-tolerant SOF path-tracking controller is tested using the vehicle dynamics simulation software *CarSim*® 2022.1 version. The vehicle model is configured with the parameters described in Table 1. The vehicle speed is assumed to be in the range $v_x \in [2, 25]$ m/s. The path-tracking controller is designed by solving the optimization problem (41), considering a maximum gain fault of $\epsilon = 0.1$, using the Robust Control Toolbox included in *Matlab* 2022b. By computing Algorithm 1, a feasible control solution has been found with an $\mathcal{H}_\infty$ robustness index of $\gamma = 9.89$. Only two iterations were required.

Two different fault scenarios are simulated to test the proposed controller:

- (A) DLC maneuver under steering actuator degradation with $\epsilon = 0.3$ and $\epsilon = 0.1$.
- (B) DLC maneuver under steering actuator saturation at $|\delta_{max} = 5^\circ|$ and $|\delta_{max} = 3^\circ|$.

The test maneuver is a Double Lane Change (DLC), designed to simulate an obstacle avoidance situation and challenge the controller under a high-risk scenario.

4.1. Case A: Loss of Effectiveness in the Steering Actuator

To evaluate the effectiveness of the proposed methodology, three cases are compared: (1) a baseline case with no steering faults, (2) a fault case without fault-tolerant control, and (3) the proposed fault-tolerant controller. All the cases are evaluated at a constant vehicle speed of $v_x = 25$ m/s under identical fault conditions.

As shown in Figure 4, the fault-tolerant controller reduces the Root Mean Square (RMS) of the lateral error from 41.13 cm to 30.30 cm with the proposed controller for $\epsilon = 0.3$ and from 80.71 cm to 39.83 cm for $\epsilon = 0.1$. This demonstrates that the proposed controller improves the tracking accuracy, particularly during the second turn when the vehicle returns to its original lane at 4.5s of the simulation. Evidently, the controller can reduce the tracking error of the vehicle even for the most extreme case, $\epsilon = 0.1$. The proposed controller also reduces the heading error, with the maximum error dropping from 10.08° to 8.20° and RMS heading error from 4.29° to 1.86° for the most severe scenario (Figure 5).

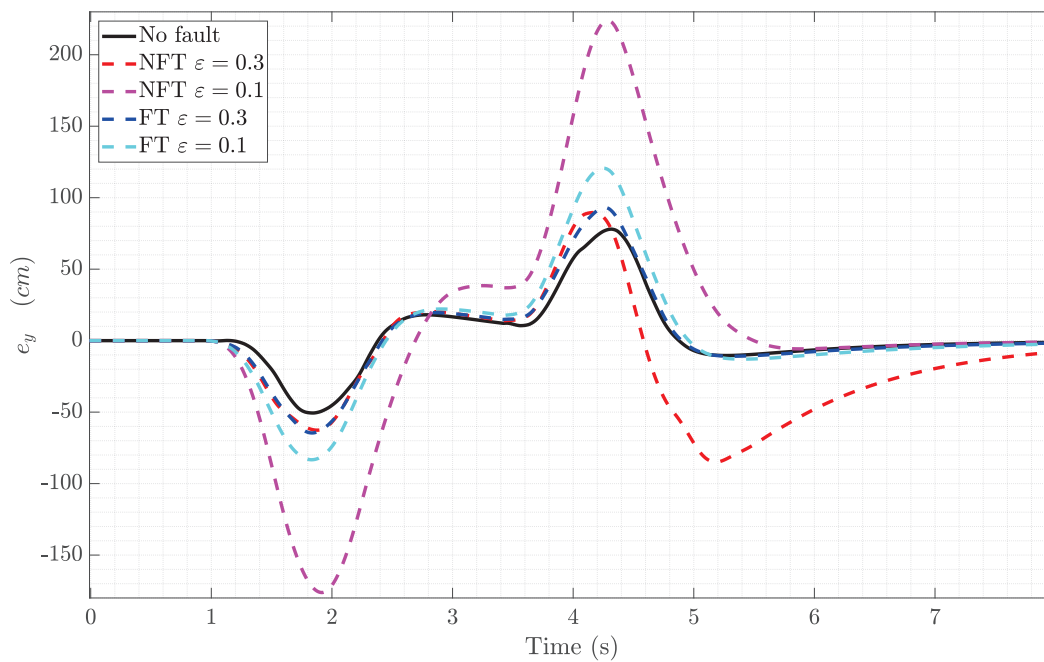


Figure 4. Lateral error for Case A.

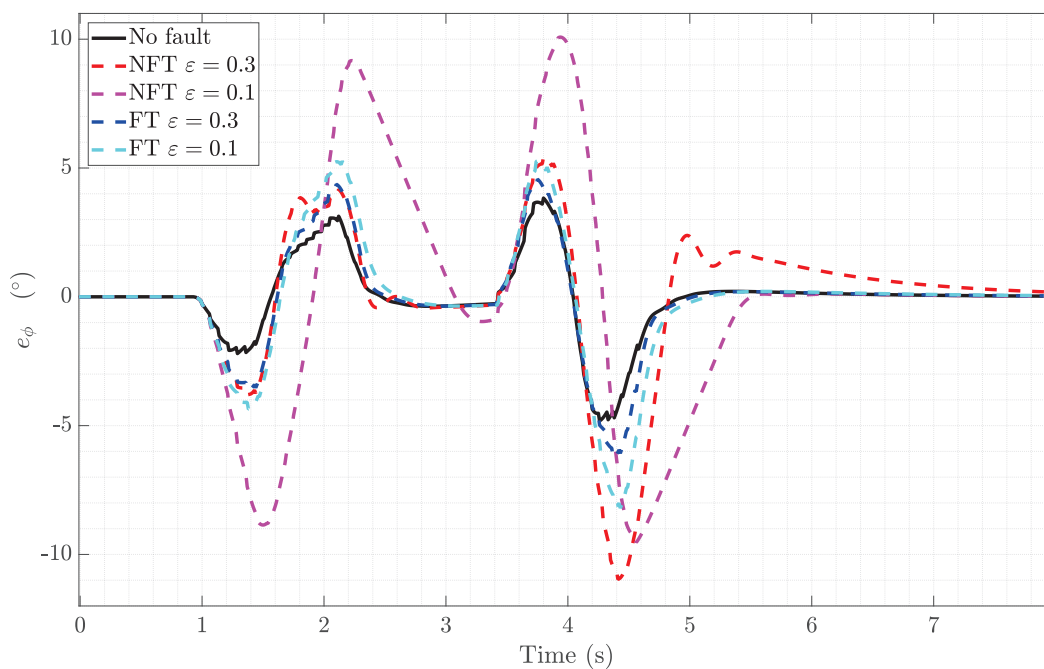


Figure 5. Heading error for Case A.

The control inputs are shown in Figure 6, which displays the steering angle input in Figure 6a and the input torque of the wheel for the fault-tolerant case in Figure 6b. Evidently, the controller demands a higher steering angle due to the actuator's reduced effectiveness, but this demand is limited by physical saturation, as shown in Figure 6a, and the motor torque compensates for this effect by adding extra torque in the wheels as in [36]. Finally, the path followed by the vehicle in each scenario is illustrated in Figure 7, highlighting the differences in tracking performance between the cases with and without fault-tolerant control.

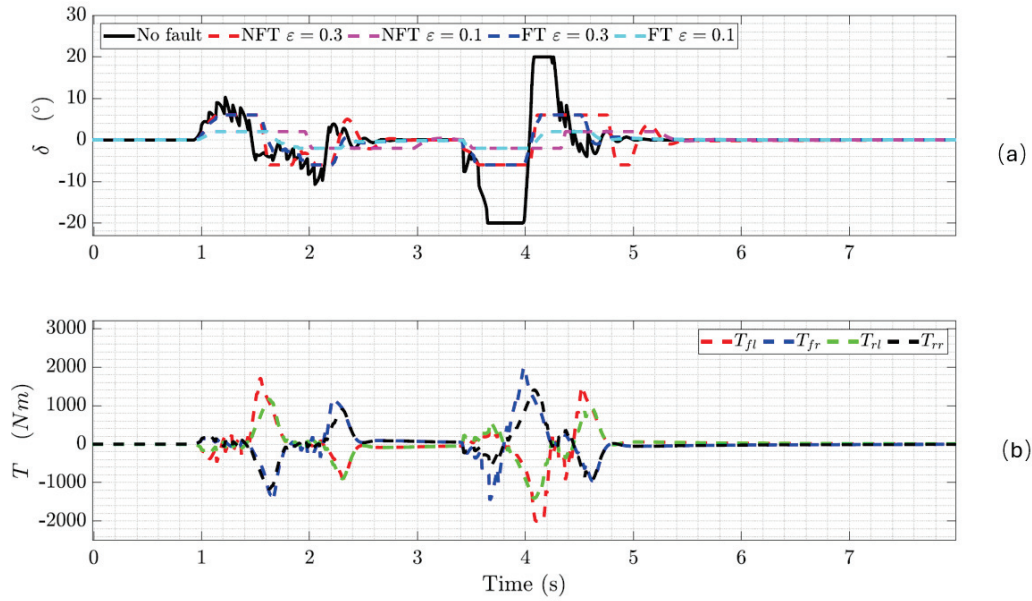


Figure 6. Control inputs for Case A. (a) Front steering angle. (b) In-wheel motor torque when $\varepsilon = 0.3$.

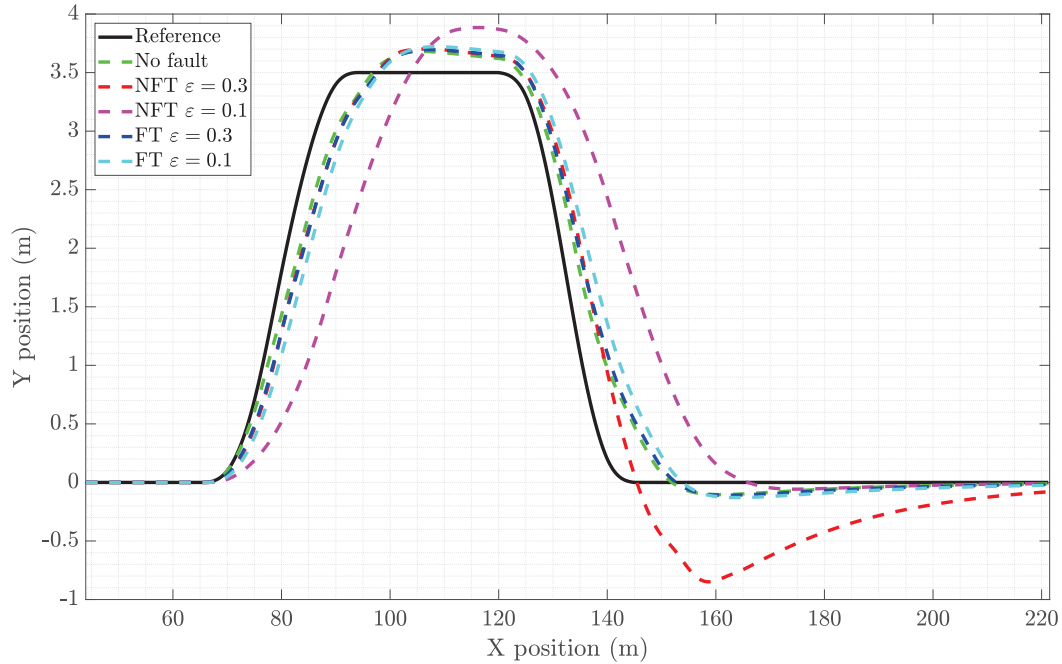


Figure 7. Path for Case A.

4.2. Case B: Steering Actuator Saturation

In this scenario, the fault limits the steering angle to a range of $-5^\circ < \delta < 5^\circ$ and $-3^\circ < \delta < 3^\circ$. As shown in Figure 8, the non-fault-tolerant controller results in a maximum lateral error of 169.09 cm for $|\delta_{max}| = 3^\circ$ in the case of the most severe fault. However, the proposed controller reduces this maximum error to 107.51, a more acceptable level. The RMS lateral error is also decreased from 46.81 cm to 30.13 cm and 66.43 cm to 35.19 cm for $|\delta_{max}| = 5^\circ$ and $|\delta_{max}| = 3^\circ$, respectively. Similarly, as in the previous case, the heading error is minimized, as shown in Figure 9, dropping from 11.86° to 7.38° for the most extreme case. The RMS of the heading error is further reduced from 2.98° to 2.33° and from 4.02° to 2.12° for $|\delta_{max}| = 5^\circ$ and $|\delta_{max}| = 3^\circ$, respectively (Figure 9).

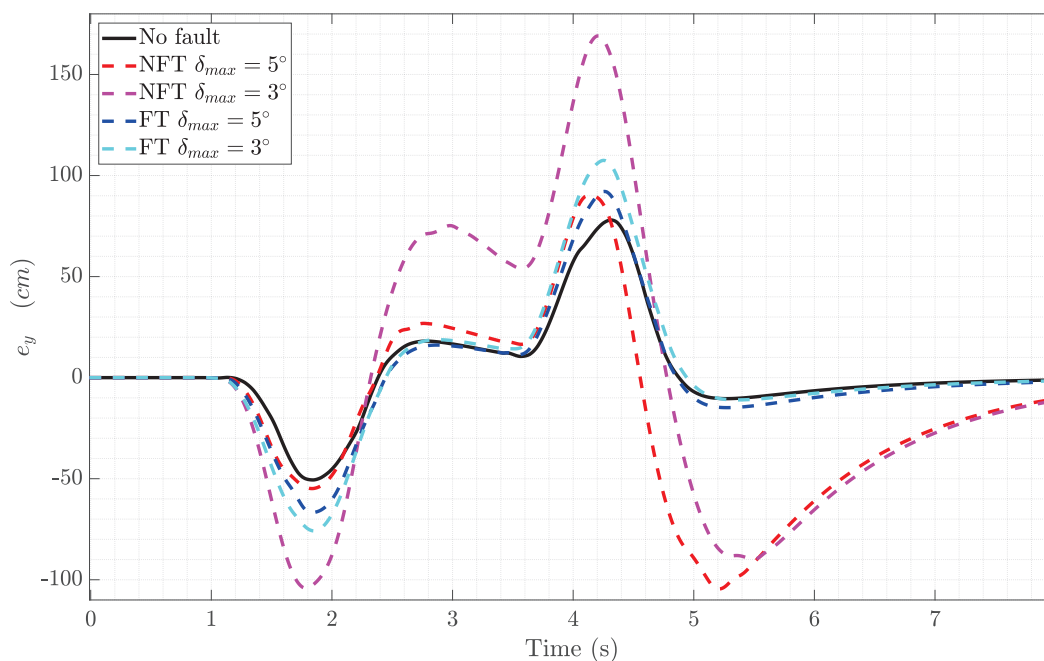


Figure 8. Lateral error for Case B.

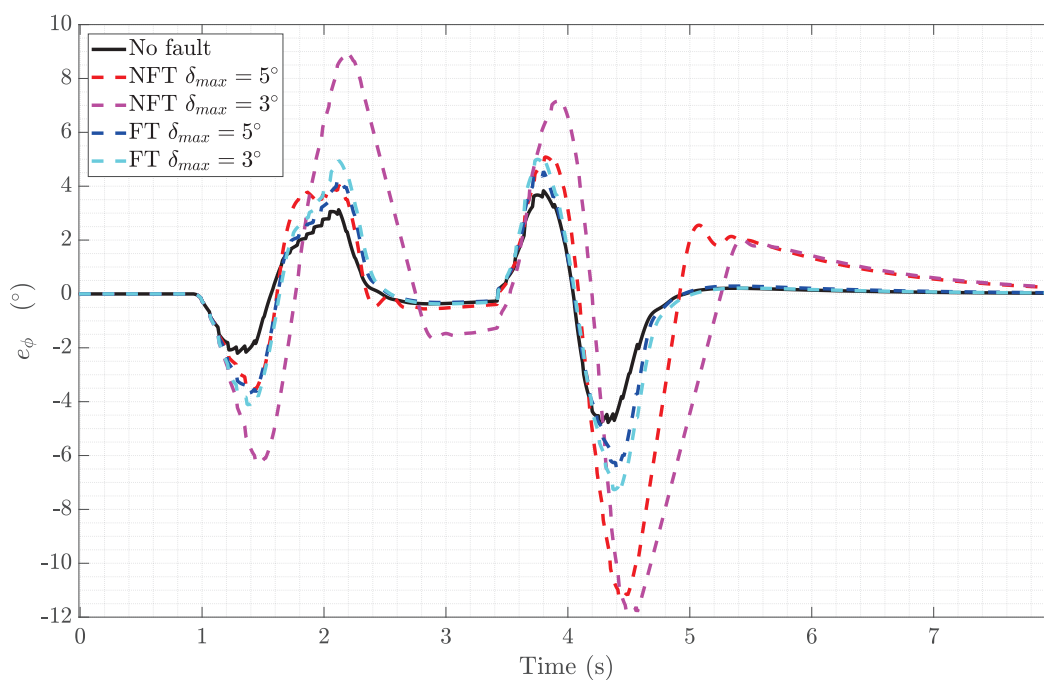


Figure 9. Heading error for Case B.

The control inputs for this case are shown in Figure 10, where the steering angle limitation caused by the fault is visible as in [30], resulting in behavior similar to the previous scenario. The path tracked by the vehicle is illustrated in Figure 11. Table 2 summarizes the results obtained.

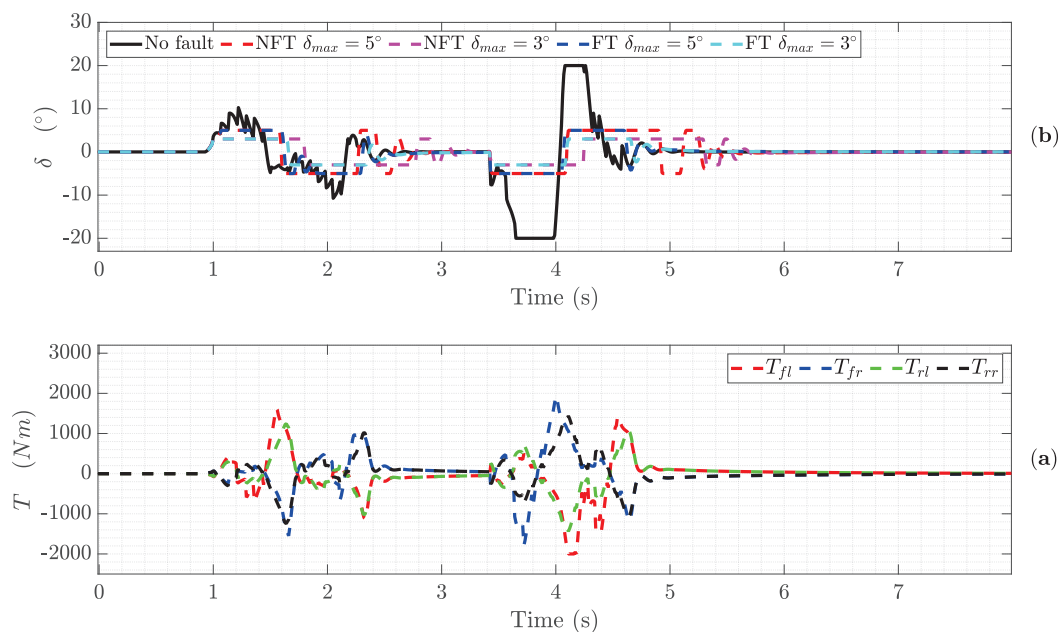


Figure 10. Control inputs for Case B. (a) Front steering angle. (b) In-wheel motor torque for $|\delta_{max}| = 3^\circ$.

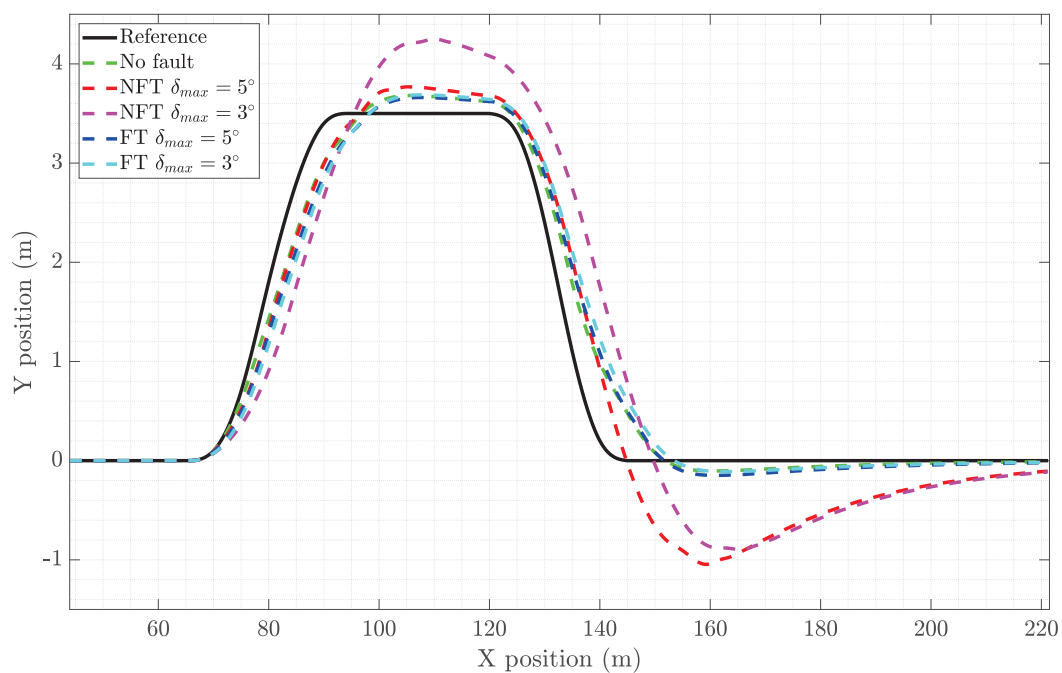


Figure 11. Path for Case B.

Table 2. Tracking errors.

Case		e_y (cm)		e_ϕ (°)	
		MAX	RMS	MAX	RMS
No fault	Reference	78.00	24.97	4.81	1.43
$\varepsilon = 0.3$	Non-fault-tolerant	89.60	41.13	10.96	2.86
	Fault-tolerant	93.21	30.30	6.24	1.85
$\varepsilon = 0.1$	Non-fault-tolerant	223.89	80.71	10.08	4.29
	Fault-tolerant	120.64	39.83	8.20	2.33
$ \delta_{max} = 5^\circ $	Non-fault-tolerant	104.55	46.81	11.32	2.98
	Fault-tolerant	92.12	30.13	6.52	1.86
$ \delta_{max} = 3^\circ $	Non-fault-tolerant	169.09	66.43	11.86	4.02
	Fault-tolerant	107.51	35.19	7.38	2.12

5. Conclusions

In this work, a novel fault-tolerant path-tracking SOF controller is developed for electric DDV vehicles, specifically designed to handle actuator faults with a flexible approach. Using an LPV approach, the controller design accounts for nonlinearities associated with varying vehicle speeds and tire behavior, using $\mathcal{H}_\infty$ theory to minimize its effects on tracking performance. A key innovation of this work is the dual-mode operation: a fault-free mode and an actuator fault mode in which the TV compensates for faults. The simulation results demonstrate the effectiveness of the controller in improving vehicle stability and reducing tracking error under fault conditions in a high-risk maneuver. The controller achieves up to a 50.65% reduction in RMS lateral error and 45.69% reduction in RMS heading error in the worst-case scenario for gain steering fault and a reduction of 36.42% for RMS lateral error and 47.26% reduction for RMS heading error for the saturation fault type.

This controller provides practical benefits for vehicle designers and engineers, offering a robust solution for path-tracking in fault conditions with ease of implementation. Future work may explore extending this approach to address more complex fault types and to enhance the controller for trajectory-tracking applications.

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Abbreviations

The following abbreviations are used in this manuscript:

AV	Automated Vehicle
DDV	Distributed Driven Vehicle
DLC	Double Lane Change
EV	Electric Vehicle
IMU	Inertial Measurement Unit
LMI	Linear Matrix Inequality
LPV	Linear Parameter Varying
LQR	Linear Quadratic Regulator
MPC	Model Predictive Control
TV	Torque Vectoring

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Article

Tesla Log Data Analysis Approach from a Digital Forensics Perspective

Jung-Hwan Lee ¹, Seong Ho Lim ², Bumsu Hyeon ², Oc-Yeub Jeon ², Jong Jin Park ¹ and Nam In Park ^{2,*}

¹ Department of Engineering, National Forensic Service Seoul Institute, Seoul 08036, Republic of Korea; ljh815@korea.kr (J.-H.L.); vortex820@korea.kr (J.J.P.)

² Department of Digital Analysis, National Forensic Service, Wonju-si 26460, Republic of Korea; shlim2000@korea.kr (S.H.L.); ksitht@gmail.com (B.H.); yeubjeon@korea.kr (O.-Y.J.)

* Correspondence: naminpark@korea.kr

Abstract: Modern vehicles are equipped with various electronic control units (ECUs) for safety, entertainment, and autonomous driving. These ECUs operate independently according to their respective roles and generate considerable data. However, owing to capacity and security concerns, most of these data are not stored. In contrast, Tesla vehicles, equipped with multiple sensors and designed under the software-defined vehicle (SDV) concept, collect, store, and periodically transmit data to dedicated servers. The data stored inside and outside the vehicle by the manufacturer can be used for various purposes and can provide numerous insights to digital forensics researchers investigating incidents/accidents. In this study, various data stored inside and outside of Tesla vehicles are described sequentially from a digital forensics perspective. First, we identify the location and range of the obtainable storage media. Second, we explain how the data are acquired. Third, we describe how the acquired data are analyzed. Fourth, we verify the analyzed data by comparing them with one another. Finally, the cross-analysis of various data obtained from the actual accident vehicles and the data provided by the manufacturer revealed consistent trends across the datasets. Although the number of data points recorded during the same timeframe differed, the overall patterns remained consistent. This process enhanced the reliability of the vehicle data and improved the accuracy of the accident investigation.

Keywords: digital forensics; log analysis; software-defined vehicle; vehicle forensics; electronic control unit

1. Introduction

Unlike analyzing a new phone or operating system, analyzing a vehicle for digital forensics is a difficult task, in terms of both software and hardware because the software of various electronic control units (ECUs) controls the hardware according to the assigned roles. As each ECU operates independently, determining the location and the form of the recorded data is difficult. Therefore, digital forensics research on vehicles has been limited to individual ECUs [1–3].

- Inspection of event data recorder (EDR) for traffic accidents;
- Analysis of dashcam to identify accident/incident videos;
- Examination of telematics and infotainment systems to understand accident/incident conditions.

However, there has been a paradigm shift in the vehicle industry owing to various environmental regulations, new business and service models, and new competitors from IT companies. To handle these changes effectively, the software must manage each ECU through an integrated approach, and connectivity between the vehicle and back-end services is crucial [4]. The application of these concepts manifests as software-defined vehicles.

Digital forensic investigators should be able to investigate incidents/accidents through integrated and controlled software-defined vehicle (SDV) modules and external connectivity [5–7]. Manufacturers must assist in this process, and clear incident investigation and resolution are required to establish credibility with consumers. Specifically, SDV-enabled vehicles require an appropriate structure to collect and record data related to safety, driver assistance, entertainment, and autonomous driving [8–10]. Depending on the manufacturer's policy, the data can be recorded inside the vehicle or, in certain situations, transmitted to a dedicated server over a wireless network [4,11].

Therefore, these data are crucial for solving crimes involving vehicles, determining the causes of vehicle accidents, and reconstructing accidents. Furthermore, because this information is recorded on multiple storage devices inside the vehicle, it can be cross-checked and verified to increase the reliability of the information. Event data recorders (EDRs), which involve the current generation of accident recording devices, are designed to investigate vehicle accidents and store data using the vehicle's impact sensors or airbag modules. EDRs were mandated by the NHTSA's 49 code of federal regulations (CFR) part 563 in 2006, which defines the accuracy, collectability, storage, and survivability of crash event data [12]. Furthermore, 49 CFR Part 563.7 emphasizes that obtaining and analyzing EDR data does not require the support of the vehicle manufacturer. This ensures transparency and objectivity of the data during the accident investigation process, mirroring the principles of integrity and verification that are crucial in digital forensics. However, the data recorded by EDR are limited to accidents with large impacts that cause airbags to deploy, and the data stored are limited to approximately 5 to 10 s of driving-related data just before the accident. Furthermore, vehicles equipped with autonomous driving functions are equipped with various sensors and record considerable data [13], but the data recorded in the EDR are limited. To address these problems, the development of a data storage system for automated driving (DSSAD) is being discussed [14], and regulations are being redefined through standardization [15]. Tesla vehicles, equipped with various ECUs for autonomous driving, feature a centralized electrical/electronic (E/E) architecture instead of the traditional design. This centralized E/E architecture provides the advantage of centralized control of the individual vehicle ECUs and is well-suited to the application of IT technologies such as over-the-air (OTA) functions [8,16,17].

The module operating Tesla's centralized E/E architecture is the media control unit (MCU), which collects and controls various data related to autonomous driving, including DSSAD. MCUs incorporate functions related to air control, body control, infotainment, and OTA, enabling digital forensic investigators to access various data [18,19]. In this study, we have limited access to data storage locations inside Tesla vehicles and used public reports from Tesla for analyzing the stored data. Additionally, in situations wherein it is challenging to obtain data according to the manufacturer's manual because of fire or impact, existing digital forensic techniques were used for analysis. Various log data from ECUs and external servers were obtained, as depicted in Figure 1.

- Restraints control module (RCM);
- Media control unit (MCU);
 - eMMC memory (Onboard);
 - MicroSDHC (Insert);
- Over-the-air (OTA)-Tesla Server.

Among the acquired data, OTA data can be documented by processing information periodically sent by the MCU to the dedicated server. This server-stored data serves as the sole record when data retrieval from internal storage media is hindered due to a major collision. Apart from these scenarios, we verified that the storage media of the MCU, serving as the centralized E/E architecture, records logs that can cross-validate data received from the restraint control module (RCM) and Tesla server. The remainder of this paper is structured as follows: Section 2 outlines the locations, characteristics, and analysis methods of the data stored in each ECU. In Section 3, a case study is presented

to demonstrate the reliability of the analyzed data by comparing them with the data from each ECU. Finally, the findings, accompanied by an in-depth discussion and conclusions, are presented in Section 4.

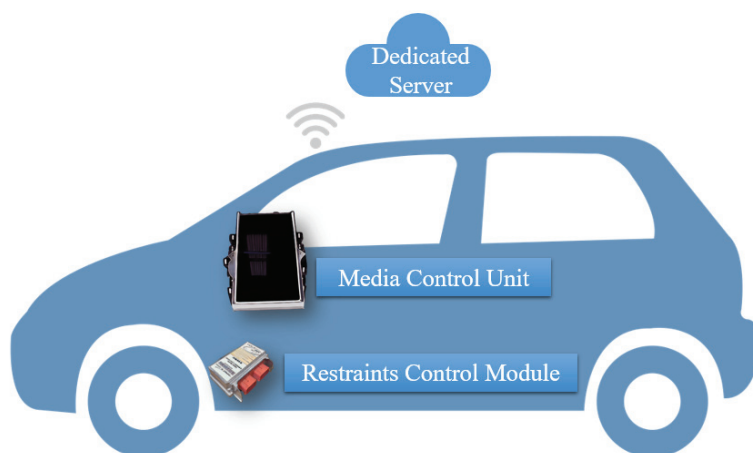


Figure 1. Data analyzable modules in a centralized E/E architecture.

2. Materials and Methods

Tesla vehicles (designed with a centralized E/E architecture), like mobile phones, receive periodic software updates for introducing new features or changing the structure of logs [20]. Therefore, the structure of the acquired data changes depending on the model and year of release as well as the last software update. Figure 2 illustrates various log data recorded in Tesla vehicles. The green boxes represent data that can be obtained from the manufacturer, while the orange boxes indicate data analyzed using the methodology proposed in this study. This section describes the features of each set of data to be analyzed and the process of data acquisition.

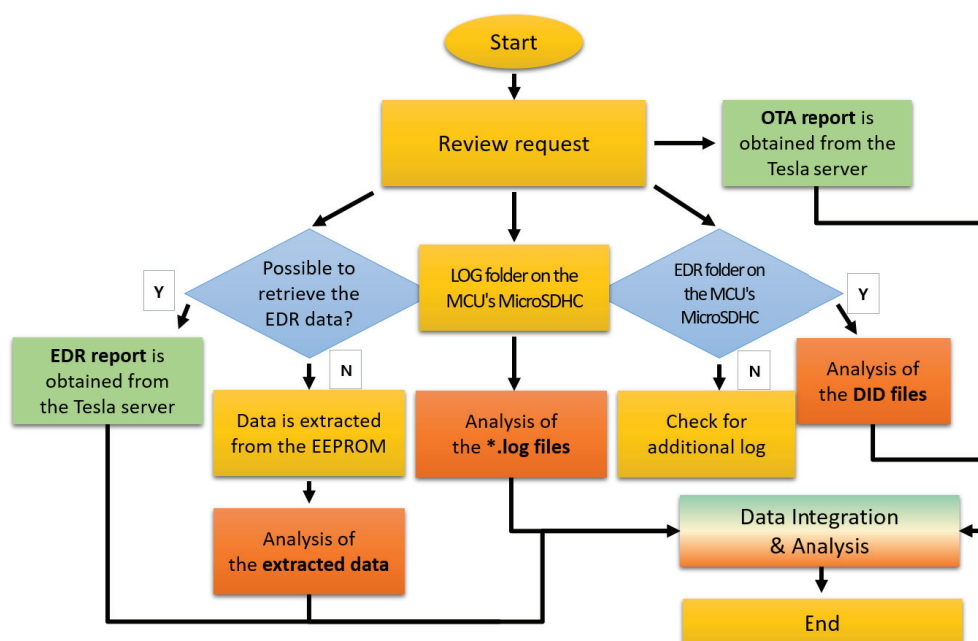


Figure 2. Workflow for Tesla vehicle analysis.

2.1. Restraints Control Module

As EDR may be mandated in each country; upon detecting a collision, the vehicle is required to store information from up to 5 s before the collision event. To extract data from the restraints control module (RCM) that comprises recorded EDRs, we used Tesla's

dedicated extraction cable and software. Two extraction methods are suggested by the manufacturer [21]. First, if the vehicle has normal power, then the data cable is connected to the RCM module in the vehicle, and the data are extracted. Second, if the vehicle does not receive power normally, the RCM module is detached from the vehicle, and the 12 V power and data cable are connected to extract the data. Next, the data are uploaded to Tesla's server and analyzed in the form of a PDF report [21]. However, this method of analysis is problematic for digital forensic researchers. First, if the RCM is damaged due to various reasons, such as fire, flooding, or a major collision, extracting normal EDR data becomes challenging. Second, the reliability of the extracted data cannot be guaranteed because the data analysis is dependent on a dedicated server.

2.1.1. Extracting Data from a Corrupt RCM

In the case of electric vehicles with RCM modules, a high probability exists that a fire will occur in a large collision [22], and the fire as well as fire extinguishing will damage the RCM, as depicted in Figure 3. Therefore, digital forensic techniques are necessary to extract data from the RCM's memory. The RCM memory used by Tesla, manufactured by Bosch, is electrically erasable programmable read-only memory (EEPROM). EEPROM is a nonvolatile memory device that retains data for long periods, even in the absence of electricity, rendering it an ideal memory method for EDRs. If the RCM's printed circuit board (PCB) is damaged because of a fire, Tesla's RCM extraction tool cannot acquire data. From a digital forensics perspective, two options are available: repair the damaged board or connect directly to the memory area. In the case of the automotive RCM, we connect directly to the memory rather than repairing the damaged board because of the wide range of damage and complexity of the board configuration. The EEPROM used by RCM incorporates a 64 Kbit serial SPI bus [23]. We extract the data after connecting to memory according to the interface-specific functions such as power, ground, clock, data I/O, etc., as depicted in Figure 4.

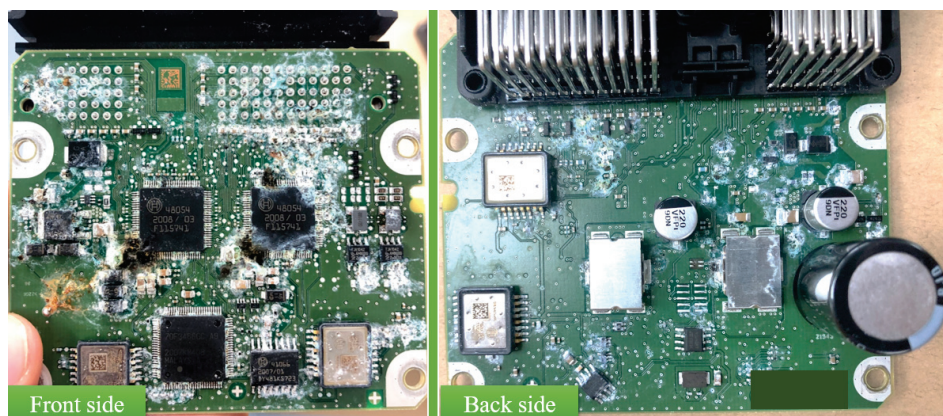


Figure 3. RCM modules damaged during a vehicle fire and its extinguishing.

The extracted data were 64 Kbit, and the extension was changed to *.edr; then, the data were uploaded to the dedicated server. However, we could not receive the analyzed report from the dedicated server. It is assumed that the data extracted through the EDR-only extraction tool and the data extracted directly from memory are different in structure, which is the reason why analytics reports are not generated on the server. We analyzed the extracted 64 Kbit data in binary form and determined that the binary data were recorded in Little-Endian form in 6-byte units, which could be reversed to determine the vehicle identification number (VIN) of the vehicle, as depicted in Figure 5.

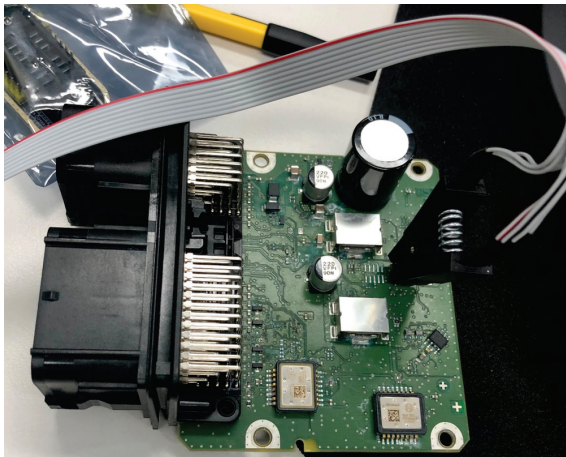


Figure 4. Direct connection to the EEPROM of the corrupted RCM module to extract data.

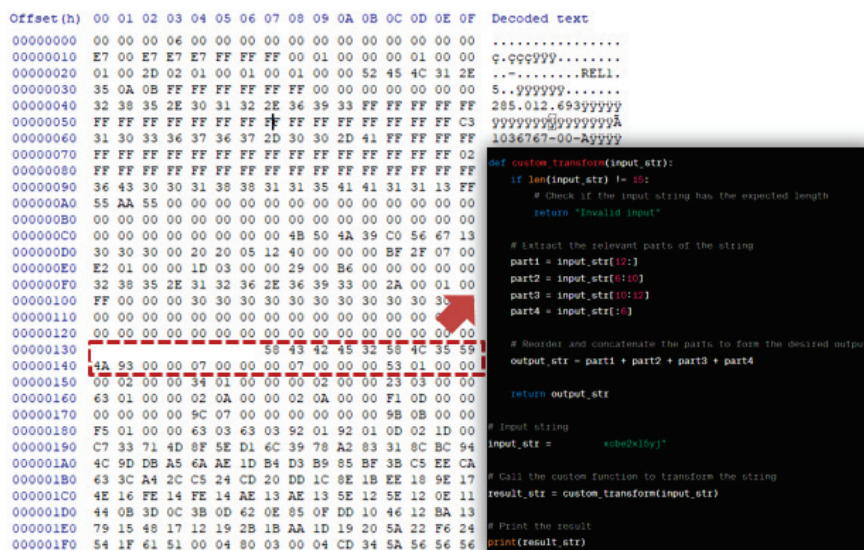


Figure 5. Partial binary data extract from the EEPROM.

2.1.2. EDR Data Validation

As described in Section 2.1, to extract EDR data from the RCM it must first be ensured that the vehicle is powered and functioning appropriately. Next, the RCM must be connected using the PCAN-USB cable and the Tesla retrieval cable; further, the Tesla EDR program must be executed on a Windows PC with the PCAN-USB driver installed. The Tesla EDR program checks for connectivity and subsequently acquires EDR data by clicking the “Run EDR Retrieval button”. At this time, the acquired data are created as an *.edr file. Finally, the *.edr file is uploaded to the Tesla Analytics Server to download the analysis report [24]. A sample of EDR reports obtained from these Tesla vehicles is published on the “EDR kit for Tesla vehicles” web page [24], and the final page of the Tesla report discloses hexadecimal data. This disclosure of data adds credibility to the analyzed results and increases the driver trustworthiness from a manufacturer’s standpoint. To analyze EDR data from the acquired data, we analyzed the publicly available Tesla reports using reverse engineering techniques [25,26] and matched the EDR data. For validation, we compared the results with the reports analyzed by the Tesla dedicated extraction tool and system. Section 3 details the values of each module for the matched cases.

2.2. Media Control Unit

The media control unit (MCU), the primary system of a Tesla vehicle, performs various functions, such as connecting to external networks (using 4/5G Simcard), driver settings,

infotainment, dashcam, and navigation [27]. Furthermore, MCUs function as integrated controllers in a centralized E/E architecture, and many different types exist depending on the model and year of the vehicle. These MCUs differ not only in hardware but also in software. However, they perform the same task: recording various log data. The MCU has two types of storage media: the primary embedded multi-media card (eMMC), which is attached to the PCB, and MicroSDHC, which is an external storage media. In the eMMC, the memory is logically partitioned into system areas and major functions using a Debian-based Linux system as the operating system. In this study, eMMC memory is not covered, and data recorded on a MicroSDHC mounted on the MCU were acquired and analyzed.

Figure 6 details the folder structure of a microSDHC card installed in two Model X vehicles, with some folders having the same structure (DTC folder: vehicle diagnostics, LOG folder: vehicle log data) and others with a different structure (RCM folder: EDR data, chg-wvfm folder: charging records). The DTC folder contains the manufacturer's vehicle diagnostic codes serially recorded with time information, and the chg-wvfm folder contains logs related to battery charging. Thus, this is not discussed in depth.



Figure 6. MicroSDHC folder structure inserted in the MCU (left: ModelX-2020, right: ModelS-2017).

2.2.1. Analyze EDR Folders

An RCM folder is recorded under the EDR folder on the MicroSDHC, and its sub-folders are assigned folder names with an 8-digit number and alphabet combination. An analysis of the folder name reveals that the folder name is 4-byte POSIX time information, recorded as the collision time the EDR data were recorded. This folder contains one *.log file and several *.bin files, and the *.log file records when the *.bin information is created. Most *.bin files are less than 20 bytes of data and contain information about what is assumed to be the serial number of each sensor. The bin files with 4-digit filenames, such as the hex data described in Section 2.1.2, have 4 Kb of data. We compared the files in this folder to the hex values in the EDR report extracted from the physical RCM and determined that they were the same. Thus, the data recorded in the physical RCM were also recorded in the MCU, and the data could be analyzed similarly to that analyzed in Section 2.1.2.

2.2.2. Various Bin Files Extracted from the EDR Folder

In the EDR folder, a number of BIN files are written with a 4-byte hex value, as presented in Section 2.2.1. The hex values of each bin file are presented in Table 1 and vary depending on the model and software version of the vehicle. The names of the bin files are written in a form similar to that of the protocol values defined in ISO 14229-1 (Road Vehicle-Unified Diagnostic Services (UDS)) [28], which is a communication protocol between automotive ECUs for diagnostics, firmware updates, tests, logs, etc. The UDS is used as a protocol at the application layer, the highest level of the Open Systems Interconnection (OSI) seven-layer model [29]. The request data parameter of UDS has a data identifier (DID), defined as presented in Table 2, which matches the name of the extracted bin file. Therefore, the bin files written to the EDR folder are assumed to be the DID of each UDS request parameter value. For example, 0xF190 indicates vehicle identification number (VIN) information, which is the unique number of a vehicle, and the extracted "F190.bin" file contains the VIN information as a hex value.

Table 1. BIN file names recorded in the EDR folder.

Vehicle Type	File Name								
ModelX-2020	f014 fd64	f015 fd65	f190 fd66	fd00 fd67	fd52 fd68	fd60 fd69	fd61 5817	fd62 5818	fd63 -
ModelS-2017	- -	- -	- -	- -	- -	- -	- -	- -	- -
Model3-2018 *	f014 fd66	f015 fd67	f190 fd68	fd60 fd69	fd61 5817	fd62 5818	fd63 -	fd64 -	fd65 -
ModelY-2020 *	f014 fe0c	f015 fe0d	f190 fe0e	fe01 fe0f	fe02 5817	fe04 5818	fe05 -	fe06 -	fe07 -

* Reference of the Tesla EDR reports [24].

Table 2. List of parts of data identifiers (DIDs) of ISO 14229 standard [28].

UDS DID Data Identifier	DID Name	DID Description
0x0100 ¹ -0xA5FF ¹	Vehicle Manufacturer Specific	This range of values shall be used to reference vehicle manufacturer specific record data
0xF010 ¹ -0xF0FF ¹	Vehicle Manufacturer Specific	This range of values shall be used to reference vehicle manufacturer specific record data
0xF190 ¹	VIN Data Identifier	This value shall be used to reference the VIN number
0xFD00 ¹ -0xFEFF ¹	System Supplier Specific	This range of values shall be used to reference the record data identifiers and input/output identifiers within the server

¹ Hexadecimal Value.

2.2.3. Analyze LOG Folders

The “LOG” folder on the MicroSDHC contains a single *.txt file and multiple 300 Mb or smaller *.log files. The *.txt file records the maximum size of a single log file (300 Mb) and the maximum number of log files (5), along with the offset and filename of the most recently recorded log. To analyze the data in the LOG folder of the MicroSDHC, we used “TeslaLogs” developed by NFI [30]. “TeslaLogs” incorporates reverse engineering techniques to analyze log data from Tesla vehicles (Model X, Y, and 3). The directory changes depending on the year of the vehicle, and the analysis capabilities vary depending on the autopilot (AP) version. However, the paper published by NFI did not identify any inconsistencies between the data provided by Tesla and the log data [31]. Furthermore, a comparison of the recorded logs in the LOG folder and the EDR folder reveals that the data recorded in the EDR folder for the same period and entry are high-resolution logs (HRL), whereas the log files in the LOG folder contain HRL and low-resolution logs (LRL) at various periods. Therefore, the MicroSDHC, where the LOG folder is stored, can store considerable data by sampling the data input to the MCU. MicroSDHC also optionally stores HRLs in case the vehicle is involved in a collision or as determined by the AP system [32].

2.3. OTA-TESLA Server

The manuals that Tesla provides to drivers contain information about various connectivity features. For example, a Bluetooth module connects with the driver’s cell phone, and a Wi-Fi module updates software or maps [27]. Furthermore, the MCUs have a national carrier’s SIM card inserted for operating 4/5G networks. This connection enables the periodic transmission of log data recorded in the vehicle to a dedicated server, as well as nonperiodic transmission of HRL data when the AP function is activated or an event such as an external impact occurs. To obtain data transmitted to Tesla’s servers, law enforcement agencies must submit a request to the manufacturer following proper legal procedures. Data acquired through this process is characterized by its limited time frame and parameters. In this study, we requested the OTA report corresponding to the time of the incident. Furthermore, if the vehicle is involved in an accident, the manufacturer can provide a time-of-accident report on a limited scale to law enforcement, in accordance with manufacturer policy [21].

The information provided is detailed with the signal name, signal description, unit, and values. From a digital forensics perspective, the data provided by the manufacturer can be cross-checked with the data inside the vehicle for reliable accident/incident analysis.

3. Implementation of the Forensic Process on a Vehicle

We analyzed two Model X vehicles from a digital forensics perspective. The first accident involved a Model X colliding at high speed with a wall in an underground parking lot and catching fire. The key issue in this case was that the driver was the designated driver at the time and claimed to have pressed the brake pedal, but the vehicle experienced an unintentional rapid acceleration. The first Model X vehicle could not receive EDR reports because the RCM was damaged, and we compared the RCM folder and LOG folder of the MicroSDHC mounted on the MCU with the OTA reports provided by the manufacturer. The second accident also involved a Model X vehicle that collided with a wall at high speed on a downhill slope in a parking lot. However, unlike the first case, no fire occurred. The driver claimed that the vehicle experienced sudden unintended acceleration. The second Model X was a normal RCM, and fortunately, we could verify the EDR report. However, the RCM folder in MicroSDHC did not exist, and we could only compare the LOG folder and OTA report from the manufacturer. Furthermore, the comparison focused on items in the log data that were recorded periodically as values, rather than items where data are recorded aperiodically; both sets of items are detailed in Table 3.

Table 3. Types of logs recorded by SDV-enabled vehicles.

Periodically Log	Aperiodically Log
Vehicle Speed	AEB State
Accelerator Pedal Pressure	Cruise State ¹
Steering Wheel Angle	Front Crash
Torque Motor	Auto Pilot State
Longitudinal/Lateral Acceleration	Auto Park Ready
Longitudinal/Lateral Delta-V data	Gear Poison

¹ This value determines how often logs are written.

3.1. Damaged Model X Log Data from a Digital Forensics Perspective-I

The Model X vehicle analyzed in this study was involved in a fire accident that damaged the PCB inside the RCM, rendering it difficult to obtain normal EDR reports. The MCU module was severely damaged and would not power up normally. The MCU contained an 8 Gb MicroSDHC, and the “RCM” folder and “LOG folder” were checked in the memory. We analyzed the extension bin file written in the RCM folder and the last recorded log file written in the offsets.txt file in the LOG folder. We conducted an evaluation of the analyzed data against the OTA report obtained from the Tesla server. The MCU’s MicroSDHC memory in the vehicle, with its two folders, and the processed OTA report from Tesla’s server demonstrate the characteristics of a software-defined vehicle (SDV). First, log records from the same timeframe are recorded both internally within the vehicle and externally on the server. Second, while the two folders on the MicroSDHC memory store data from different ECUs, they are physically stored on a single memory unit.

3.1.1. Comparison of LOG Folder and OTA Report

Figure 7 presents a comparison of the analyzed values from the MCU’s LOG folder with the OTA report’s vehicle speed and accelerator pedal press for the same period and entry. Figure 7 details data from approximately 10 min before the accident, and the data analyzed from the LOG folder in the front and the OTA report in the back were almost equal. However, although the data were logged periodically, there were periods with no values logged. This is assumed to be caused by millisecond packet delays when sending data from the sensors of each ECU to the central E/E architecture, the MCU through the CAN network, or by the calculation process of the MCU. This is why multiple values of

the same item are stored simultaneously. In this case, just before the collision the driver pressed the accelerator pedal hard, and the speed increased rapidly just before the collision. Analysis reveals that the vehicle maintained a high speed despite minimal accelerator input between 500 and 600 s prior to the collision. This observation may be attributed to external factors, such as downhill road conditions. Generally, a proportional relationship between accelerator pressure and vehicle speed is observed.

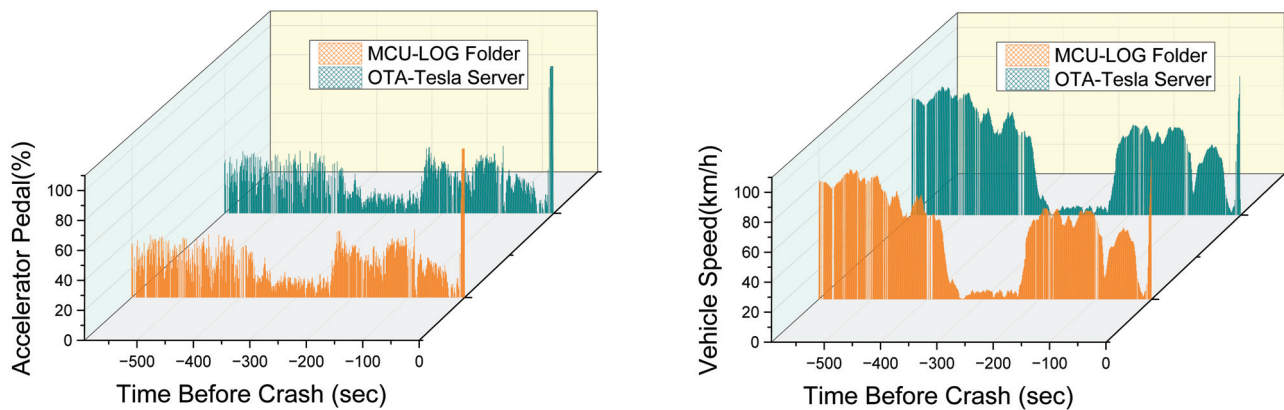


Figure 7. Compare LOG folder and OTA report (**left:** Accelerator Pedal Position, **right:** Vehicle Speed).

3.1.2. Comparison of RCM Folder, LOG Folder, and OTA Report

The graph on the left in Figure 8 presents a comparison of the steering wheel angle in the LOG folder and the OTA report for the same period. As depicted in Figure 7, the same values are shown for most of the time. The figure on the left shows the steering wheel angle for the 10 min before the collision. The right side of the steering wheel is represented by positive values and the left side by negative values. The large change in values from 100 s before the collision is likely due to the increased steering angle as the car enters the parking lot. The right graph in Figure 8 depicts three types of steering wheel data: RCM folder data, LOG folder data, and OTA report. The data from the RCM folder at the back detailed the most HRL, whereas the LOG folder and OTA reports were represented by LRL. However, all three data types depicted the same trend: the driver steered approximately 20° to the left and right just before the collision. In this case study, the RCM module was found to be damaged, and no manufacturer's report was available. However, comparison with data from the RCM folder in the memory mounted on the MCU suggests that the data in the RCM device and the RCM folder are identical. Additionally, it was observed that the RCM folder data contains fewer stored items but offers higher resolution in recorded values. Conversely, data in the LOG folder and OTA report contains a greater number of stored items, albeit at a lower resolution.

In addition to the three data types presented in the research report, the pre-collision data analyzed from Model X includes dozens of additional parameters stored at both periodically and aperiodically. From a digital forensics perspective, interpreting data from various modules using multiple methods, as in this case, enhances reliability. This approach enables more accurate accident investigations through an evaluation against traditional methods that rely solely on manufacturer reports.

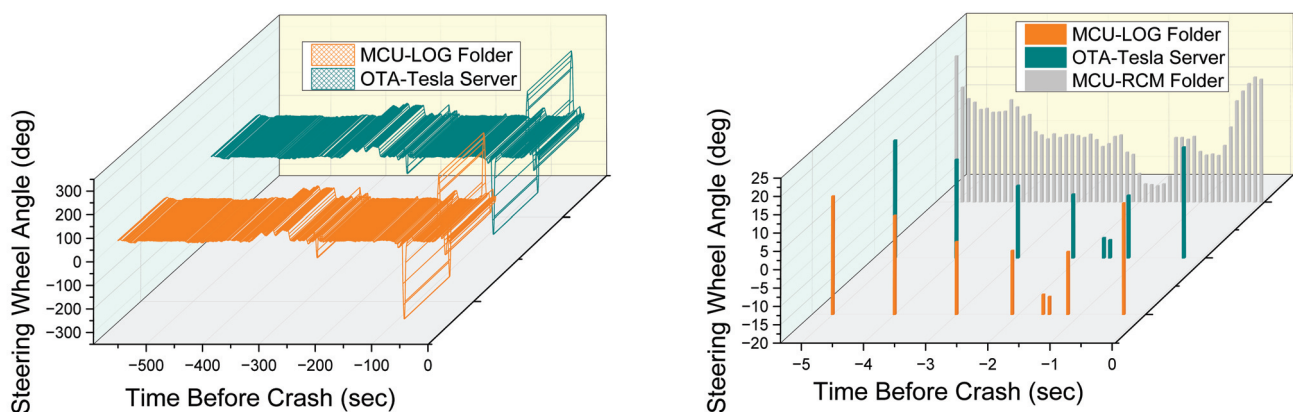


Figure 8. Compare steering wheel angle (**left:** LOG folder—OTA report, **right:** RCM folder—LOG folder—OTA report).

3.2. Damaged Model X Log Data from a Digital Forensics Perspective-II

The vehicle analyzed in this section was produced in 2022, two years after the vehicle discussed in Section 3.1, and because the EDR was not damaged we could generate an EDR report. However, the RCM folder on the MicroSDHC mounted on the MCU did not exist. The MicroSDHC mounted in the MCU did not have an RCM folder; instead, it comprised a CHG-WVFM folder in which the charging history could be viewed, as depicted on the right in Figure 6. Therefore, this section presents a comparison of three types of data: the log folder on the MicroSDHC, the OTA report, and the EDR report. A key characteristic of the software-defined vehicle (SDV) observed in this vehicle is that the configuration of stored data can vary depending on the software version. SDVs frequently receive software updates via OTA, which can introduce new features or, as in this case, alter the method of log recording.

3.2.1. Comparison of the LOG Folder and OTA Report

Figure 9 depicts a graph comparing the LOG folder and the OTA report for two items (vehicle speed, accelerator pedal), matching the data in the LOG folder to the OTA report approximately 3 min before the accident. The OTA report provided by the manufacturer details more period data than the EDR data, but less period data than the data recorded in the LOG folder. Additionally, the data displays information from different time periods depending on the activation of autopilot and engine start times specific to each incident. This, similar to the vehicle analyzed in the previous Section 3.1, indicates an apparent proportional relationship between accelerator pedal pressure and vehicle speed. Notably, however, in the 60 to 100 s prior to the collision, vehicle speed consistently increases despite minimal pedal pressure, which may be attributed to road characteristics such as a downhill slope.

The steering wheel angle and longitudinal acceleration values in Figure 10 depict positive values on the right and negative values on the left. The two values are consistent with most data, with the accelerator pedal in Figure 9 being pressed just before the collision to increase speed, which increases the longitudinal acceleration value.

3.2.2. Comparison of the OTA Report and EDR Report

The comparisons between data received from OTA reports and data obtained from the vehicle's EDR are shown. Most data recorded by the EDR are those recorded 5 s before the accident, but some items have values recorded from 300 s before the accident, such as longitudinal acceleration values, as depicted in Figure 11. Additionally, the resolution of values recorded in the OTA report varies depending on the vehicle's autopilot status, with only two values for longitudinal acceleration recorded in the five minutes leading up to the collision. The values demonstrate similar trends for the steering wheel, accelerator pedal, and vehicle speed, as presented in Figure 12.

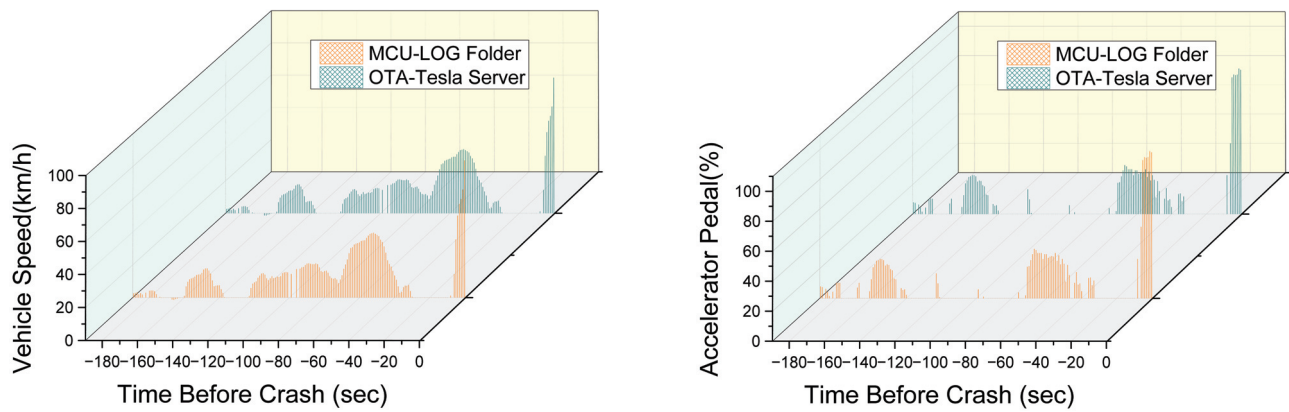


Figure 9. Comparison of the LOG folder and OTA report (Vehicle Speed, Accelerator Pedal Position).

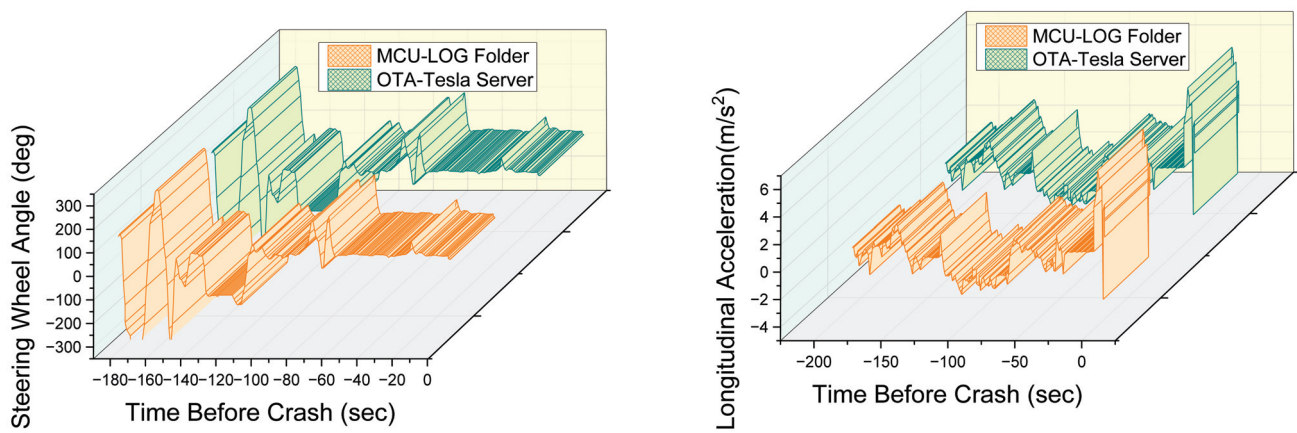


Figure 10. Comparison of the LOG folder and OTA report (Steering Wheel Angle, Longitudinal Acceleration).

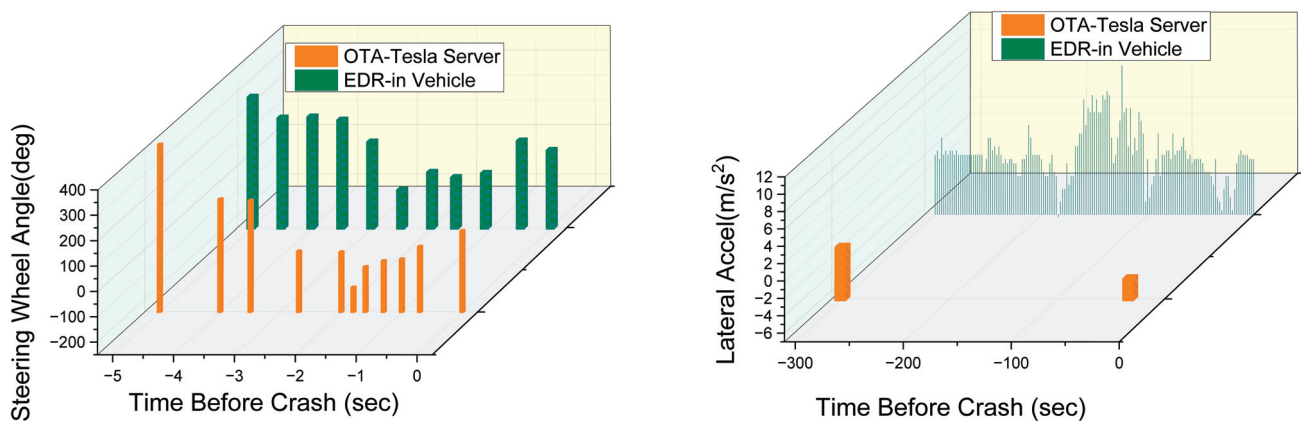


Figure 11. Comparison of OTA reports with in-vehicle EDR data-1.

Figure 12 below compares pedal pressed values and vehicle speed data from the OTA report and EDR data. Notably, OTA report data is recorded aperiodically, whereas EDR data is logged periodically. This discrepancy arises because the OTA report data is first collected from various sensors within the vehicle, then converted to text by the MCU, and subsequently packetized for transmission. During this process, values from each sensor are sampled before storage, which likely results in non-continuous data logging. In contrast, EDR data appears to be recorded periodically, as it is gathered through the vehicle's CAN network, where sensor values are received and stored at regular intervals.

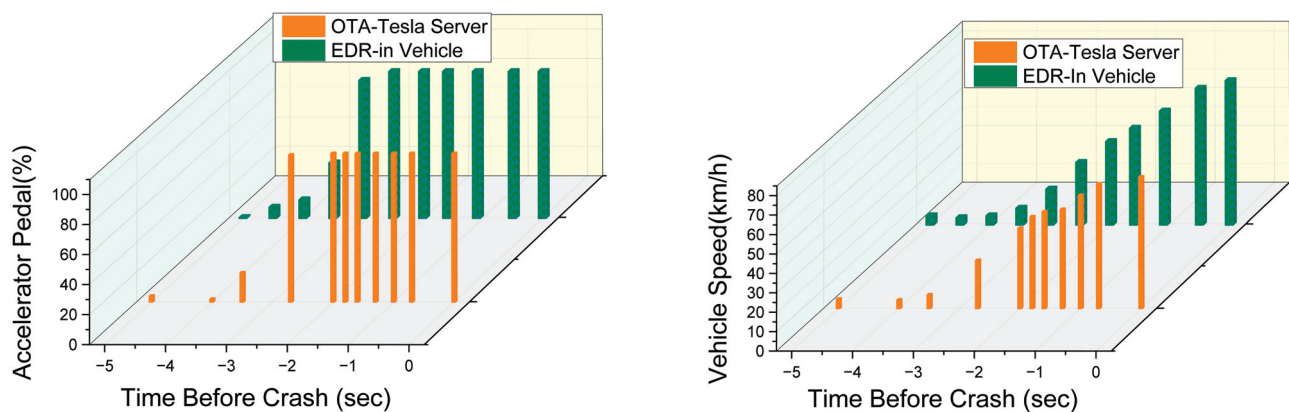


Figure 12. Comparison of OTA reports with in-vehicle EDR data-2.

3.3. Discussion

The data analyzed by all three methods demonstrate several characteristics. The bin files recorded in the RCM folder store data from 5 s before the incident for a limited number of items. The data in the LOG folder and the data in the OTA report have mostly the same values for the same items at the same time. Even items that are logged periodically in the LOG folder and OTA reports are not recorded every second, and time lag exists. The data recorded in the RCM folder has a higher resolution than the LOG folder and OTA reports. There are a higher number of parameters analyzed in the data recorded in the LOG folder than in the OTA report, and saved parameters vary depending on the CAN communication network that is grouped. Finally, the data stored vary depending on the software version, and similar to mobile phones, software updates occur frequently. In this study, only four parameters of data are described, but dozens of parameters of data are stored in the pre-crash analysis data of Model X, both periodically and aperiodically. In terms of digital forensics, reliability can be increased by interpreting data in various ways in various modules, as in this case. This also allows for more accurate accident investigation than relying solely on manufacturer reports. Finally, various data recorded in the vehicle include personal information, and the collection and analysis of such information require lawful legal procedures. We obtained the data through lawful procedures with the consent of the owner. Furthermore, personal information, such as the vehicle identification number (VIN), was anonymized to ensure that the data could not be used to identify individuals before its disclosure. The OTA reports described in the data can also be requested only by the vehicle owner or legally authorized entities under restricted conditions. Careful and cautious handling of such information is essential.

4. Conclusions

In this study, various log files recorded in Tesla vehicles were identified, acquired, analyzed, and validated from a digital forensics perspective. From a digital forensics perspective, accessing the data in the vehicle is difficult, and limited data are stored. However, in the case of recent vehicles designed as SDVs, log data must be stored in one place because of the central E/E architecture, and this study confirmed that the MCU of Tesla vehicles demonstrates this capability. Through this process, a more accurate investigation of accidents and incidents is anticipated by cross-referencing traditional event data from EDR with OTA and central controller logs. Furthermore, although not addressed in the current study, future research is planned to include additional analysis of the MCU main embedded memory and the autopilot system.

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Article

Toward User-Centered, Trustworthy, and Grid-Supportive E-Mobility Ecosystems: Comparing the BANULA Architecture Against Existing Concepts

Lukas Smirek ^{1,*}, Jens Griesing ², Tobias Höpfer ³ and Daniel Stetter ³

¹ Institute of Human Factors and Technology Management (IAT), University of Stuttgart, Allmandring 35, 70569 Stuttgart, Germany

² OLI Systems, Silberburgstraße 112, 70176 Stuttgart, Germany; jens.griesing@my-oli.com

³ Fraunhofer-Institute for Industrial Engineering (IAO), Nobelstrasse 12, 70569 Stuttgart, Germany; tobias.hoepfer@iao.fraunhofer.de (T.H.); daniel.stetter@iao.fraunhofer.de (D.S.)

* Correspondence: lukas.smirek@iat.uni-stuttgart.de

Abstract: Advances in electric vehicles and charging infrastructure technology have given the electrification of road traffic a positive momentum. Nowadays, it is becoming more and more evident that the related energy and financial processes of the current e-mobility ecosystem are reaching their limits. This leads to usability losses for end users as well as administrative and non-causation-based financial burdens on various energy system participants. In this article, use cases are inferred from the literature, the aforementioned challenges are discussed in more detail, and strategies for addressing them are presented. Furthermore, the information system architecture of the BANULA project, with its core elements of open communication standards, virtual balancing areas, and blockchain components, is explained. BANULA addresses the aforementioned challenges by holistically considering the needs of all participants. A special focus of the project is implementing and investigating the concept of virtual balancing areas. This concept has been available since 2020 but has not been implemented in the market yet. To the best of the authors' knowledge, BANULA is the first project that utilizes current legislation to transfer charging infrastructure to virtual balancing areas in conjunction with distributed ledger technology to support related processes. In the first step, the BANULA implementation prototype targets the German e-mobility ecosystem, but applicability to other states in the European Union is planned. Using an independent framework, the BANULA architecture and its prototypical implementation are evaluated. The authors show that the unique combination of virtual balancing areas and the related processes, enhanced through distributed ledger technology, has the potential to contribute to a user-centered, trustworthy, and grid-supportive e-mobility ecosystem.

Keywords: charging; infrastructure; mass market; data acquisition; virtual balancing area

1. Introduction

Innovations in the field of battery and charging technology have led to increased acceptance and a continuously growing number of electric vehicles (EVs) in road traffic. The cost of lithium-ion batteries has decreased from USD 649 per kWh in 2013 to USD 152 per kWh in 2023 [1]. The global fleet of EVs has increased from 7.2 million in 2019 [2] to nearly 42 million in 2024 [3]. On the one hand, this presents a great opportunity to reduce greenhouse gas emissions. On the other hand, the increasing number of EVs poses challenges to current electric grids on technical, organizational, and process levels. Charging

EVs involves EV drivers and participants from the e-mobility, energy, and financial sectors. Many of today's challenges arise from the present role model and the related distribution of energy-economic responsibilities among the involved roles.

In the context of this article, the roles of the charge point operator (CPO), electric mobility service provider (EMSP), and roaming platform are the most important roles in the e-mobility sector.

CPOs are responsible for building, operating, and maintaining charging points (CPs) that are used by EV drivers to charge their EVs. In order to gain access to a CP, EV drivers require a charging contract with an EMSP. EMSPs offer charging contracts to end users, provide charging cards/apps, and invoice charging sessions.

Frequently, companies take the role of CPO and EMSP at the same time to provide charging services at their CPs to EV drivers. However, if EMSPs want to offer electric power through the charging infrastructure of other CPOs, bilateral contracts or contractual relationships via intermediary roaming platforms are mandatory to provide access to the CP for EV drivers.

From an electric grid perspective, the relevant roles include the distribution grid operator and the electricity supplier. Electricity suppliers sell energy to consumers like companies, households, or CPOs. Electricity suppliers have to project the electricity consumption of their customers for every 15-min interval throughout the day and are financially responsible for the balancing energy required to close the gap between the projections and the real measured energy consumption. Therefore, larger consumers like manufacturing plants have meters that measure the energy consumption for every 15-min interval throughout the day. For a long time, such meter infrastructure was too expensive for smaller consumers. Hence, simple meters have been and are still used to measure consumed energy. Usually, these meters are read only once a year for billing purposes. The shortcoming of this method is that it is not possible to project the energy consumption of an individual consumer, and, consequently, projection deviations cannot be allocated to each 15-min interval.

Distribution grid operators (DSOs) operate electric grids on high, medium, and low voltage levels and connect consumers, like production plants, households, and CPs, to the electric grid. Operating a grid also involves forecasting the energy consumption of all consumers who do not have a 15-min meter infrastructure and taking on the burden of being financially responsible for deviation compensation (balancing energy), regardless of the electricity supplier they use.

The related processes are explained in more detail in Section 4.1. For now, it is important to know that electricity suppliers are only financially responsible for the required balancing power if their consumers have a 15-min sharp-meter infrastructure. If this is not the case, the costs and risks are shifted to the DSO.

In theory, the e-mobility ecosystem, with its roles of CPOs, EMSPs, and roaming platforms, has found appropriate solutions to provide EV drivers with wide access to CPs. Also, the electricity ecosystem has worked quite well for a long time. However, both systems have shortcomings, each on its own, and even more so when considering them together. Figure 1 is showing how the different roles from the e-mobility and electricity sector are currently related to each other and how they work together for EV charging. The shortcomings of this approach are illustrated by the following use cases (UCs).

Even though there are roaming platforms available, in today's e-mobility ecosystem, many EV drivers are forced to or feel the need to have charging contracts with multiple EMSPs [4]. This is because EMSPs do not have contracts with all CPOs to access the charging infrastructure. Consequently, EMSPs' charging services may not be available at every CP. This leads to a fragmented and inconvenient user experience, as described in [4].

The inconvenience is so great that there is a willingness among users to pay for unified access to the charging infrastructure (UC: unified access) [4].

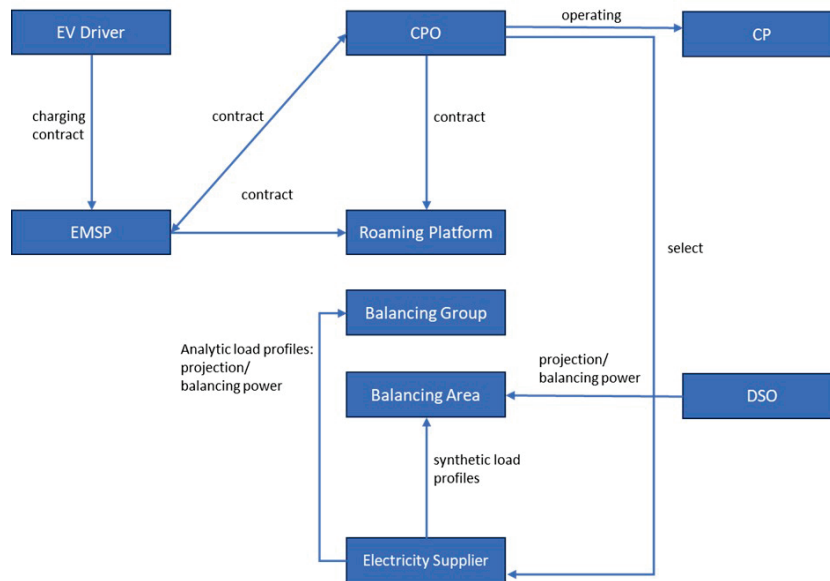


Figure 1. Parties in the e-mobility and electricity sectors that are involved in EV charging.

From a power grid perspective, in Germany, CPOs are responsible for the electricity supply at their CPs. Charging electricity is allocated on a balance to the CPO and its electricity supplier [5]. This means that drivers who have charging contracts with EMSPs can only charge their EVs using the electricity provided by their EMSP if the EMSP is also the CPO of the CP. In roaming operations, where the EMSP and CPO are different entities, the CPO procures the electricity and resells it to the EMSP with a markup that has to be paid by the end customer. In other words, roaming EMSPs bill their customers for the electricity that EMSPs buy from the CPOs providing the CP. In this case, EMSPs cannot make statements or advertise the origin of the billed electricity (e.g., green electricity, cooperative procurement, etc.). Hence, from an energy economics perspective, there must be a relationship between charging energy and its provider, the EMSP. In essence, the charged electricity needs to be allocated to the EMSP (UC: electricity allocation).

Due to the growing number of EVs, the need for balancing energy, i.e., the difference between predicted and actual charging energy, has significantly increased in recent years, as discussed by Enzenhöfer [6]. Figure 2 shows the increasing amount of required delta energy in one of Germany's control areas. Currently, CPOs are responsible for procuring electricity and predicting the charging loads, while EMSPs, respective of their customers, use the charging energy. This creates a responsibility gap between the party projecting and procuring the electricity (CPO) and the party consuming the electricity and causing the deviation between projected and real electricity usage (EMSP). Consequently, the costs of forecast deviations are borne by the CPO. Moreover, since most CPs do not have a 15-min sharp meter, the costs have to be borne by the CPO's distribution system operator (DSO), rather than the party using the electricity that is causing the deviation, the latter being the EMSP. From the authors' perspective, the responsibility for projecting, procuring, and billing electricity should be consolidated into one entity, with all rights and obligations (UC: responsibility).

Studies like [7] have highlighted that clearing houses and roaming platforms have strong market power that can be abused. The German Federal Cartel Office also concluded in [8,9] that CPOs frequently act as regional monopolists. Hence, another use case is fair competition among all parties involved (UC: competition).

Due to the growing number of decentralized components, like EVs, battery storage, and renewable energy sources, congestion management has become increasingly important in today's electric grids [10]. As highlighted in [11], using EVs as flexible assets could become an important strategy to support congestion management. However, the current data fragmentation in electric grid-related applications [12], particularly in e-mobility and energy data structures, hampers coordination between transmission system operators (TSOs) and DSOs [13]. Overcoming data fragmentation between the electricity and e-mobility ecosystems is, therefore, essential (UC: data availability).

EVs have the potential to provide services to stabilize and support the grid, such as balancing power. In the future, these services will be provided by numerous small and anonymous entities, rather than TSOs' large power plants, as they are currently. Building trust with small and distributed flexibilities on a large scale is, therefore, necessary (UC: trust).

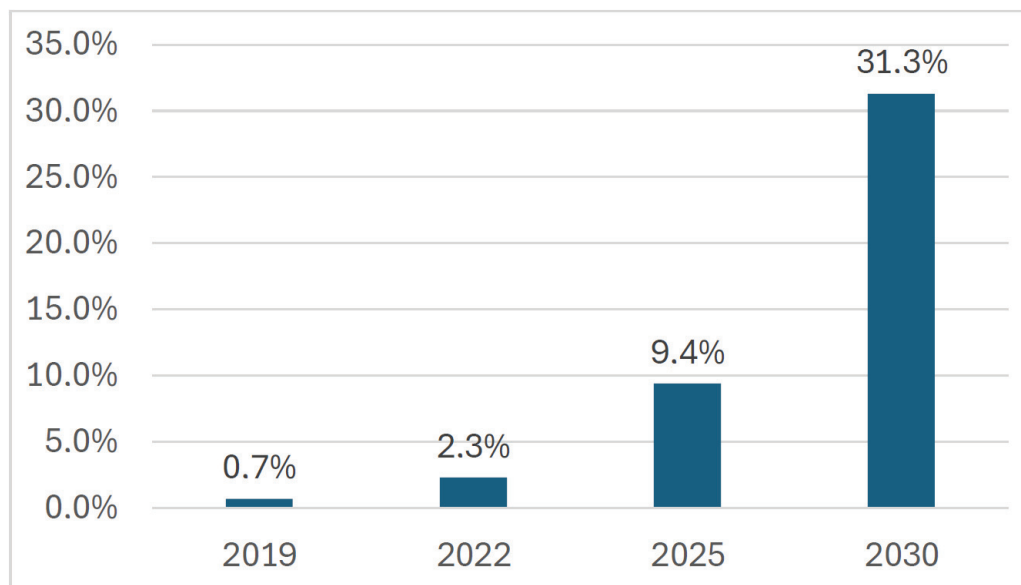


Figure 2. Ratio of model-based delta energy vs. the amount of delta energy in 2019 due to increased EV charging in the control area of the German TSO, Transnet BW, based on data from [6].

This paper is structured as follows. Section 1 provides a general insight into the role models in the e-mobility and electricity sectors. Also, six use cases are defined, which are used in Section 4 for validation. Section 2 gives some background knowledge on the BANULA project, its origin, its organization, and its scientific contributions. This section also shows how the concepts of the BANULA project have been addressed in other scientific contributions. In Section 4.1, we give a general introduction to electricity systems and their organization in balancing areas and balancing groups. Building on this information, we explain the approach of virtual balancing areas and highlight the organizational and technical concepts of the BANULA project. In Section 5, the BANULA architecture is evaluated using the framework defined by Hoess et al. [14].

2. Materials and Methods

In 2020, the German Federal Grid Agency (Bundesnetzagentur) published a concept [15] that seemed appropriate for addressing several problems related to the increasing number of EVs and the related rising loads and processing on the electric grid. The concept was further complemented by [16]. As shown in Section 3, this concept has not been adopted by the market. However, several future members of the BANULA project found that the approaches described in [15,16] were well suited to address the problems currently discussed by experts in the electricity and e-mobility sectors. Possible reasons for the non-implementation of the concept include network effects arising from the simultaneous participation of network operators, EMSPs, CPOs, and other participants in the electricity and e-mobility sectors.

Hence, a group of eight partners established a consortium and applied for funding to support the BANULA project. In the consortium, all market participants involved in EV charging are represented, including transmission grid operators, distribution grid operators, electricity suppliers, EMSPs, roaming platforms, and research institutions. The aim of the BANULA project is twofold. First, the ideas described in [15,16] should be implemented to evaluate the feasibility of the concept within the current legal and regulatory framework.

The second aim of the project is to develop a solution to address challenges that are currently pending in the electricity and e-mobility ecosystems. Therefore, the concepts described in [15,16] should be complemented by further technologies to find a holistic solution.

In regular expert workshops, BANULA project members discussed the problems and related requirements of current electricity and e-mobility ecosystems. In total, six shortcomings were identified, and all of them were confirmed by an extensive literature review.

Several contributions have been published by BANULA project members. A first article to indicate the necessity of addressing the growing amount of balancing power and how it should be managed by the BANULA concept was published by Enzenhöfer [6]. Other important scientific articles closely related to the project include [5,17,18]. These articles focus more on the different roles of the market participants in the BANULA ecosystem. In [18], the first consideration of market participants, along with their adversarial or supportive intentions toward the BANULA ecosystem, was discussed. The article also examined the circumstances under which blockchain (BC) technology might best fit the requirements for the large-scale implementation of the BANULA architecture.

This article extends the authors' work presented in [19] and focuses on the technological aspects of the BANULA implementation and its potential applications. The architecture and a discussion of how the requirements are satisfied by the architectural design can be found in Section 4.

3. Related Works

Albrecht et al. stated in 2018 that there are only very few markets with ready BC applications. The authors investigated the question of "How and by which factors is the implementation of blockchain technologies in energy sector use cases affected?" [20]. A very important aspect of the work by Albrecht et al. was the distinction between different BC technologies and the business areas to which they apply.

Considering the concept of virtual balancing areas (VBAs), two prototypes were developed to test the concept in Germany. In 2022, a prototype was developed within the Rebeam project [21,22]. A group of four companies developed a prototype to test VBA processes in Germany, which has been ongoing since 2023 [23]. Unlike the BANULA implementation, in [23] there was no BC used, which restricted the possibility of business cases. Refs. [21,23,24] remain in prototype status, and none of them have had a significant impact

on the German e-mobility ecosystem. Also, none of them were accompanied by scientific investigations or discussions, as is done with the presented BANULA architecture. Aside from these prototypes and the BANULA project, there are no known VBA-related projects.

The evaluation framework used in this paper is based on the work presented by Hoess et al. [14]. However, there are some major differences between their work and the presented BANULA architecture. While [14] remains theoretical, within the BANULA project, a concrete architecture has been developed that will be realized in a prototype during the project's runtime. Beyond this, an operational deployment of the BANULA system is planned after the completion of the research project.

Ferreira et al. [25] proposed and developed an EV prototype system enhanced with Self-Sovereign Identity (SSI) for identity management in a decentralized system, aiming to eliminate the need for charging cards and address interoperability. BC technologies are applied to support the identity management process of users charging their vehicles and to record energy transactions. With regard to the use of SSI, Ref. [25] seems to be more advanced than the BANULA implementation in its current state. However, Ref. [25] requires proprietary hardware for execution and focuses primarily on the relationships between EV owners, EMSPs, CPOs, and CPs. The BANULA approach goes beyond this and considers processes and roles in the broader electricity environment. Both systems utilize off-chain cloud-based storage for efficient BC transactions.

Fluhr and Lutz [26] developed a morphology for use-case types of EV integration into the power grid and instantiated two use-case types. They took a holistic approach and defined four requirements for an information system architecture. Al-Saif et al. [27] presented a literature review on BC applications in EV electricity trading. They defined seven challenges and six opportunities for the use of BC technology in energy trading. From our perspective, these requirements are directly related to blockchain technology and are too technical and narrow a focus for our purposes. Since the BANULA project aims to integrate its concepts, processes, and technologies into the real EV and energy markets, we used an evaluation framework with a broader focus, as proposed in [14].

Although the presented requirements and opportunities have a rather technical focus, Al-Saif et al. [27] pointed out that the implementation of BC technology in the energy sector can be influenced by various technological, social, and organizational challenges. Furthermore, they elaborated on the possibilities of smart contracts in EV applications.

In [28], principles for a 21st-century grid were discussed. According to Bronski et al., a modern grid should be decentralized, recursive, and exhibit private transparency. They emphasized that grids should not only be distributed but also decentralized at both the technical and organizational levels.

4. The BANULA Approach in the Context of the Current Electricity Ecosystem

The BANULA project [29] holistically addresses the problems illustrated in the use cases defined in Section 1. Instead of starting from scratch, the project builds on the existing German legislative and regulatory framework defined in [15,16]. The goal is to evaluate the practical feasibility and economic viability under the current framework conditions. On this basis, weaknesses can be identified, and improvements can be suggested.

4.1. The Current Electricity Ecosystem

To keep the physical grid in balance, monetize the related efforts, and enable trade, electric grids are organized into balancing areas and balancing groups. Physical grid sections are organized into balancing areas, with each balancing area having a metrological

separation from neighboring grid sections and one responsible DSO. Within a balancing area, only one load profile method (either synthetic or analytical) is used.

To supply electricity in a grid section, market participants like electricity suppliers or traders require a balancing group within the relevant balancing area. A balancing group is more or less an energy account or table that shows, for each 15-min interval throughout each day, which producers are supplying energy and which users are using it. Every party responsible for a balancing group is required to provide a 15-min projection of its customers' energy consumption and a schedule indicating from which producers the energy is coming one day in advance. The deviation between projected and actual measured consumption is known as the balancing energy. The party responsible for the balancing group is invoiced by the balancing group coordinator, usually the TSO. In the case of synthetic load profiles, the DSO is responsible for paying the balance of energy.

Figure 3 is showing the organisation of electricity grids with the concepts of balancing areas and balancing groups. Due to the harmonization of the European energy systems and markets, these ideas and concepts are more or less the same all over Europe.

In the context of e-mobility, CPs are always linked to the balancing group of the CPO's supplier. If synthetic load profiles are used, the burden of the balancing energy falls on the DSO rather than the CPO. The significant expansion of charging infrastructure and its inadequate representation in synthetic load profiles are placing an increasing burden on DSOs (UC: responsibility).

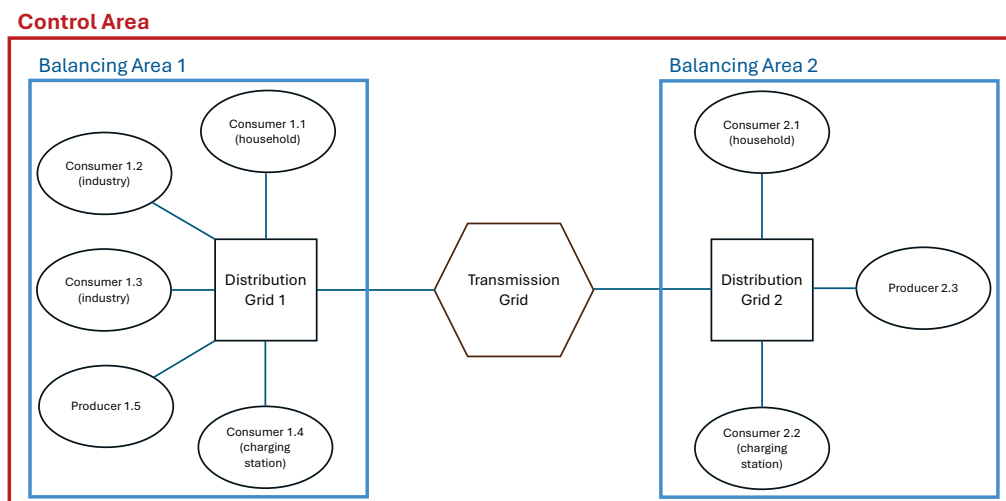


Figure 3. Organizational aspects of the current electricity ecosystem with its concepts of balancing groups and balancing areas. Charging stations are treated as regular consumers.

4.2. BANULA in Terms of the Energy Sector

The BANULA concept [29] is based on the current regulations of the Federal Network Agency BK6-20-160, Annex 6, regarding [15] (English: “network access rules for enabling an accurate energy quantity allocation for electromobility”) and the related model specified in the associated BDEW application guide [16]. Referring to this legal and regulatory framework, the introductory use cases in BANULA are addressed by three key elements:

- Grouping all charging stations into VBAs;
- Adapting the role and process model to the e-mobility ecosystem;
- Providing a platform for secure and real-time data exchange between market participants.

In a VBA, CPs within a control area are organized and balanced in a separate grid area with a dedicated grid operator. A suitable measurement infrastructure separates the VBA from the connected neighboring distribution grids. Balancing energy must be managed

within VBAs to prevent DSOs from procuring the amounts of balancing energy generated by charging processes (UC: responsibility). Utilizing the concept of VBAs has implications for the roles of CP, CPO, and EMSP.

In the adapted role model, CPs are no longer seen as energy consumers, as it is today; instead, they show characteristics of grid infrastructure components that transmit the charging energy to consumers. In this case, a consumer groups all charging transactions that can be related to a specific charging contract, regardless of where the charging takes place. For CPOs, this means that they no longer bill the charging energy. Instead, they take the role of an infrastructure provider and can charge an infrastructure fee to EMSPs that use the CPOs' charging infrastructure to sell the charging energy.

Access to CPs must be non-discriminatory for all EMSPs. This ensures competition among EMSPs (UC: competition), and for EV drivers, it means the availability of contractually ensured charging conditions at any CP (UC: unified access).

The adjusted role model states that participating EMSPs need a balancing group in the VBA. Once a charging process is started at any CP, the EMSP is identified, and the amount of energy consumed is attributed to the balancing group of the respective EMSP or its supplier. This means that a real change of supplier occurs at the CPs (UC: electricity allocation) and ensures that EV drivers always obtain charging energy directly from their EMSP rather than from the resold energy of the CPO (UC: electricity allocation). Therefore, the EMSP is responsible for projecting and procuring the charging electricity, as well as for procuring the balancing energy. Furthermore, there is the hypothesis that EMSPs have the most suited data for projecting charging electricity, so that consequently the need for balancing power will decrease.

Figure 4 illustrates the organisational aspects of the electricity system in context of the BANULA approach. Table 1 shows the most important aspects of and differences between today's e-mobility and electric ecosystems and how they are redefined by VBAs and the BANULA concepts. A discussion containing more detailed role-specific advantages and disadvantages can be found in Stetter et al. [17,18].

The next section describes the data and process management.

Table 1. Roles and responsibilities within the e-mobility and electric ecosystems: today and in virtual balancing areas.

Role	Today	Virtual Balancing Area
CPO	Responsible for operating/maintaining their CPs; responsible for energy supply. Business model: sells energy.	Responsible for operating/maintaining their CPs. Business model: infrastructure fees.
EMSP	Issues user contracts	Issues user contracts; provides charging electricity; responsible for projecting charging electricity; financially responsible for deviations from projections
Charging networks	Roaming: provides access to CPs of different CPOs	BANULA : provides access to CPs of different CPOs; provides access to charging contracts related to energy
Electricity supply	Related to charging points	Related to charging contracts
Charging point	Electricity consumers	Can be seen as grid infrastructure

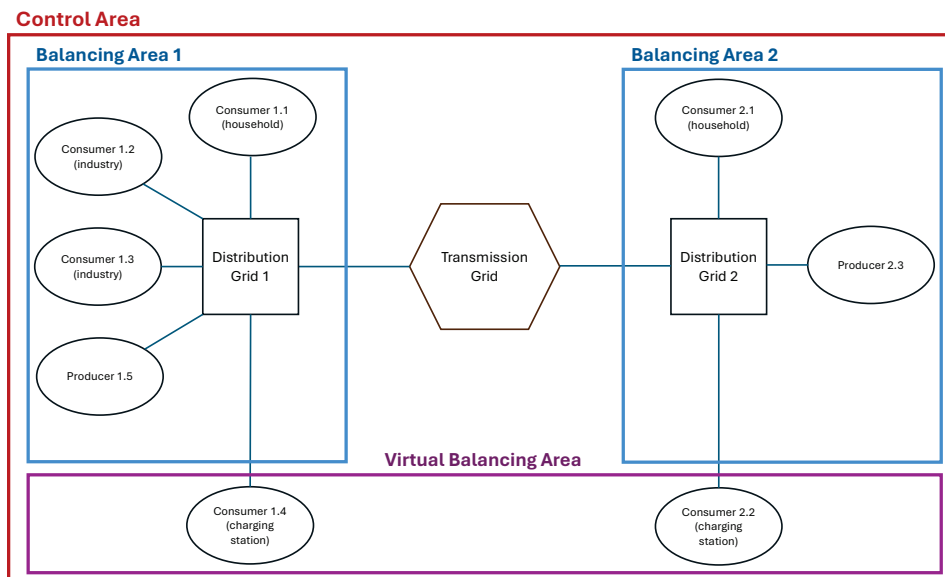


Figure 4. Organizational aspects of the electricity ecosystem with its concepts of balancing groups and balancing areas as it is applied in the BANULA ecosystem. Charging stations are treated as grid infrastructure components and charging electricity is related to charging contracts.

4.3. BANULA in Terms of Information and Communication Technology

First and foremost, the BANULA architecture was designed from the beginning with the aim of bridging existing IT systems used by market participants in the e-mobility sector with those in the energy sector.

With regard to CPOs, this means that they are able to use their established charging infrastructure with CPs connected via OCPP to their respective charge point management systems (CPMSs). The system is extended by linking the CPMSs via the open charge point interface (OCPI) protocol to the BANULA network to exchange information, mainly charging details records (CDRs) and user authorization data. User authorization data are sent by EMSPs via the OCPI to the BANULA network.

Figure 5 is giving an overview on the communication and information exchange in the BANULA network. It is important to note that the BANULA network is not a central platform but rather a cluster of decentralized components. It contains nodes of the open charge network (OCN) routing the required messages, complemented by a cluster of remote procedure call (RPC) nodes that can be addressed. Based on the data provided by CPMSs and EMSPs, RPC nodes can provide higher-level services to all participants involved. It also includes interfaces to the Ethereum BC and RPC nodes that can provide higher-level business or analytical data. A typical service is the energy allocation and market communication service. It is responsible for assigning the charging electricity to the correct EMSP's balancing group, as well as distributing the balancing group data to relevant market partners such as EMSPs, DSOs, and TSOs. Hence, in the BANULA network, the OCPI serves as a uniform interface for market participants in the e-mobility sector, connecting them with those in the energy sector. Doing so contributes to overcoming the problems of data fragmentation and satisfies the requirement of (UC: data availability).

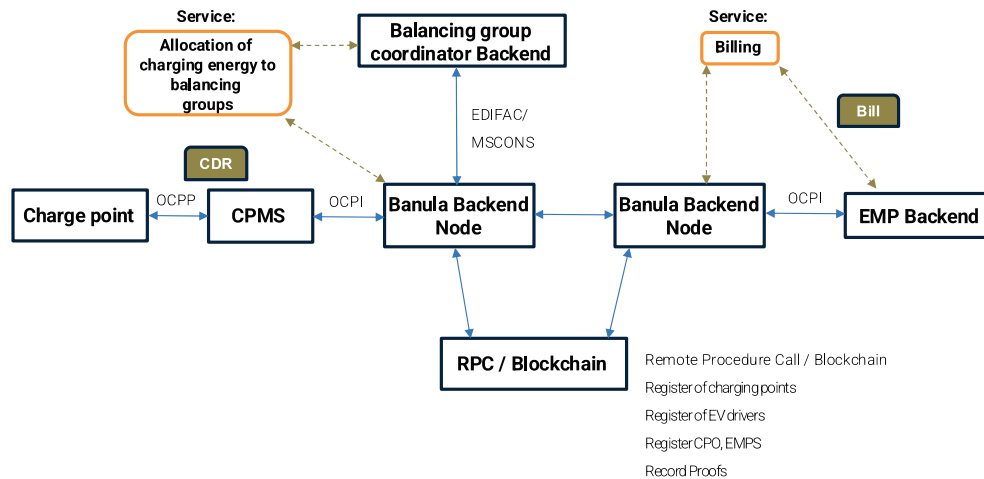


Figure 5. BANULA communication and information exchange overview.

4.4. The BANULA Workflow

In Figure 6 the main ideas of the BANULA workflow are shown. If users want to use a BANULA CP of their choice, they must first authenticate themselves at the CP using either an RFID card or a smartphone app (UC: unified access). Apps provided by EMSPs are preferred. A user who wants to charge his EV at any CP sends a request to his EMSP, and the EMSP backend authorizes the request and sends it via the BANULA OCN nodes to the CPMS and a BANULA verification service. The verification service logs the authorization for the charging transaction to the BC.

At the same time, the CPMS and CP verify the user's credentials and authorize the charging process. Once the charging process is completed, the charging information is sent from the CP to the CPMS via OCPP. The CPMS creates an extended CDR, containing the electricity usage in a 15-min resolution and the EV driver's contract ID. The extended CDRs are sent from the CPMS to the BANULA network using the OCPI protocol [30]. The CDRs are routed by the OCN nodes of the BANULA network to the relevant market participants and services.

The most important market participant that directly receives CDR information is the EMSP, which accesses the CDRs for billing purposes. Additionally, a verification service receives the CDRs and writes hashes of them to the energy web chain [31]. As shown in Section 4.3, this enables data verification and building trust between different participants in the ecosystem (UC: trust).

Finally, the CDRs are sent to the market communication service. There, based on the contract IDs, the received 15-min energy time series of the CDRs are allocated to the identified EMSPs' balancing groups. The market communication service coordinates the communication of the VBA to all related market partners in the energy sector. This is performed using standardized market processes and data exchange formats.

Table 2 is a summary on how the BANULA architecture addresses the different UCs on a technical level.

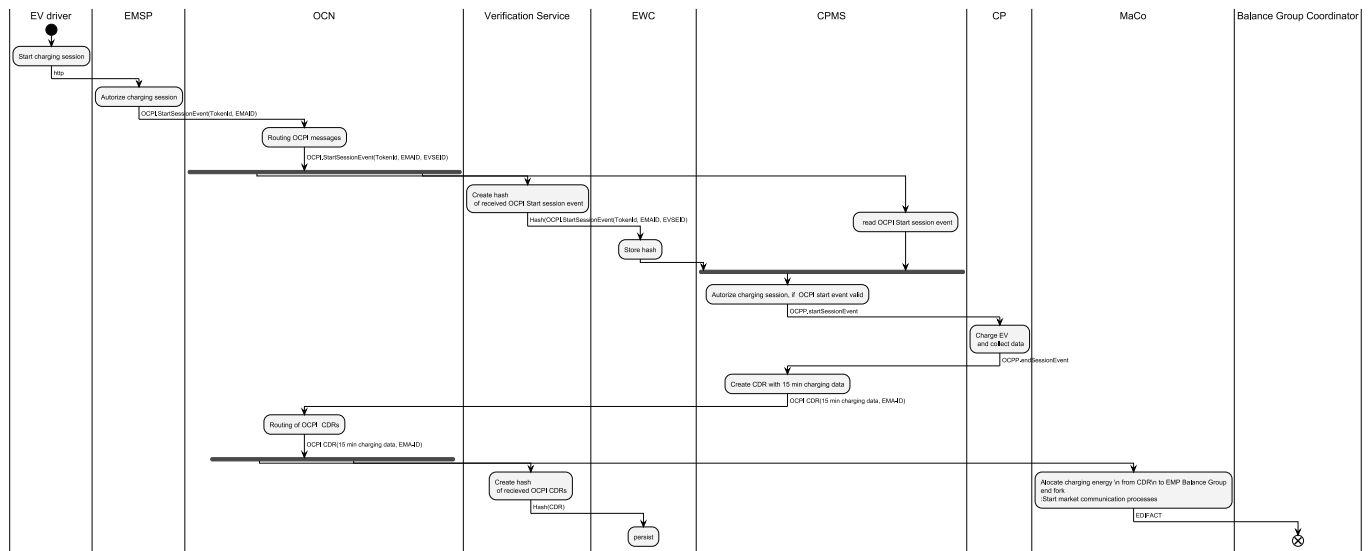


Figure 6. BANULA core workflow.

Table 2. Architectural design and its relationship to requirements.

UC Name	Problem in Current System	Solution within BANULA
Unified access	Many EV drivers have more than one charging card/app due to limited availability of EMSPs at CPs	Decentralized networks and balancing groups ease the access of EMSPs to CPs; one contract at all CPs
Electricity allocation	Used charging energy at a certain CP is always allocated on a balance to the CPO independent of the user's EMSP	EMSPs have their own balancing group to which charging energy is allocated.
Responsibility	Balancing power is allocated to CPOs or DSOs and not to EMSPs	Separation of CPs from distribution grids and grouping them into separate VBAs; EMSPs require their own balancing group
Competition	Low competition at CPs	Non-discriminatory access for EMSPs to CPs
Data availability	Data fragmentation	BANULA network with OCN nodes; interfaces to Ethereum BC; RPC nodes to provide higher-level business or analytical data
Trust	Trust can only be built between large partners that are well known to each other, but not with a huge amount of anonymous partners	Utilizing BC technology for data verification and integrity

5. Evaluation

Our evaluation is based on [14], where Hoess et al. presented six design objectives (DOs) and 18 matching design requirements (Rs) that can serve as a “starting point for researchers to develop a design theory for eRoaming and similar service systems” [14]. The design objectives and requirements were identified via a structured literature review and validated via semi-structured expert interviews. The following section discusses the BANULA architecture in the context of the referenced framework.

5.1. Design Objective 1—Disintermediation

In today's e-mobility environment, the presence of central actors like roaming platforms or clearing houses often carries the risk of the potential abuse of market power and increased systemic costs. Therefore, the intention is to avoid the concentration of market

power (R1) by developing eRoaming systems that are independent of intermediaries [14]. The BANULA project addresses this requirement from multiple perspectives.

From an organizational perspective, BANULA is an open-source project [32]. Since the codebase is not controlled by a single organization and can be accessed and modified by anyone who wants to contribute to its development, the risk of vendor lock-in or monopolistic misuse of market power can be avoided. The same applies to the OCPP and OCPI protocols used [30]. Both are open standards with wide acceptance, which allows for greater collaboration and innovation among developers. Building on standard protocols makes it easy for CPOs to connect to and participate in the BANULA network and enables them to leverage its benefits.

In terms of market communication, BANULA is based on the standard MSCONS format, and there are multiple commercial products available to support it.

From a technical perspective, the use of BC technology as a central concept in the BANULA architecture was chosen to enable a distributed data structure. Storing data across multiple network nodes enhances security and reduces vulnerability to attacks. Furthermore, a decentralized network enables communication and avoids dependency on any given party. For example, the roles of CPO, EMSP, or power supplier can deal and communicate with each other without relying on a centralized component, reducing the risk of vendor lock-in.

From a system-level and business perspective, it is intended that CPOs can either operate their own VBA or join the BANULA VBA that will be operated by a BANULA organization. Having one VBA for all CPOs within a control area creates opportunities for both large and small CPOs to participate in the BANULA ecosystem. This means that even small CPOs with a limited number of charging points can join the ecosystem and benefit from its advantages.

For EMSPs, BANULA enables the direct sale of energy to customers (EV drivers) without the need for an intermediary rent seeker as it is in today's ecosystem.

In conclusion, the objective to avoid the concentration of market power (R1) is addressed at various levels within the project, including project organization, technical implementation, and system-wide considerations, making it possible to mark this requirement as fulfilled.

5.2. Design Objective 2—Accountability

Every actor involved in a charging event must be authenticated (R2) [14]. In terms of EV drivers, the BANULA architecture enables the use of common authentication mechanisms. The current prototype implementation supports app-based and RFID card authentication, as well as ad hoc charging with the support of credit or debit card payment options. When RFID tags are used for authentication, the issuing EMSP must provide either a whitelist of acceptable tokens to all CPMS in the BANULA network or authenticate and authorize at the time the RFID card is read at the charging point. Despite being less secure, whitelisting is recommended by the OCPI protocol to avoid waiting times and offer a better user experience.

In the context of BANULA, the preferred method is authentication via an EMSP app. When approaching CPs, EV drivers use a smartphone app to start a charging attempt. The EMSP generates an authorization token. To initiate the charging transaction, the EMSP forwards the authorization token via the OCPI protocol to the CPO and triggers the start of a charging session.

Aside from charging via a contractual relationship between the EV driver and their EMSP, ad hoc charging needs to be supported by European legislation. EV drivers must be able to charge their EVs without a contract at the charging station by using their credit

cards or other external payment providers. In this case, authorization is still performed by an EMSP providing ad hoc charging at the CP. However, it is not based on a contract or knowledge of the customer, only on the grounds of securing the needed funds. The authorization event contains a pseudo-anonymous ID to ensure that the charging transaction can be related to the user.

In addition to authorizing charging events, it is also necessary that, in the case of misuse, cancellation, or expiration, an EMSP can revoke the permission and the respective contract (R3) [14]. Since every charging session in the proposed BANULA network needs to be authorized by an EV driver's EMSP, the authorization can also always be revoked by the EMSP. If pre-authorization (whitelisting) is used, the authorization can be removed by sending a new invalid authorization token. When using app authorization, the EMSP can choose not to send a valid authorization token; as a result, the charging session cannot be initiated.

Once a charging transaction has taken place, reliable eRoaming must also ensure that charging events cannot be declared invalid retroactively [14] due to non-repudiation or data integrity (R4) [14]. In the BANULA network, only digitally signed messages are accepted by the different nodes. Upon submission of a message, the signatures are validated against an entry in the BC registry. Additionally, data integrity may be ensured by storing the hashes of events or CDRs on the BC. Every participant who has access to the original CDRs now has technical proof of the correctness of the CDRs and no longer relies solely on trust.

Storing the hashes of events on the BC not only allows users to verify the amount of charged energy but also enables many other use cases. For example, authorization tokens issued by the EMSP are part of the start session command, which is also sent via the network. Hence, the authorization of the charging session by the EMSP can be proven by the CPO. Since CPOs have received the tokens from the EMSP, the EMSP can no longer question the responsibility for a charging process. Consequently, CPOs can charge service fees to EMSPs, and the allocation of charging energy to the EMSP's balancing group cannot be contested by that EMSP.

Additionally, when storing the hashes of the CDRs on the BC, they are used and structured as Merkle Trees. This allows for verification that a specific 15-min series of a charging process is included in a balancing group's daily aggregate time series. Moreover, the same kind of Merkle proof can be used to verify that the sum of all energy charged in a 15-min time interval across all EMSPs of a particular charging station, along with its default self-power, is equal to the meter operator-measured energy at the grid connection point.

In summary, the use of the OCPI authorization mechanism fulfills the requirements for authorization (R2) and the possibility to revoke the permission and the respective contract (R3). The integration of BC technology satisfies the requirement for non-repudiation and data integrity (R4). Hence, all requirements from the design objective "accountability" are met.

5.3. Design Objective 3—Efficiency

For the sake of economic efficiency, end-to-end process automation (R5) [14] is inevitable.

In the BANULA architecture, the whole process, from the first user contact at the CP to the final steps of distributing the EMSP's balancing group data, is based on standard protocols, such as OCPP and OCPI, and for the prototype, the German standardized electricity market communication protocol. As shown by the first prototype, integration with payment providers is also possible, closing the circle for the user.

From the authors' point of view, standardized, machine-readable information exchange between CPOs and EMSPs (R6) can also be considered fulfilled by the process chain

described in (R5). Using the quasi-standard OCPI for data exchange between CPOs and EMSPs enables not only automated data exchange but also the continuous utilization of existing processes.

In addition, for interoperability reasons a standardized ID schema (R7) [14] is essential. In the first prototype, EMAID [22] was used to identify charging contracts sent via OCPI. The next step in the BANULA project will involve the use of digital identities as defined in [33] and digital signatures. However, one shortcoming of OCPI is that the used message field is too short to hold a Decentralized Identifier (DID). An alternative approach could be to use a separate protocol to enable authentication [21], as used in the Rebeam project [24]. However, BANULA aims to have an integrated approach within the OCPI protocol.

DIDs serve as the basis for trustworthy public registries (R8) [14]. Hoess et al. [14] highlighted the fact that public registries “can additionally provide information on certified charging points”. In the BANULA system, a registry with master data on the BC contains DIDs and other metadata about different market participants, such as CPOs, along with their charging points, or EMSPs. The goal is to choose trustworthy partners and to provide possibilities for secure and reliable data exchange by making use of DIDs.

In addition, in terms of registries for market participants, other registries are also under discussion. The stored data can serve as a basis for further services or smart contracts. Examples include pricing/tariff registers so that EMSPs can publish their pricing structures and users can verify the correct prices when charging their EVs.

Location services with information about charging station availability can be used by users to find appropriate charging stations. In future versions, smart contracts can be applied to verify CPOs’ promised availability of their CPs.

To this end, we can state that all requirements in this design objective are met.

5.4. Design Objective 4—Data Protection

There is no doubt that eRoaming solutions should comply with data protection regulations, such as the GDPR or the CCPA, and that correlations between personally identifiable and charging-related information beyond information required for eRoaming should be avoided (R9) [14].

This requirement is addressed in the BANULA data concept using pseudo-anonymous contract ID numbers and market location IDs. Only market participants with a legitimate need to know are able to relate these IDs to specific users, typically participating EMSPs.

However, pseudo-anonymous data alone are not sufficient. It is also important that the confidentiality of sensitive data is ensured (R10) [14] and that only authorized entities are able to access charging-related information, as data minimization based on the need-to-know principle (R11) can, for instance, help CPOs and EMSPs only receive information that is directly relevant to authentication and billing [14].

In the current BANULA implementation, only the hashes of CDRs are written to the BC so that data can be verified, but the original data remain with the directly involved parties. Therefore, sensitive information, for example, regarding which identity charges how much, and where, is not stored on-chain. This fulfills (R10) and (R11).

To avoid the centralized storage of data (R12), the BANULA architecture was designed from the beginning with a focus on decentralized structures. CDRs are exchanged between partners using the OCPI protocol [30], and the energy web chain [31] is used as BC technology to store the CDR hashes. Sensitive data about charge details may be stored by the respective market roles and may be exchanged only between related market partners.

In summary, all requirements in this design objective are addressed by an appropriate data structure on the BC.

5.5. Design Objective 5—Usability

Targeting a wide user group requires that eRoaming solutions be easy to use and require at most as many user interactions as traditional charging systems (R13) [14].

This requirement can only be partially evaluated, as it also involves systems from external participants, such as CPOs and EMSPs, and the BANULA architecture can only provide the required interfaces and organizational framework. The main idea is that EV drivers can bring their own contracts to the charging station and use them with one card and/or app. Consequently, by having only one contract and bill, the system becomes easier to use.

In order to counteract user reservations against BC, the BANULA implementation simplifies the signing-up process through the concept of account abstraction [34]. Instead of using wallets secured with cumbersome seed phrases that are typically used in the BC context, the BANULA wallet integration enables authenticating and restoring access using either the username or password. These concepts from the Web 2.0 environment are well known and understood by a wide range of user groups. Using an e-mail account for authentication facilitates the recovery of an account or wallet [34]. However, as mentioned above, signing up for an EMSP's respective charging contract involves the EMSP's customer registration process, which is outside the scope/control of the BANULA architecture.

Another requirement is the principle of one face to the customer (R14). That is, seamless eRoaming should be possible using a single contract, app, or RFID card [14]. This requirement is identical to the use case of unified access. It is addressed by the core concept of VBAs and the idea of a real supplier change at CPs. This goes hand in hand with the paradigm shift away from assigning charging energy to CPOs and instead to the user's EMSP's balancing group. Users can use RFID cards and/or apps for authentication at CPs provided by their EMSPs. If there are appropriate offers, the same contract can be used both at home and for public charging. It should be noted that this requirement is very narrow. The possibilities enabled by the real supplier change at the CP enable many more business cases than simply bringing one's own contract to a different charging location. This topic is elaborated on in more detail in (R17) below.

For a good user experience, factors other than onboarding or the charging event are important. Price transparency is also important. This includes non-discriminatory pricing and transparent communication of tariffs (R15) [14]. In the BANULA ecosystem, there are mainly two pricing components visible to the user: one related to the charging energy determined by the user's EMSP, and one determined by the CPO whose infrastructure is used. Information about both components is included in the CDRs based on the standard OCPI format, which can be made available to EV drivers and EMSPs responsible for billing the charging contract. For example, a tariff for net energy usage and a tariff for a parking fee could be applied.

Considering all participants in the ecosystem, eRoaming systems should be easy for CPOs and EMSPs to apply and require no more implementation effort than current solutions (R16) [14].

As mentioned before, the BANULA architecture extensively utilizes standard protocols like OCPI and OCPP. Although the intention is to minimize additional effort, adding new features or improving functionality and interoperability may require some additional effort.

In addition to the technical feasibility, the flexibility of eRoaming solutions to grant business model independence (R17) may also help the innovation and adoption of eRoaming [14]. From our perspective, this is more of an organizational issue than a technical one. Using OCPP and OCPI for communication allows the transmission of not only energy time series but also tariff data in CDRs. This is important for developing business models. In general, the BANULA network is a means to exchange data but does not impose restrictions

on how EMSPs utilize their balancing groups. Giving EMSPs full flexibility in managing their balancing groups in conjunction with the verification possibilities of the BC enables a wide spectrum of business cases. For example, using the two concepts together makes it possible to relate the electricity input and output to each other. This makes it possible for EMSPs to provide a charging service that relates solar power from home to an EV driver's charging process at any CP. In another use case, it is possible that EMSPs verify that only green energy is used for charging.

The architecture lends itself to fostering an ecosystem of further business cases. Many value-added services may be built by leveraging the open interfaces of the standard protocols and using the decentralized infrastructure. Examples of these services could include data visualization or forecasting services.

To this end, we can state that all requirements in this design objective are met, apart from (R13) and (R16). Both requirements can only be partially evaluated because they involve EMSPs as external parties and are at the edge of the system.

5.6. Design Objective 6—Scalability

A major focus of the BANULA project is integrating into the current e-mobility and energy system landscape. Hence, the requirement stated in [14] that “eRoaming systems should also consider their scalability to handle at least as many transactions as centralized eRoaming systems (R18) without outages or long response times” is crucial. It is important to note that the evaluation of this requirement is still ongoing. However, certain design decisions have been made to address it.

First, the architecture is built on established and well-understood protocols, like OCPI and OCPP, so that CPOs and EMSPs are familiar with the daily operation and can use their existing and already optimized technical infrastructure. A major concern and lesson from related works is the slow transaction speed of current BC systems. Being aware of this architectural design, decisions have been made. Hence, only data with rather slow modification ratios, such as master data, are stored on the BC. In contrast, data that are expected to be large in volume and transaction ratio, such as energy and charging time series, are stored off-chain, with only their hashes stored on-chain. This approach ensures data integrity while reducing the load on the BC system.

So far, it can only be stated that the design process has addressed this requirement, but the final evaluation can only be performed through a large-scale field trial. Such a trial is planned for the first half of 2025.

5.7. Evaluation Summary

To this end, it can be stated that by far the majority of the requirements defined by Hoess et al. [14] have been met. Only (R13) and (R16) in DO 5 cannot be evaluated because they involve EMSPs as external participants, so the processes are not completely known. Also, scalability (R18) can only be theoretically evaluated. From a theoretical perspective, appropriate measures have been taken; however, practical proof must still be provided. Therefore, further progress in this project must be made.

6. Summary and Future Work

In this paper, we identified six use cases with their associated requirements that cause problems at the intersection of the current e-mobility system and the electricity system. We presented the BANULA architecture, which aims to address these requirements by making use of the concept of VBAs. We presented an approach that not only provides EV drivers with access to charging points, as in today's roaming systems, but also allows them to bring their own contracts and EMSPs to the charging station.

From a research perspective, this paper primarily focuses on the theoretical evaluation of the BANULA architecture. It was shown that all initially defined use cases and design objectives have been addressed on a conceptual as well as on a technical level by the BANULA architecture. However, the discussion needs to be complemented by legal and economic perspectives, along with appropriate use and business cases. Moreover, some aspects must be evaluated in field tests. One such hypothesis is that EMSPs can make better projections than CPOs. The continuation of this hypothesis is whether the reduced necessity for balancing energy is significant enough to impact overall grid fees.

In addition, there are organizational and techno-organizational aspects that are yet to be judged. With the current prototype, only a very limited number of charging transactions have taken place. Hence, it has not yet been shown that the required processes related to VBAs are working as expected on a large scale in everyday business. The interpretation of the regulatory framework with regard to the required metrological infrastructure is also essential. From the perspective of the current project, it must be stated that a strict interpretation of current metrological guidelines can be prohibitive to the whole idea of VBAs.

The organizational validation of processes on a large scale and of different metrological concepts will be an integral part of the upcoming field test, which will be conducted in 2025. CPs will be available in at least three out of the four control areas in Germany. There will be a fleet of 15 EVs for testing purposes, and a roadshow through Germany will be conducted to demonstrate the cross-control area availability of the system. Besides the CPs at the locations of BANULA project members, there will be collaborations with at least three external CPOs to build up test CPs.

Another topic to be addressed within the project is assessing the applicability of the BANULA concept to other regulation frameworks, mainly in the European Union. The underlying protocols such as OCPP and OCPI, which form the technical foundation, are widely used throughout Europe. Also, the format MSCONS has a common international base with national adjustments. Moreover, the European electricity market is becoming increasingly integrated from an organizational perspective. For example, Tennet, one of the active TSOs in Germany, also operates as a TSO in the Netherlands and Belgium. This provides a solid foundation for transferring the BANULA concept from the German market to other European countries.

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Abbreviations

The following abbreviations are used in this manuscript:

VBA	Virtual Balancing Area
MSCONS	Metered Services Consumption
CPO	Charge Point Operators
CP	Charging Point
EMSP	Electric Mobility Service Providers
UC	Use Case
DSO	Distribution System Operator
TSO	Transmission System Operator
BC	Blockchain
OCN	Open Charge Network
CPMS	Charge Point Management System
OCPP	Open Charge Point Protocol
OCPI	Open Charge Point Interface
RPC	Remote Procedure Call
CDR	Call Detail Record
RFID	Radio Frequency Identification

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Article

AI-Based Prediction and Safety Measures for Electromechanical Brake Three-Phase Motor Faults

Hyun Jee

HL Mando Global R&D, 21 Pangyo-ro 255 beon-gil, Bundang-gu, Seongnam-si 13486, Gyeonggi-do, Republic of Korea; hyun.jee@hlcompany.com

Abstract: In the development of future automotive systems, safety and performance are crucial considerations. The reliable operation of Drum-type Electromechanical Brakes (D-EMBs), key components responsible for vehicle braking, is essential. Previous research has predominantly focused on post-fault response strategies, emphasizing fault detection and diagnosis. However, this study aimed to enhance vehicle safety by predicting motor faults in the D-EMB system and developing corresponding measures. Utilizing AI-based FFT (Fast Fourier Transform) analysis, in this research, we successfully developed a technology for the early detection of motor faults, achieving an accuracy of over 80%. This study contributes to improving the safety of future automobiles and the development of innovative safety technologies.

Keywords: D-EMB (drum-type electromechanical brake); FFT (fast Fourier transform); three-phase motor; fault prediction; explainable data

1. Introduction

Drum-type Electromechanical Brakes (D-EMBs) are a brake-by-wire system for future automobiles. This system enables braking control solely through electrical and electronic devices, eliminating all hydraulic lines present in conventional braking systems. This configuration contributes to vehicle lightweighting and enhances energy efficiency while also facilitating integration with advanced driver assistance systems. Due to these characteristics, D-EMBs are emerging as a key technology for future vehicles, especially electric and autonomous vehicles. However, as a critical component, D-EMBs directly impact vehicle safety and performance. Malfunctions in this system can compromise braking capability, posing potential safety risks. For this reason, D-EMBs are classified as an Automotive Safety Integrity Level D (ASIL-D) safety-critical product under the ISO 26262 standard [1], making early fault detection and prevention essential priorities.

This paper, based on an initial study presented at EVS37 [2], introduces a method for predicting motor faults in the D-EMB system, thereby preventing potential hazardous situations in automotive environments. Unlike previous research focused primarily on post-fault diagnosis, this study proposes an early fault prediction approach for D-EMB motors. Prior research predominantly emphasized diagnosing and addressing faults after their occurrence; however, such post-event strategies only address problems that have already manifested. In this study, we developed an AI-based model using Fast Fourier Transform (FFT) analysis to detect and predict motor faults in order to prevent hazardous scenarios that may arise during vehicle operation and significantly enhance vehicle safety.

Additionally, instead of using current waveforms, the AI model developed in this study leverages frequency and amplitude data obtained through FFT on current data for motor state prediction. This provides an objective basis for distinguishing between faults and normal states. This approach is designed to overcome the limitations of traditional fail-safe logic, supporting safer driving through real-time monitoring and early-warning systems.

The AI algorithm proposed in this study is designed for application in HL Mando's D-EMB products, overcoming the limitations of existing fail-safe (F/S) logic by enabling

preemptive responses to motor faults. Such research opens possibilities for application not only in D-EMB systems but also across various advanced automotive technologies, contributing to increased safety and reliability in the future automotive industry.

2. Prior Research

Previous studies on the D-EMB system primarily focused on developing post-fault safety mechanisms, concentrating on redundancy to ensure stability after actuator failures [3]. Although these approaches helped maintain a certain level of safety, they failed to account for changes in motor performance or vehicle stability before faults occurred. Consequently, this reactive approach emphasized post-fault response, which limited its ability to fully eliminate potential hazards posed by motor failures.

This study aims to overcome these limitations by proposing a method for predicting mechanical faults in the motor. Preliminary research has shown that mechanical faults, such as bearing failures, rotor imbalance, and misalignment, account for 74% to 92% of total motor failures [4]. Given that these faults directly impact driving performance and safety, early prediction and preventive measures are essential.

Past studies typically used the waveform patterns of three-phase currents and vibration data to train models and perform fault diagnostics [5,6]. These studies evaluated motor conditions by analyzing vibration data and current signals, but they faced challenges in providing numerical evidence for prediction results. AI models are often regarded as “black boxes”, making it difficult to interpret outcomes, and their reliance on data quality and quantity can be high. Additionally, their computational resource requirements make them challenging to apply in real-time systems.

To address the limitations of AI models based on vibration and current waveforms, this study employs a data transformation method. Prior studies applied FFTs, wavelet transforms, and Hilbert transformations to convert waveform data from vibrations and current, thereby providing numerical support for AI model predictions [7]. FFTs are widely used to analyze frequency characteristics by converting time-series data, like vibrations or current, into the frequency domain. The wavelet transform allows for simultaneous signal analysis in both the time and frequency domains, enabling detailed analysis of high- and low-frequency components. The Hilbert transform is used to extract rate-of-change and phase information from signals along with frequency characteristics.

The primary limitations of conventional AI models include the need for additional sensors and high computational complexity. Although previous research using FFTs demonstrated effective results for detecting bearing defects [8,9], it required additional sensors, such as vibration or flux sensors, which increased component costs for vehicle applications. This cost factor places an economic burden on large-scale production and commercialization stages. Additionally, studies using wavelet [10] and Hilbert [11] methods to predict motor faults showed increased memory and time complexity, making them unsuitable for vehicle systems with limited computational resources.

To address the limitations identified in previous studies, this research considers the formulas, time complexities, and memory usage of signal-processing methods such as the FFT, wavelet transform, and Hilbert transform, which have been used to analyze vibration and current waveforms in earlier works.

The formula for the wavelet transform is

$$\text{CWT}(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \quad (1)$$

where CWT represents the continuous wavelet transform, $f(t)$ is the signal to be analyzed, and $\psi_{a,b}(t)$ is the wavelet function modified according to scale a and position b . The time complexity of the wavelet transform is $O(n \log n)$, and it generally entails high memory usage, which depends on the scales used and the complexity of the function.

The Hilbert transform is defined as follows:

$$H(f(t)) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{f(\tau)}{t - \tau} d\tau \quad (2)$$

When used directly, the time complexity of the Hilbert transform is $O(n^2)$, making it inefficient. However, using an FFT-based approach can reduce the time complexity to $O(n \log n)$. Nevertheless, this approach incurs additional time overhead due to the FFT computation.

The formula for the FFT is as follows:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i \frac{2\pi}{N} kn} \quad (3)$$

where X_K is the signal in the frequency domain, x_n is the signal in the time domain, and N is the number of samples. The time complexity of the FFT is $O(n \log n)$, which is efficient. Therefore, this study chooses to employ FFT-based method to minimize time complexity while achieving high-resolution signal analysis.

This study seeks to utilize only data measured within the existing system, without requiring additional sensors. This contributes to improved cost efficiency and reduced system complexity. To address the resource constraints in vehicle systems, the FFT methodology is applied, minimizing computational memory and time complexity to overcome the limitations of previous studies. Using only the motor's operational current, this study employs a FFT to predict four motor states—normal, bearing fault, rotor imbalance, and misalignment—and proposes appropriate response measures upon fault prediction.

Through FFT analysis, the operational characteristics of the motor can be clearly revealed, objectively supporting model prediction results and providing a basis for fault diagnosis. This approach offers higher accuracy and reliability than conventional methods, enabling continuous condition monitoring during vehicle operation via integration with real-time monitoring systems.

Ultimately, this study explores how to enhance vehicle safety by applying motor fault prediction technology based on interpretable data in the D-EMB system, presenting new possibilities for future safety technologies. This approach can be applied to advanced transportation technologies such as autonomous vehicles, contributing to accident prevention and safety enhancement.

3. Research Methodology

In this study, the D-EMB system from HL Mando was utilized. The D-EMB system consists of a three-phase motor and various sensors, allowing precise measurement of the motor's performance. For experimentation, a test target system including a controller, a data collection device, and safety features was configured.

3.1. Hardware Configuration

The motor specifications are outlined in Table 1. To simulate major mechanical faults in the motor, namely, bearing faults, rotor imbalance, and misalignment, artificial faults were intentionally created.

Table 1. Motor specifications.

Motor	
Type	BLAC/IPM
Rated current [Arms]	50
Phase voltage [Vrms]	4.37
Torque [Nm] @ 1000 rpm	1.37

3.1.1. Bearing Fault

Figure 1a illustrates the process of bearing fault generation. Improper and inaccurate lubrication are significant causes of bearing faults. To replicate this condition, bearing grease was removed using hexane and ultrasonic cleaning, thereby creating a state of insufficient lubrication.

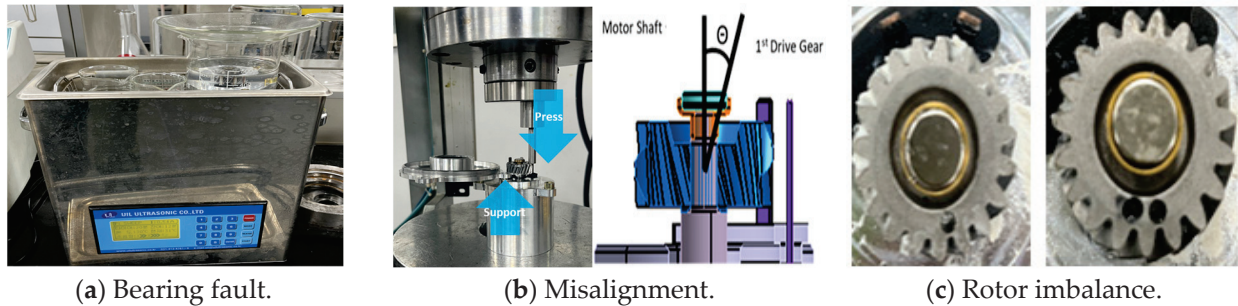


Figure 1. Motor fault creation process.

3.1.2. Misalignment

Figure 1b depicts the process of misalignment generation. The primary form of misalignment is angular misalignment, where the axis centerlines intersect but are not parallel. To create this condition, misalignment was introduced by twisting the 1st drive gear shaft. Before twisting, the angular misalignment (θ) was 0.16 degrees, which increased to 0.66 degrees after twisting.

3.1.3. Rotor Imbalance

Figure 1c demonstrates the process of rotor imbalance generation. Rotor imbalance occurs due to mass eccentricity or the creation of holes in the rotor. To mimic this condition, holes were drilled into the rotor. To observe the progression of fault severity, measurements were taken after creating the first hole and then again after adding a second hole during the degradation process.

3.2. Experimental Setup and Scenario Development

Figure 2a depicts the experimental setup. The setup includes the motor mounted on the D-EMB assembly for measurement. A power supply, replacing the vehicle battery, provided 13.5 V to the D-EMB system. Measurements were conducted using CANoe and CANape equipment.

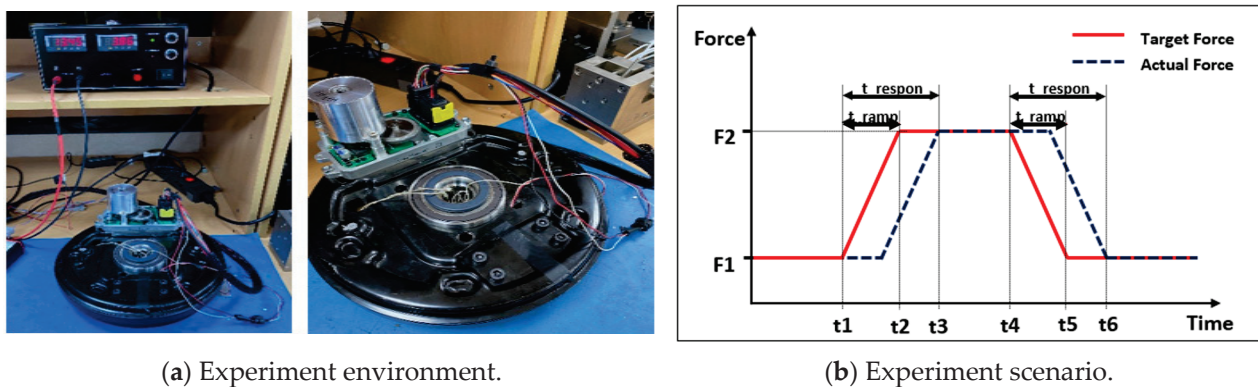


Figure 2. Experiment environment and experiment scenario.

Figure 2b illustrates the motor operation scenario. The scenario is as follows: The execution process consists of one complete set. Initially, the D-EMB assembly starts in a

clamping forceless state. The motor initially operates at approximately 3000 rpm, decelerating as a load is applied when the brake pad makes contact with the disc. It continues to function during the rising phase until the target clamping force, F2 (2500 N), is achieved, at which point it stops. This is followed by a 3 s hold. Subsequently, the motor reverses direction to lower the actuator back to the clamping forceless state, F1 (0 N), during the falling phase. The operation times for both rising and falling were set to 1 s each.

3.3. Data Collection

The signals measured are as shown in Table 2. These signals can be measured within the existing vehicle system without the need for additional sensors. The representative categories of the total 14 signals include the three-phase current of the motor, motor position, motor torque, required braking force, measured braking force, motor RPM, battery voltage, and motor overload detection signal. However, the system does not output the W-phase current in the motor's three-phase current (U, V, W). Instead, it estimates the W-phase current using U-phase current and V-phase current and outputs the direct-axis current and quadrature-axis current after D-Q transformation. In other words, U-phase current, V-phase current, direct-axis current, and quadrature-axis current were measured.

Table 2. Measured signals.

No.	Category	Signal
1	three-phase motor current (U/V/W)	PhaUI.Ampr
2		PhaVI.Ampr
3		IdMeasd.Ampr
4		IqMeasd.Ampr
5	Motor position	Stat_mmPos
6	Motor torque	Stat_MotTrq
7	Required braking force	ClmpFrcReqR
8		ClmpFrcReqL
9	Measured braking force	ClmpFrcSnr
10	Motor RPM	MotAgSpdRaw.AgSpd
11	DC link voltage	BattU.U
12	Motor performance influencing factors	RackPosn
13	Motor deterioration judgment signal	OverHeatProtn
14		OverLoadProtn

In this study, a total of 3 motors were used. Initially, data in the normal state were collected. Measurements were taken for each normal-state motor 200 times, resulting in a total of 600 sets of normal-state measurement data. Subsequently, faults were artificially induced in each motor, and the corresponding faulty data were measured 200 times for each fault type. To further examine performance degradation according to fault severity, measurements were taken for an exacerbated rotor imbalance fault 200 times. The measurement dataset is outlined in Table 3.

Table 3. Measurement dataset.

Data Classification		Training Data	Testing Data
Normal	Normal	600	94
Fault	Bearing fault	200	90
	Misalignment	200	93
	Rotor imbalance	400	99
Total		1400	376

3.4. Data Analysis

3.4.1. Input Variable Selection

The FFT is widely used to transform time series data into the frequency domain to analyze frequency characteristics. This increases the accuracy of fault diagnosis and provides efficiency suitable for real-time monitoring. While existing AI models require high computational resources and additional sensors, this study utilizes FFT to predict faults without the need for extra sensors, thereby reducing economic burdens and enhancing efficiency. This methodology overcomes the limitations of previous research, providing more accurate and reliable results for predicting mechanical failures in motors.

Using the FFT method, each current dataset was converted into amplitude and frequency. When the four current datasets were transformed using FFT, the result was eight variables, as shown in Table 4. During the execution of Scenario 1, approximately 635 peaks were generated through the FFT transformation. A one-way ANOVA (Analysis of Variance) was performed to analyze the relationship between the transformed eight variables and motor status, focusing on the 63 peaks that correspond to the top 10% of amplitudes.

Table 4. Variables.

No.	Current	FFT
1	UI	Amplitude (UI)
2		Frequency (UI)
3	VI	Frequency (VI)
4		Amplitude (VI)
5	Iq (quadrature current)	Frequency (Iq)
6		Amplitude (Iq)
7	Id (direct current)	Frequency (Id)
8		Amplitude (Id)

One-way ANOVA is a statistical method used to compare the mean differences between multiple groups, assessing whether the means are significantly different. In this study, one-way ANOVA was selected to evaluate the relationship between the eight variables derived from the FFT and the motor status. This method systematically assesses the relationships among variables and helps to reduce the complexity of the data by identifying significant variables, thereby enhancing the model's efficiency.

As the amount of input data increases, memory usage rises; therefore, one-way ANOVA was repeatedly performed while reducing the number of peaks for efficient data management. The analysis revealed that statistically significant variables were reliably derived until using the top 49 peaks, confirming this was the optimal number of peaks. Consequently, five statistically significant variables were selected from the eight variables for model evaluation. The variable selection process and the corresponding results are presented in Table 5.

In conclusion, the analysis of the relationship between the variables transformed by FFT and the motor status through one-way ANOVA yielded significant variables. This optimized the model's input data and reduced data complexity, resulting in enhanced model performance.

The results derived from PCA (Principal Component Analysis) played a crucial role in improving the performance of the motor fault diagnosis model. PCA functions by reducing the dimensions of the data while preserving the largest variance. In this study, four principal components were analyzed, and their explained variance ratios are presented in Table 6.

Table 5. One-way ANOVA results.

Current	FFT (Top 49)	F-Statistic	p-Value (0.05)
UI	Frequency (UI)	173.831	2.45 ^{−112} ***
	Amplitude (UI)	85.493	3.18 ^{−55} ***
VI	Frequency (VI)	391.82	1.13 ^{−252} ***
	Amplitude (VI)	41.756	6 ^{−27} ***
Iq (quadrature current)	Frequency (Iq)	2.619	0.049 *
	Amplitude (Iq)	1.002	0.391
Id (direct current)	Frequency (Id)	1.509	0.21
	Amplitude (Id)	1.29	0.276

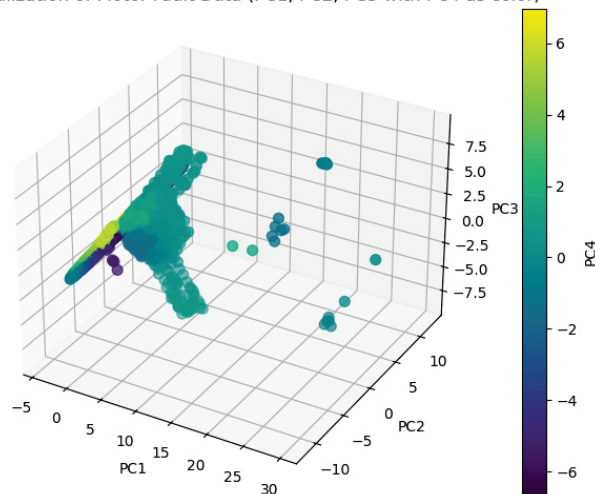
$p \leq 0.05$ (*), and $p \leq 0.001$ (***)

Table 6. Explained variance ratios of Principal Components.

Principal Component	Explained Variance Ratio	PCA Component				
		1	2	3	4	5
1	0.35	0.55	0.06	0.56	−0.13	0.61
2	0.28	0.08	−0.71	0.07	0.69	0.08
3	0.14	−0.73	0.01	0.68	0.01	0.04
4	0.12	0.08	0.70	0.07	0.71	−0.04

The Principal Component results are as follows: Principal Component 1 (34.15%), Principal Component 2 (27.70%), Principal Component 3 (13.97%), and Principal Component 4 (12.10%). When combined, these principal components explain a total of 87.02% of the variance. This indicates that the principal components derived from PCA encompass most of the important information in the original data. Even the first two principal components can explain 61.85% of the variance, meaning that they alone can account for most of the data's variability. A graph illustrating these principal components, with the first three as axes and PC4 represented by color, is shown in Figure 3.

PCA Visualization of Motor Fault Data (PC1, PC2, PC3 with PC4 as color)

**Figure 3.** PCA visualization composed of 4 Principal Components.

Moreover, the Principal Components resulting from PCA reflect the correlations between the original variables, serving as useful characteristics for identifying fault conditions. For instance, Principal Component 1 is a combination of FFT frequency and amplitude data, which may show a correlation with specific motor states. These analytical results will serve as an important criterion for selecting input variables in future model construction.

3.4.2. Model Selection

In this study, various models were trained using measurement data to find a suitable model, and the results of motor classification were evaluated. Initially, representative supervised learning classification models such as K-NN, Naive Bayes, SVM, Decision Trees, and MLP were selected. Additionally, ensemble methods like Random Forest were employed, and models with excellent performance in regard to time series data, such as RNN, were also used.

The training data in Table 3 consist of a total of 1400 samples, which were split in an 80:20 ratio. Of these, 80%, equivalent to 1120 samples, were used for training, and the remaining 20%, or 280 samples, were utilized for validation. The model's accuracy was calculated as the average through 5-fold cross-validation. Additionally, the accuracy of each model was individually assessed using 376 test data points that were not utilized in the training and validation processes, as shown in Table 7.

Table 7. Data partitioning.

Data Classification	Data Partitioning (80%:20%)		Test Data
	Training Data (80%)	Validation Data (20%)	
Count	1120	280	376
Total	1400		376

Initially, the goal was to examine the basic performance of the models without tuning the data. Five statistically significant variables identified previously were used as input values for the models, considering all peaks observed for each variable. The output of the models was set to represent the motor's state. Upon examining the results presented in Table 8, it is evident that the model utilizing current waveform data generally achieved higher accuracy than the model using FFT data. However, there are limitations to explaining why a motor is predicted to be faulty based solely on current waveforms. Accordingly, the objective of this study is to reach the performance level of the model using only current data by adjusting the model utilizing FFT data. Random Forest, which achieved the highest accuracy in the test data when trained using FFT data, was selected as the basic model for this study.

Table 8. Results of model trained with current and FFT data.

Accuracy		Current		FFT (ALL Peak)	
	Data	Validation Data (280)	Test Data (376)	Validation Data (280)	Test Data (376)
Supervised learning	KNN	88.4%	84.6%	42.5%	29.0%
	Naive Bayes	71.1%	50.5%	56.9%	31.9%
	SVM (RBF)	91.7%	85.9%	52.0%	40.7%
	Decision Trees	90.5%	47.9%	72.9%	63.0%
	MLP	96.9%	80.9%	53.0%	41.2%
Ensemble	Random Forest	97.6%	79.0%	79.6%	77.7% *
Deep learning	RNN (LSTM)	42.9%	39.4%	86.1%	24.2%

Selected model (*).

3.4.3. Selection of Evaluation Metrics

A Confusion Matrix, a commonly used tool, was utilized. Through a Confusion Matrix, accuracy, precision, recall, and F1-Score can be calculated. Since this study aims to predict whether a motor is faulty, minimizing the occurrence of high false-positive costs is crucial. High false-positive costs are additional costs incurred due to incorrect positive judgments, such as additional tests, inspections, and customer responses. Among the performance metrics, F1-Score was chosen as the evaluation metric for this study, as a higher F1-Score indicates lower false-positive costs.

3.4.4. Identification of Performance Deterioration Factors Due to Motor Faults

In the D-EMB system, the Clamping Force is considered the most crucial factor for vehicle braking performance. Pearson correlation analysis was conducted based on Clamping Force as a reference for all measurement data, which are the measured signals shown in Table 2. The results are shown in Table 9, where Stat_mmPos has a high Pearson correlation coefficient of 0.987 with respect to Clamping Force, and the Pearson correlation coefficients for quadrature-axis current and direct-axis current are 0.887 and 0.881, respectively.

Table 9. Model accuracy determined using current and FFT variables.

Priority	Variables	Pearson Correlation Coefficient
-	ClmpFrcSnr	1
-	ClmpFrcReqL	0.988
1	Stat_mmPos	0.987
-	Stat_MotTrq	0.915
2	IqMeasd.Ampr	0.887
3	IdMeasd.Ampr	0.881
-	PhaVI.Ampr	0.225
-	ClmpFrcReqR	−0.071
-	BattU.U	−0.865
-	PhaUI.Ampr	NaN
-	MotAgSpdRaw.AgSpd	NaN
-	OverHeatProtn	NaN
-	OverLoadProtn	NaN
-	RackPosn	NaN

ClmpFrcReqL is the target value that the system should reach, and it is not a criterion for performance judgment. Stat_MotTrq can be inferred through IqMeasd.Ampr. BattU.U is not considered a significant factor as the tests were conducted in the same voltage environment.

4. Results

4.1. Validity of Input Variable Selection

Figure 4 depicts the changes in the F1-Score of the Random Forest model trained on the five statistically significant input variables derived from Table 5 based on the number of peaks. The analysis confirmed that there is no significant improvement in accuracy once the number of peaks exceeds 40. Notably, when each variable was used independently, the frequency (Iq) variable derived from the quadrature current had the highest F1-Score, and the F1-Score peaked when all five variables were combined. This indicates that the frequency of quadrature current significantly contributes to the model's predictions and suggests that setting the minimum number of statistically significant peaks to 49 is reasonable.

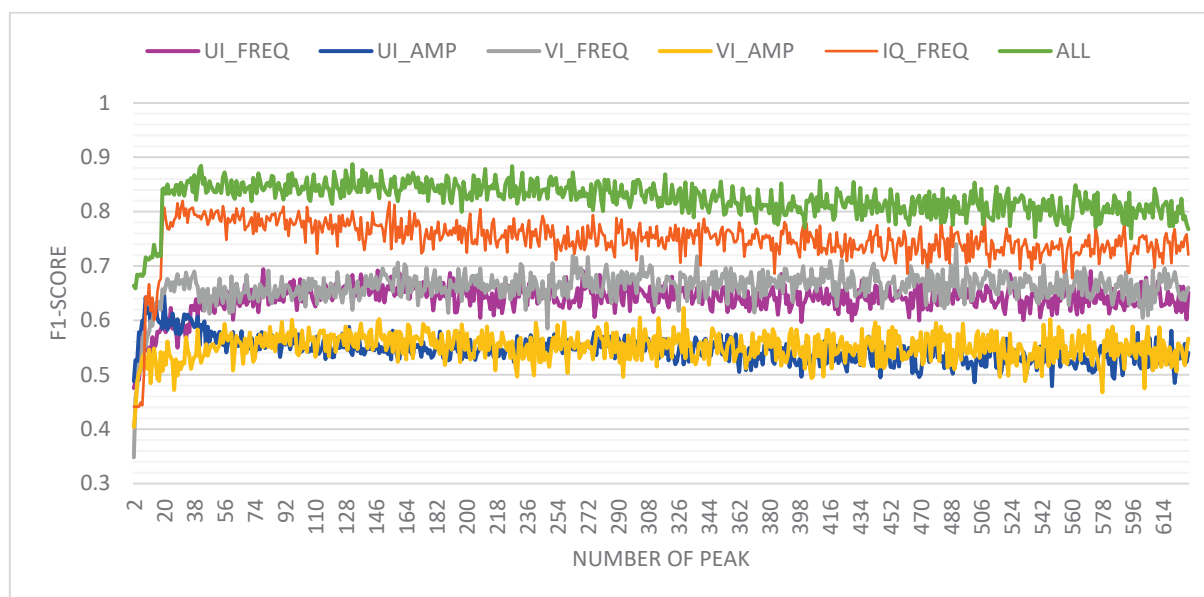


Figure 4. F1-Score according to the number of peaks.

The selection of such variables and the number of peaks hold significant importance for optimizing model performance and reducing computational resources. The contribution of the frequency (Iq) variable is particularly notable, as it is sensitive to changes in current and can effectively detect signs of failure. These results can also reduce economic burdens when applied to real-time monitoring systems for fault prediction, contributing to improving the accuracy and efficiency of fault diagnosis.

To clearly demonstrate the validity of this analysis, the relationship between changes in the F1-Score and the number of peaks was visualized in a graph, illustrating that the optimal number of peaks is 49. This allows for an intuitive understanding of the limits of accuracy based on the number of peaks and emphasizes how the research findings can be applied to real-time predictions and maintenance in industrial settings. For instance, the potential for the frequency (Iq) variable to quickly detect patterns of periodic performance degradation could be discussed in the context of its use as an early-warning system for motors. Through additional data visualization and deepening the implications, the rationale for variable selection and its potential for industrial application can be clarified.

4.2. Fine-Tuning Model Sensitivity

Weights of 15% were applied to the normal state of the motor. The model's decision is based on the probability of the motor states, with the higher probability being the result. For instance, if the probability of the normal state is 30% and the probability of any fault is 31%, the model classifies the state as faulty. However, when the motor is predicted to be faulty, it can still operate adequately, albeit with degraded performance, and meet the system requirements. Therefore, to correct this, weights were assigned to the normal state, and a fault is detected only when the fault probability is 15% higher than the normal probability. This is a compensatory method aimed at reducing fault detection sensitivity. A high fault detection sensitivity leads to unnecessary costs due to frequent inspections.

Tables 10 and 11 show that applying a weight of 15% to the normal state results in a decreased probability of classifying a normal motor as faulty. Although there is an increase in the probability of classifying a faulty motor as normal, this study focuses on the early prediction of faults. Therefore, as there are safety mechanisms in place in the event of an actual fault occurring, this adjustment is deemed acceptable.

Table 10. Unweighted model prediction results.

Test Data (376)				Prediction				
State		Normal	Fault			Normal (Sum)	Fault (Sum)	
			Bearing Fault	Misalignment	Rotor Imbalance			
Actual	Normal	84	5	1	4	84	10	
	Fault	Bearing fault	12	78	0	0	27	255
		Misalignment	9	15	66	9		
		Rotor imbalance	6	7	11	69		

Table 11. Model prediction result with 15% weight added to the normal state.

Test Data (376)				Prediction				
State		Normal	Fault			Normal (Sum)	Fault (Sum)	
			Bearing Fault	Misalignment	Rotor Imbalance			
Actual	Normal	91	1	0	2	91	3	
	Fault	Bearing fault	6	84	0	0	56	226
		Misalignment	39	0	60	0		
		Rotor imbalance	11	0	7	75		

4.3. Experimental Results

After confirming the input variables and the number of peaks through the experimental results, model tuning was conducted, and the results are presented in Table 12. The model-tuning results showed an improvement in overall fault detection accuracy. In particular, the deep learning model exhibited high accuracy with respect to the validation data but low accuracy with respect to the test data due to overfitting. This suggests that the deep learning model requires sufficient data and additional training strategies for stable performance. On the other hand, the Random Forest model demonstrated high performance, showing that combining multiple decision trees increases prediction accuracy and helps prevent overfitting. This model exhibited better generalization performance than individual models, especially in cases with complex and volatile data, achieving the research-goal accuracy of over 80%.

Table 12. Results of model trained with tuned current and FFT data.

Accuracy		Current		FFT (49-Peak)	
Data		Validation Data (280)	Test Data (376)	Validation Data (280)	Test Data (376)
Supervised learning	KNN	89.2%	84.3%	50.6%	36.4%
	Naive Bayes	71.1%	52.1%	70.7%	58.8%
	SVM (RBF)	91.8%	85.1%	62.6%	47.1%
	Decision Trees	89.4%	66.0%	75.7%	73.1%
	MLP	95.9%	79.8%	62.7%	40.7%
Ensemble	Random Forest	97.1%	82.5%	84.9%	84.3% *
Deep learning	RNN (LSTM)	42.9%	39.4%	86.1%	49.2%

Selected model (*).

The process of using one-way ANOVA to select statistically significant variables was a crucial factor in enhancing the efficiency of the model. ANOVA-based feature

selection removed unnecessary variables, retaining only the core variables, thus speeding up the learning process and reducing memory usage. While deep learning models are advantageous when interactions among variables are important, the Random Forest model using FFT demonstrated efficiency by achieving a level of accuracy similar to that of predictions based on existing current data.

The results of PCA (Principal Component Analysis) also had a significant impact on model performance. Analyzing four principal components revealed that the explained variance ratios for these components were 34.15%, 27.70%, 13.97%, and 12.10%, collectively explaining a total of 87.02% of the variance. This indicates that the principal components derived from PCA contain most of the important information from the original data. Notably, the first two principal components alone accounted for 61.85% of the variance, meaning that these two components can explain most of the variability in the data. These analysis results served as important criteria in the process of selecting input variables and contributed to improving the model's predictive performance.

Future research will require additional data to improve the performance of the deep learning model. Data that reflect seasonal factors and various load conditions can contribute to enhancing the generalization performance of this deep learning model. Moreover, additional statistical tests can be conducted to verify the significance of the one-way ANOVA results, thereby increasing the reliability of the variable selection process. Further investigation of deep learning models capable of learning complex interactions among variables is also a direction for future research conducted to enhance fault prediction performance.

Moreover, as shown in the scenario described in Figure 2b, the model successfully detected and predicted faults even under dynamic RPM variations between 0 and 3000 during the process of reaching the target clamping force.

4.4. Actions Based on Results

The factors contributing to performance degradation due to faults can be analyzed for each fault type through Figure 5. In the case of bearing failure, both I_d and I_q currents tended to increase, while the Clamp Force decreased. A similar pattern was observed in cases of rotor imbalance, whereas in the case of misalignment, all variables, including I_d current, I_q current, and Clamp Force, were found to decrease. Changes in these variables play a crucial role in the model's ability to predict the motor's fault condition, enabling appropriate actions to be taken based on specific patterns.

In particular, this study expands upon the torque compensation algorithm proposed in prior research following fault detection. By predicting faults and implementing compensation, it aims to extend the lifespans of motors that have experienced performance degradation and prevent safety incidents. This algorithm compensates for performance degradation through the braking of other motors when a fault is detected.

Figure 6 illustrates the fault prediction strategy used for the D-EMB motor studied. Under normal conditions, the motor operates as expected. However, upon entering the first stage of fault, it detects internal faults and executes the wheel torque control strategy. In the second stage of a fault, both internal and external faults are detected, and the system is designed to notify the operator via the Human-Machine Interface (HMI) to allow for a quicker response. This operational mechanism maximizes the effectiveness of fault prevention and early-warning systems, contributing to the enhancement of the motor's stability and safety.

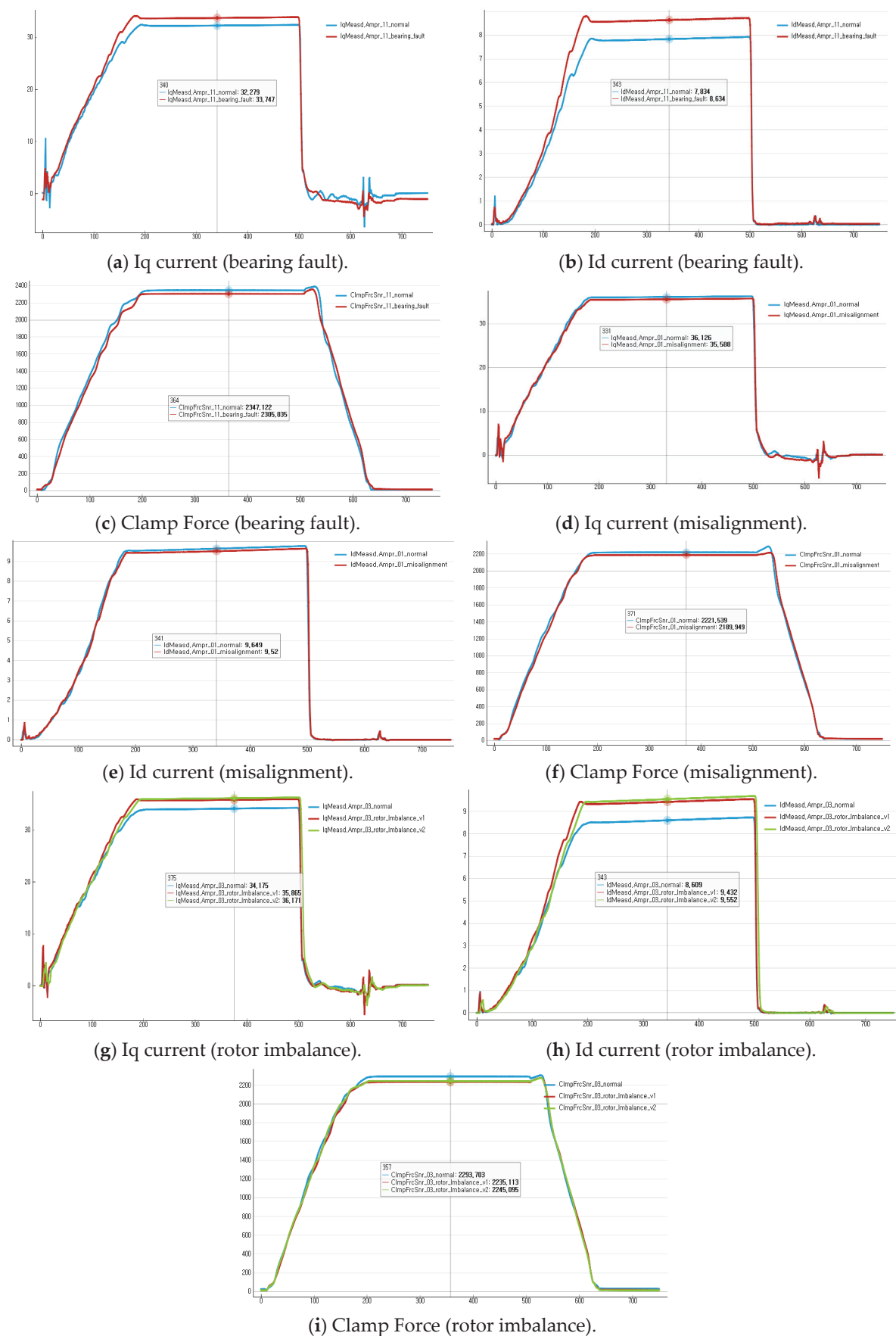


Figure 5. Degree of motor performance deterioration with respect to key variables for each fault.

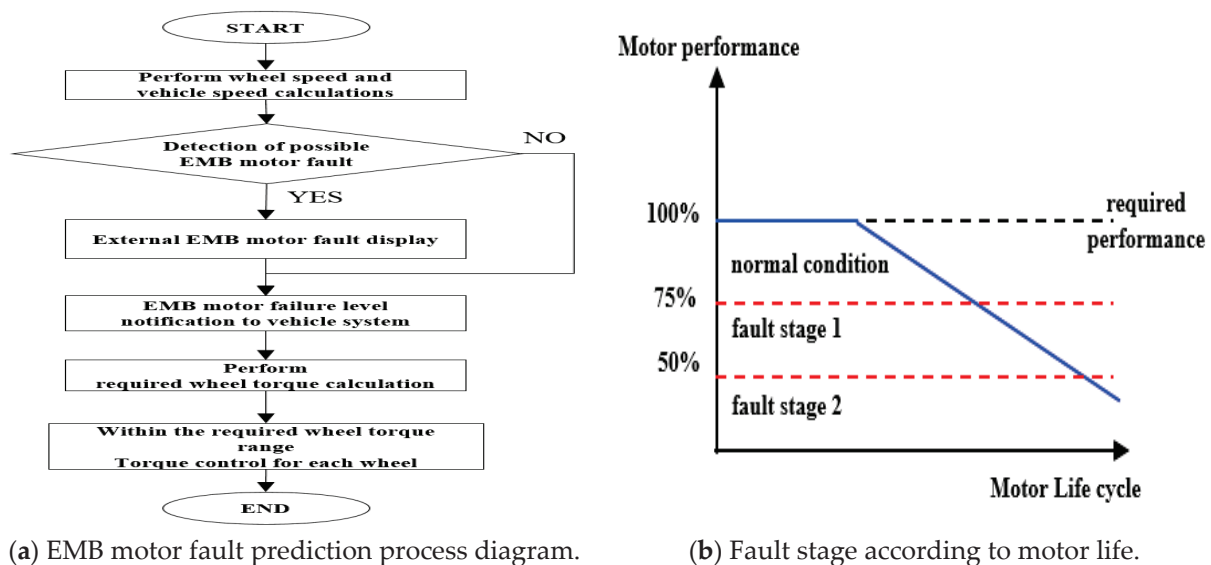


Figure 6. EMB motor fault prediction process diagram.

4.5. Summary

In this study, current waveform data from each of the three phases were transformed into numerically interpretable formats using a Fast Fourier Transform (FFT). This transformation enabled the analysis of current waveform data based on frequency bands and amplitude for each phase, which were critical for identifying key features, such as the types of faults. Specifically, the amplitude and frequency components extracted from the three-phase current data were used for model training to detect motor faults.

The FFT-transformed features, derived from the three-phase current data, were carefully selected based on their statistical relevance to motor state assessment. These selected features were subsequently combined and tested across various machine learning models, leading to the development and tuning of a predictive model for motor faults in the D-EMB system.

The developed three-phase motor fault prediction model achieved an impressive accuracy of over 80%, ensuring transparency and reliability in its predictive results. This model is effective not only in predicting faults but also in detecting performance degradation due to faults. While the clamping force data were not used for model training, they played a key role in assessing fault severity. These data allowed the model to evaluate the severity of faults, consequently informing control strategies for fault prediction and response. By assessing the degree of performance decline during the prediction process, the model assists in implementing timely corrective actions.

Moreover, the outcomes of this research are expected to enhance motor maintenance and operational efficiency. Future studies should focus on integrating this model into real-time monitoring systems to further advance fault prediction and response strategies.

5. Conclusions and Recommendations

In this research, we successfully utilized AI-based FFT analysis to predict motor failures in the D-EMB system. The developed model contributes to predicting failures with high accuracy and effectively identifies their severity. These predictive models have the potential to significantly enhance vehicle safety, enabling the development of innovative safety mechanisms that address faults before they impact vehicle operation.

The proposed model was specifically trained and validated via a three-phase motor system used in the D-EMB assembly. While the model demonstrates high accuracy within this context, its applicability to other motor types, such as induction motors, or three-phase motors of different sizes, has not been evaluated. To generalize the model for broader use, additional training data covering diverse motor types, operational conditions, and

sizes would be required. Future work will aim to investigate the model's robustness and adaptability across these varied scenarios.

Future research must focus on further validating the model's performance across various experimental environments to ensure its effectiveness under diverse real-world conditions. In particular, efforts should be directed toward improving the model's adaptability and reliability by incorporating a wider range of driving scenarios and environmental factors. Additionally, it is crucial to conduct research that systematically gathers and analyzes performance degradation data according to the severity of failures, which will ultimately improve model robustness and accuracy.

Moreover, future research directions should ensure the technical rigor of the proposed models, allowing thorough explanations and justifications of technical aspects. Clarity and precision in conveying complex concepts will be vital. Additionally, exploring the integration of predictive models with other vehicle systems and incorporating cutting-edge technologies and techniques like IoT, V2X communication, and edge computing will be a key challenge and an exciting area for future development.

The findings of this study can also extend to other advanced transportation technologies, such as autonomous vehicles. With their reliance on advanced data analysis and real-time decision-making, these technologies are poised to enhance the safety of autonomous driving systems, contributing to safer, more reliable driving experiences. However, discussions on the practical integration and standardization of such technologies within the automotive industry will be necessary to ensure their successful implementation and compliance with current regulatory frameworks, such as ISO 26262 and AUTOSAR.

The primary contribution of this study lies in its application of AI and data analysis technologies within the automotive industry, which may also be leveraged in other fields, offering substantial potential for cross-industry innovation. This work paves the way for future automotive technologies, particularly in autonomous vehicles, and opens up opportunities for broader technological advancements.

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Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the authors.

Conflicts of Interest: Hyun Jee is an employee of HL Mando. The paper reflects the views of the scientists, and not the company.

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Article

Charting the Path to Electrification: Analyzing the Economic and Technological Potential of Advanced Vehicle Powertrains [†]

Ehsan Sabri Islam *, Ram Vijayagopal and Aymeric Rousseau

Argonne National Laboratory, 9700 South Cass Avenue, Lemont, IL 60439, USA; rvijayagopal@anl.gov (R.V.); arouseau@anl.gov (A.R.)

* Correspondence: eislam@anl.gov; Tel.: +1-630-252-2841

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Abstract: The U.S. Department of Energy’s Vehicle Technologies Office (DOE-VTO) is driving advancements in highway transportation by targeting energy efficiency, environmental sustainability, and cost reductions. This study investigates the fuel economy potential and cost implications of advanced powertrain technologies using comprehensive system simulations. Leveraging tools such as Autonomie and TechScape, developed by Argonne National Laboratory, this study evaluates multiple timeframes (2023–2050) and powertrain types, including conventional internal combustion engines, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). Simulations conducted across standard regulatory driving cycles provide detailed insights into fuel economy improvements, cost trajectories, and total cost of ownership. The findings highlight key innovations in battery energy density, lightweighting, and powertrain optimization, demonstrating the growing viability of BEVs and their projected economic competitiveness with conventional vehicles by 2050. This work delivers actionable insights for policymakers and industry stakeholders, underscoring the transformative potential of vehicle electrification in achieving sustainable transportation goals.

Keywords: electric vehicle; light duty; simulation

1. Introduction

The evolution of powertrain technology, including advances in internal combustion (IC) engines, battery systems, electrification, and lightweight materials, is crucial for reducing vehicle fuel consumption and emissions. Quantifying the impact of these advancements typically involves metrics such as fuel consumption and carbon dioxide (CO₂) emissions per mile, especially when evaluated on standardized regulatory driving cycles such as the Urban Dynamometer Driving Schedule (UDDS) or the Federal Test Procedure (FTP) [1]. System simulation has emerged as a dominant tool for assessing the long-term impact of these technologies as it allows for the evaluation of complex vehicle models that integrate various technological innovations [2].

Innovations in IC engines, battery systems, and regenerative braking strategies have emerged as critical enablers for improving energy efficiency and reducing emissions [3,4]. Regulatory frameworks such as EURO (Europe) [5], Tier 3 (United States) [6–9], and Japan’s Post-New Long-Term Standards play a pivotal role in driving the adoption of advanced technologies, including electrified powertrains and lightweight materials [10–13]. These regulations set stringent performance targets that necessitate continuous advancements in vehicle technologies to ensure compliance. Meeting these standards is further supported by

technological innovations such as material substitution, battery chemistry advancements, and streamlined manufacturing processes, as highlighted in recent studies [14,15].

While these studies focus on specific aspects of vehicle electrification, a comprehensive analysis integrating fuel economy, cost, and performance across multiple powertrain configurations and timeframes remains limited. This work bridges this gap by leveraging advanced simulation tools to evaluate the long-term potential of vehicle electrification technologies. By combining insights from energy efficiency metrics, emissions testing regimes, and cost modeling, this study provides a holistic perspective on the evolution of vehicle technologies [16].

The U.S. Department of Energy's Vehicle Technologies Office (DOE-VTO) has played a central role in guiding the development of these technologies by establishing performance targets in areas such as IC engines, transmissions, fuel cell systems, and vehicle electrification [17]. The analysis presented in this study uses the Autonomie simulation tool, developed by Argonne National Laboratory, to rigorously assess the implications of these advancements [18]. Autonomie enables a detailed examination of powertrain configurations, including conventional IC vehicles, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). These simulations align with DOE-VTO performance targets and include improvements in fuel efficiency, reductions in total cost of ownership (TCO), and compliance with regulatory standards [14,15].

The analysis also extends to the cost implications of advanced vehicle technologies. Using TechScape [19], a complementary cost modeling tool, this study evaluates manufacturing and operational costs, providing detailed insights into how these advancements drive economic feasibility [17]. Regulatory driving cycles, including UDDS, FTP, and US06, serve as the foundation for evaluating vehicle performance across a range of powertrain configurations and electrification levels [14,15]. By focusing on the small SUV vehicle class—a key segment in terms of energy consumption and emissions—this article offers a representative analysis of how future technologies can impact both fuel economy and costs.

Economic considerations are critical to the adoption of advanced powertrains. The decreasing cost of batteries and electric motors has made HEVs, PHEVs, and BEVs increasingly attractive to consumers. Studies by Nykvist and Nilsson [20] and Ziegler and Trancik [21] highlight rapid declines in battery pack costs, driven by improvements in manufacturing processes and material efficiencies. These trends are essential to achieving cost parity between electrified and conventional vehicles, solidifying the viability of electrified powertrains in the long term.

The broader objective of this study is to contribute to the ongoing discussions about the future of automotive technologies as the industry transitions toward electrification and away from traditional gasoline-powered vehicles. Through a combination of rigorous simulation and in-depth cost analysis, this article offers valuable insights into the potential benefits and challenges of advanced vehicle technologies. The findings aim to inform policymakers, manufacturers, and researchers about the opportunities for accelerating the shift to sustainable transportation solutions.

2. Procedure

The evaluation framework outlined in this article hinges on a thorough examination of different vehicle technology targets specified by the U.S. DOE-VTO, with an emphasis on understanding the impact of these advancements over multiple timeframes, from 2023 through 2050. This longitudinal analysis offers an in-depth view of how powertrain technologies evolve over time, with a particular focus on the implications for vehicle performance, energy consumption, and cost efficiency. Figure 1 shows the simulation framework for the study.

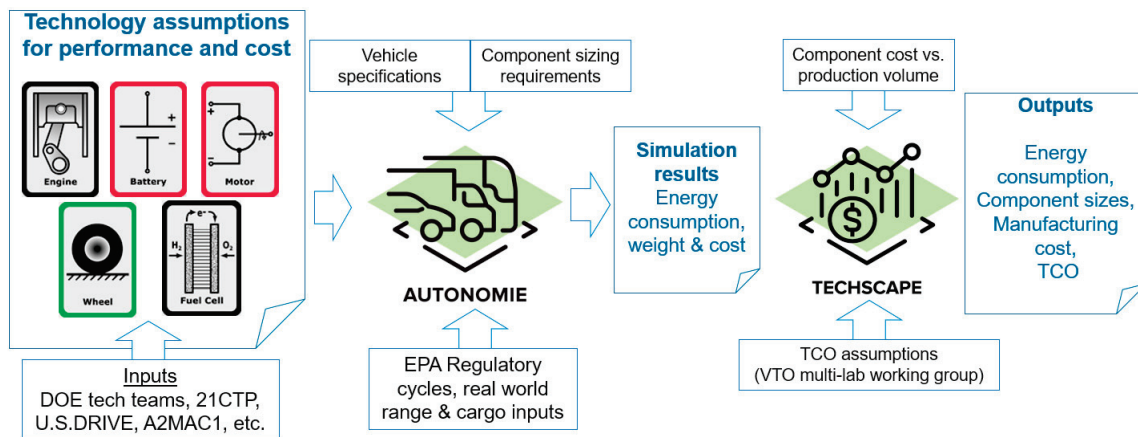


Figure 1. Argonne integration simulation framework.

The simulation framework is divided into three critical steps:

1. **Assumptions collection:** The first step involves gathering detailed assumptions regarding powertrain technology progress from publicly available U.S. DOE-VTO targets and reports [14,17]. This includes parameters like engine efficiency, battery energy density, electric motor specific power, and advancements in lightweighting technologies. These assumptions form the foundation for the vehicle models developed in this study. The data in Table 1 were sourced from government reports, including DOE vehicle performance targets, ICCT studies on electrification trends [8], and industry benchmarks [12,13]. These data ensure alignment with state-of-the-art knowledge in powertrain technologies.
2. **Powertrain and vehicle simulation:** In the second step, the Autonomie vehicle system simulation tool [18] is employed to size powertrain components and build the vehicle models from the ground up, using the collected assumptions. The tool simulates energy consumption based on different vehicle types—conventional internal combustion engine (ICs) vehicles, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs)—and applies the U.S. DOE-VTO performance targets. Autonomie ensures that the simulated vehicles meet critical specifications like 0–60 mph acceleration time, gradeability, and maximum speed. The energy consumption is calculated over standard regulatory drive cycles such as the UDDS, FTP, and US06 cycles [15,20].
3. **Cost evaluation:** The final step utilizes the TechScape tool to compute the manufacturing cost and total cost of ownership (TCO) of the vehicles. By combining the outputs of Autonomie with cost estimates for advanced powertrain components—such as electric machines and batteries—the TCO analysis provides a comprehensive economic perspective on the potential adoption of advanced vehicle technologies using TechScape [19].

The overall procedure is designed to offer insights into the transformative potential of future vehicle technologies, particularly in terms of both performance and cost. For instance, by 2050, engine efficiency is projected to increase to 47% in the high-progress scenario, while battery pack energy densities for BEVs may exceed 337 Wh/kg, driving significant reductions in vehicle weight and energy consumption. Additionally, manufacturing costs are expected to decrease dramatically due to improvements in lightweight materials and economies of scale in battery production, as shown in Table 1.

The detailed examination of these assumptions, particularly for future years like 2035 and 2050, allows for a comprehensive understanding of how powertrain technologies are

expected to progress. The methodology provides a solid foundation for the subsequent analysis of vehicle sizing, energy consumption, and cost.

Table 1. Technology assumptions.

	2023	2025		2035		2050	
	Low	Low	High	Low	High	Low	High
Conventional Engine Peak Efficiency (%)	36	38	43	42	45	44	47
Hybrid Engine Efficiency (%)	40	40	46	41	48	43	50
Electric Machine Cost (USD/kW)	12	9	6	4.8	3.2	2.25	1.5
Specific Power @ 70% SOC—HEVs (W/kg)	2750	3000	4000	4500	5500	5000	6000
Battery Pack Energy Density—PHEV (Wh/kg)	100	136	140	147	165	144	189
Battery Pack Energy Density—BEV (Wh/kg)	189	189	244	255	308	298	337
Battery Pack Cost—HEVs (USD/kW)	20	20	16	18	14	17	13
Battery Pack Cost—PHEV (USD/kWh)	200	150	110	90	75	70	60
Battery Pack Cost—BEV (USD/kWh)	140	128	95	90	70	70	60

2.1. Autonomie Vehicle Modeling

Autonomie employs a physics-based modeling approach to simulate energy flows and performance across powertrain components. The tool integrates vehicle-specific parameters (e.g., weight, aerodynamics, drivetrain) with regulatory drive cycles (UDDS, FTP, US06) to calculate fuel economy, energy consumption, and performance metrics. The primary assessment indicators used in this study include:

- Fuel consumption: measured in L/100 km or kWh/100 km for electrified powertrains.
- Powertrain power: calculated as the required engine or motor output in kW.
- Component costs: focused on manufacturing costs of batteries and electric motors.
- Total cost of ownership (TCO): a metric integrating vehicle purchase price, maintenance, and energy consumption.

Simulations were conducted on a high-performance computing system, ensuring accurate and scalable modeling across timeframes and vehicle configurations.

The key parameter settings for vehicle modeling and simulation included:

- Battery energy density: projected to increase from 189 Wh/kg (2023) to 337 Wh/kg (2050) based on DOE-VTO performance targets.
- Electric motor efficiency: improved from 90% (2023) to 95% (2050).
- Vehicle weight: assumes reductions of 10–20% due to lightweighting strategies, such as the use of high-strength steel and composites.
- Drive cycles: standardized regulatory cycles (UDDS, FTP, US06) were used to ensure consistent evaluation of fuel economy and emissions.

These parameter assumptions are derived from DOE reports, industry benchmarks, and peer-reviewed literature. This setup allows for a detailed analysis of the performance and cost trajectories of advanced powertrains across multiple timeframes.

2.2. Vehicle and Components Sizing

The accurate sizing of vehicle components is essential to ensure that each simulated vehicle meets the performance targets established by the U.S. DOE-VTO. The assumptions outlined in the previous section serve as critical inputs to the vehicle sizing algorithms, which are tailored to each specific vehicle class. These algorithms ensure that vehicles meet key performance specifications, including the 0–60 mph acceleration targets shown in Table 2.

Table 2. Vehicle classification, performance categories, and characteristics.

Vehicle Class	Performance Category	0–60 mph Time (s)	Frontal Area (m ²)	Drag Coefficient	Rolling Resistance
Compact	Base/Premium	9/7	2.3	0.31	0.006
Midsize	Base/Premium	8/6	2.35	0.3	0.006
Small SUV	Base/Premium	8/6	2.65	0.36	0.006
Midsize SUV	Base/Premium	9/7	2.85	0.38	0.006
Pickup	Base/Premium	7/7	3.25	0.42	0.006

The sizing process is highly iterative. The vehicle models are built from the ground up, with every component from the engine to the battery pack being designed to meet specific performance criteria. For instance, the engine power is sized to meet the acceleration and gradeability targets for conventional vehicles while the electric motor and battery pack are sized to capture all of the regenerative braking energy for hybrid vehicles. This iterative process ensures that each assumption (e.g., specific power, efficiency) influences key vehicle characteristics (e.g., curb weight, energy consumption) and that the system converges after 5 to 10 iterations to meet all specifications.

Specific algorithms are employed for different powertrain types (e.g., conventional, series hybrid, electric) and applications (e.g., HEV, PHEV, BEV). Figure 2 illustrates the various steps involved in sizing a conventional vehicle powertrain. The same approach is applied to hybrid and plug-in hybrid powertrains, with the necessary modifications to account for electric machine and battery power levels.

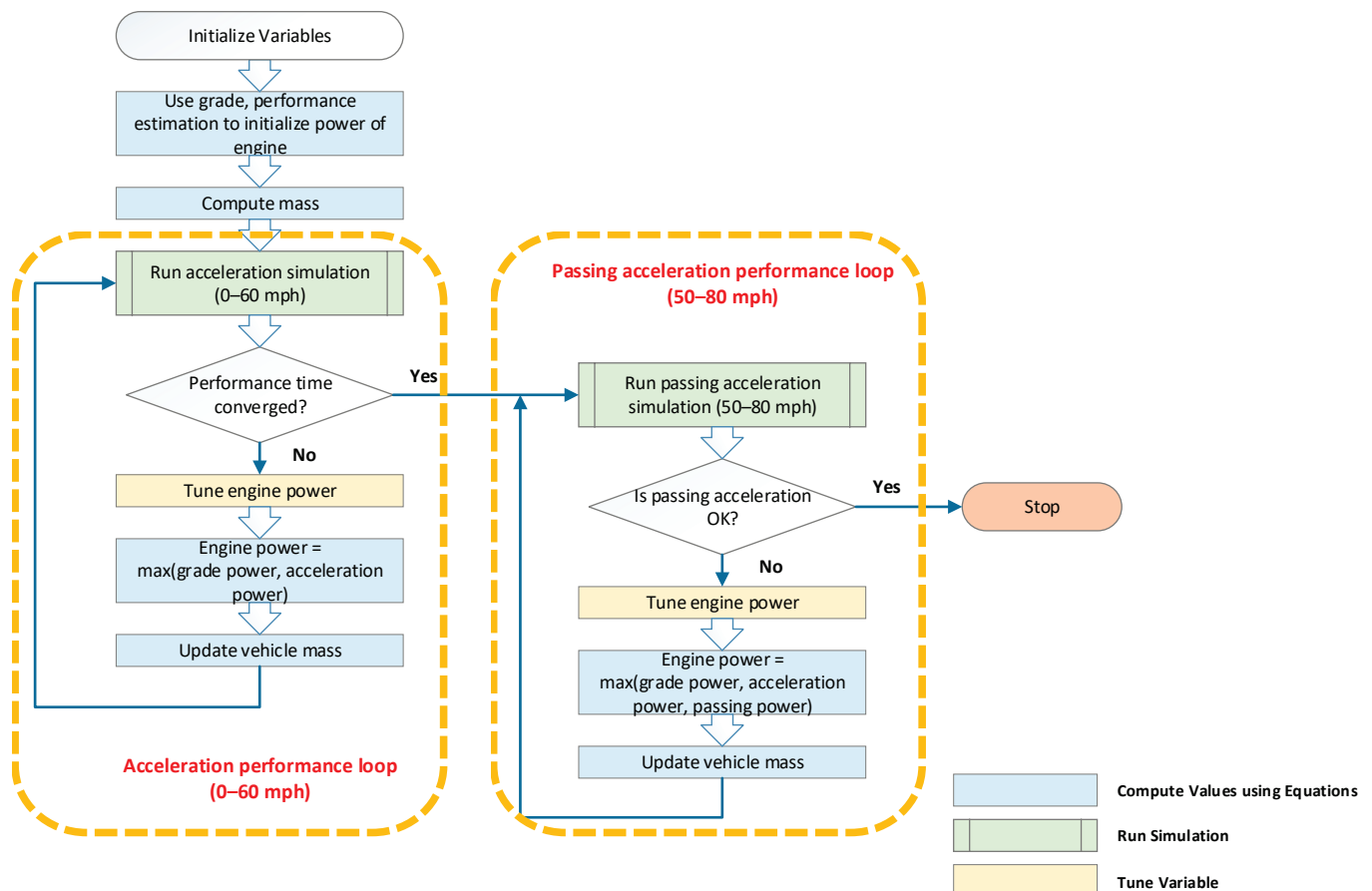


Figure 2. Conventional powertrain sizing algorithm. Reprinted with permission from Ref. [22]. 2024, Islam.

For HEVs, the sizing process assumes that the electric machine and battery are capable of capturing all regenerative energy from the Urban Dynamometer Driving Schedule (UDDS) cycle. The internal combustion engine and electric generator are then sized to meet gradeability and performance requirements, ensuring that the vehicle meets all acceleration and load-bearing targets.

For PHEVs, which operate with a specific electric-only range (e.g., 20 or 50 miles of all-electric range, AER), the power levels of the electric machine and battery are designed to ensure that the vehicle can operate in electric mode for the duration of the US06 cycle, which represents more aggressive driving conditions. While the sizing process is primarily concerned with ensuring that the vehicle meets these performance targets, a blended control strategy is used during energy consumption assessments to optimize overall performance.

Finally, for BEVs, the battery's usable energy capacity of the battery pack was calculated to meet the vehicle's combined driving cycle mileage as defined by EPA sticker values. This approach ensures consistency in assessing performance while accounting for advancements in battery energy density and manufacturing efficiency [20,21].

This sizing methodology, combined with the advanced simulation tools employed in this study, allows for a robust evaluation of future vehicle performance across multiple powertrain types and electrification levels.

3. Results and Observations

This section presents a detailed examination of the simulation results, highlighting the sizing of key components and their impact on fuel economy and cost. By simulating vehicles across a range of powertrains and performance categories, the results offer a clear perspective on the evolving role of electrification and powertrain advancements.

3.1. Component Sizes

The analysis begins by examining the engine power sizing across different vehicle classes and electrified powertrains, with a focus on the small SUV category. For example, over the period ranging from 2023 to 2050, engine power gradually decreases from 170 kW to 130 kW for conventional vehicles as a result of improvements in lightweighting and component efficiency. The premium category, which has more aggressive performance targets, shows a slightly higher engine power compared with the base category, as illustrated in Figure 3.

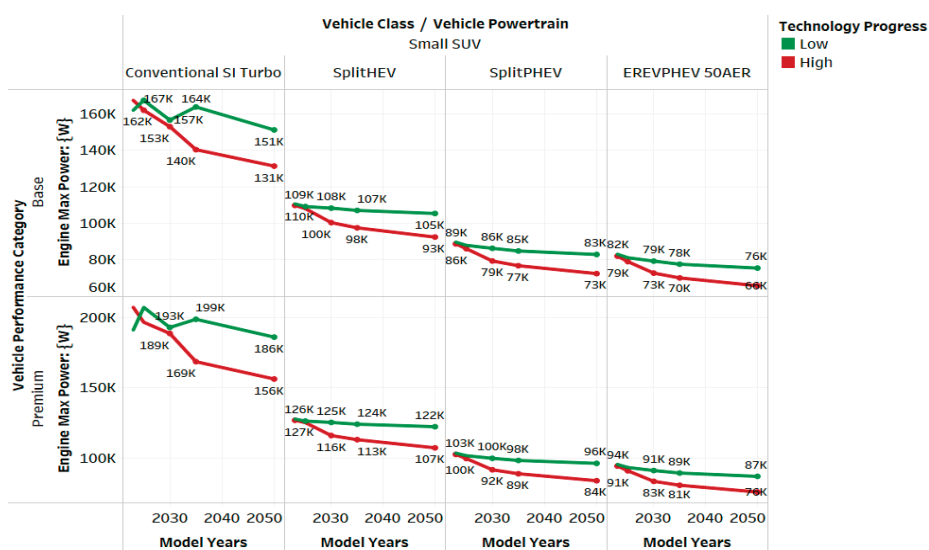


Figure 3. Engine peak power for small SUVs across performance categories.

The trend in engine power reduction is consistent across all powertrain types, including conventional, hybrid, and plug-in hybrid vehicles. For example, the engine peak power for midsize SUVs decreases by 10–15% between 2023 and 2050, driven by advancements in lightweight materials and aerodynamic improvements [14,15].

Motor power also follows a similar downward trajectory. As shown in Figure 4, the motor peak power for small SUVs decreases over time, with significant reductions being observed for BEVs and PHEVs. The improved efficiency of electric machines, combined with advancements in battery technology, enables these reductions while maintaining or improving vehicle performance. By 2050, motor power is expected to be reduced by approximately 25–30% compared with 2023 levels, due to the combined effects of vehicle lightweighting and advanced powertrain technologies [14].

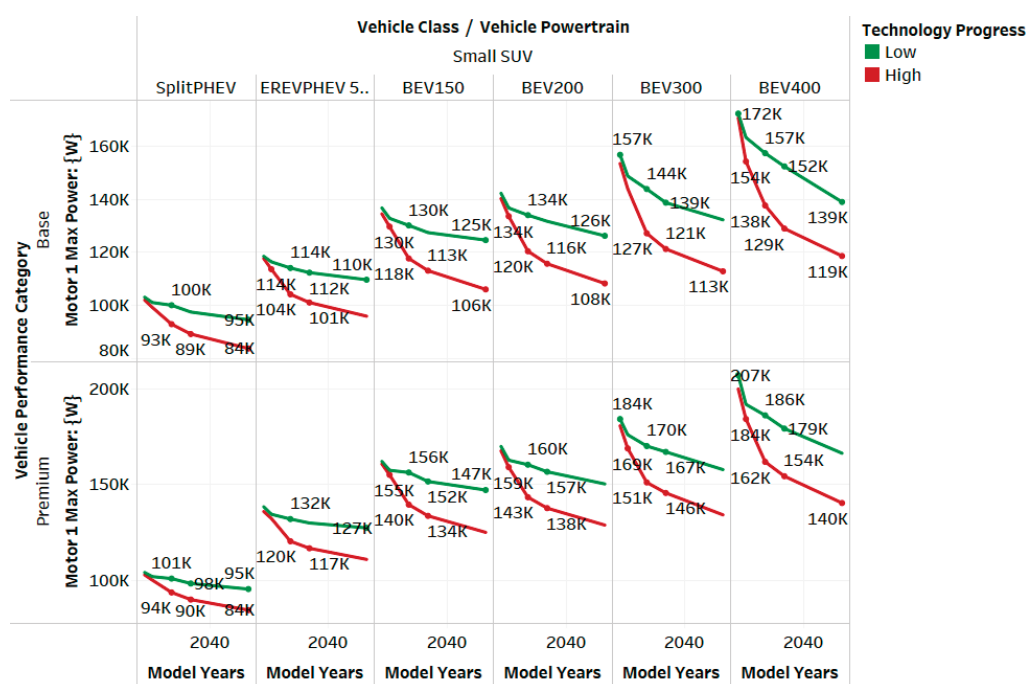


Figure 4. Motor peak power (W) for small SUVs across performance categories.

In addition to motor and engine sizing, the total energy required by the battery packs in electrified vehicles also declines over time. Figure 5 illustrates the total battery energy required for small SUVs across different electrified powertrains. For example, BEVs with a 200-mile range (BEV200) see a 35% reduction in battery energy requirements by 2050 under the high-progress scenario compared with 2023, reflecting technological advancements in battery chemistry [23,24]. This reduction reaches almost 40% for BEVs with a 400-mile range (BEV400) due to improvements in battery energy density and overall vehicle efficiency [18,23].

These reductions in engine, motor, and battery sizes highlight the impact of continuous technological improvements, particularly in component efficiency and lightweighting. By optimizing vehicle performance through better component sizing, future powertrains are expected to achieve significant gains in both fuel economy and cost savings.

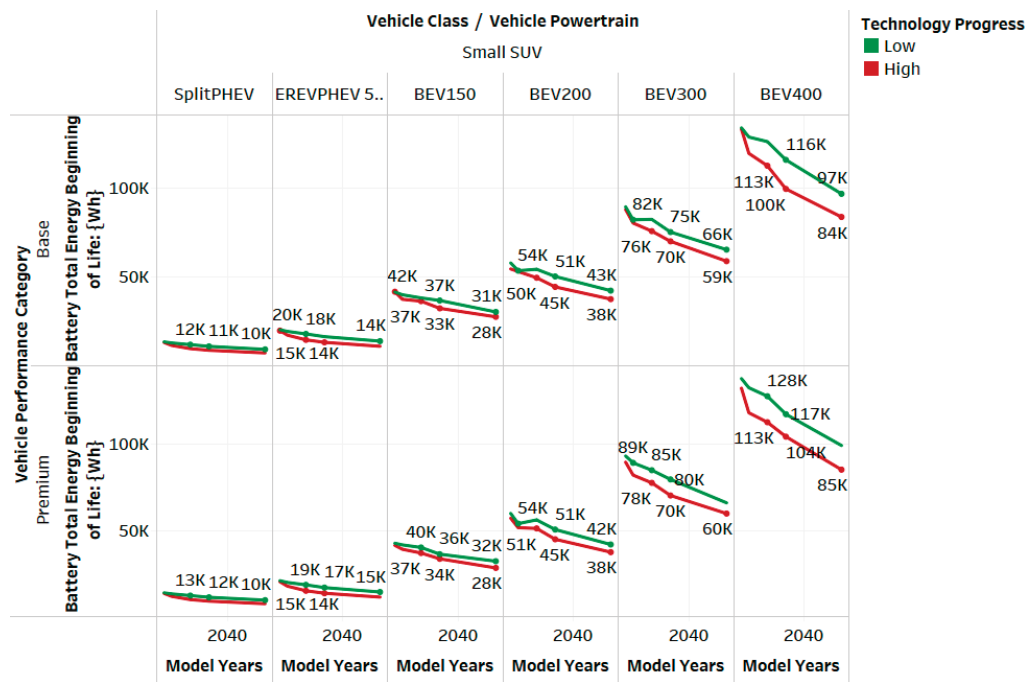


Figure 5. Battery total energy for small SUVs across performance categories.

3.2. Energy Consumption

The energy consumption analysis builds upon the component sizing results, offering insights into how fuel consumption evolves across different powertrains. Figure 6 shows the adjusted fuel consumption (utility-weighted for PHEVs) based on the EPA-combined cycle label for small SUVs.

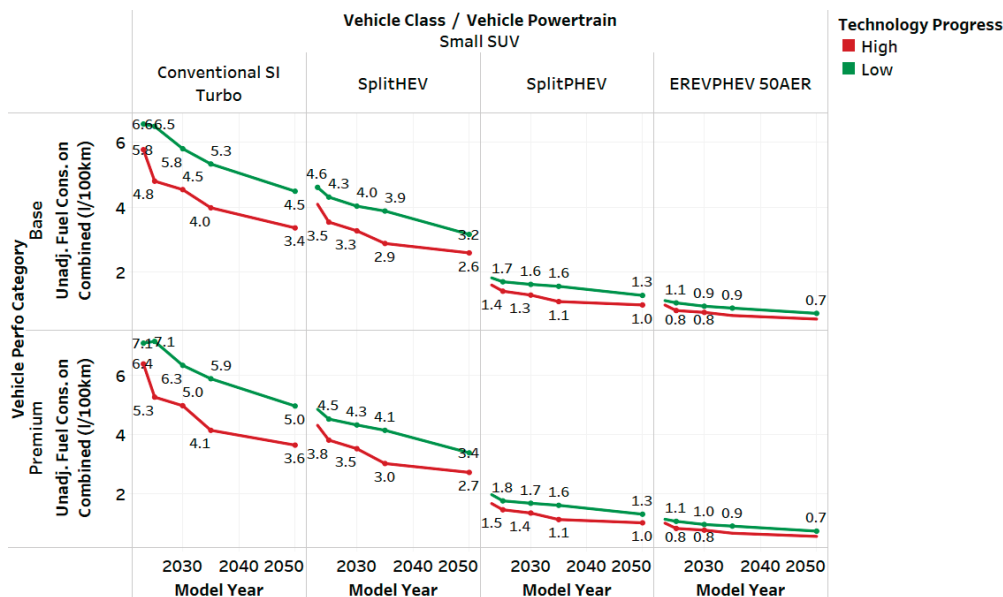


Figure 6. Unadjusted fuel consumption (utility-weighted for PHEVs) on the EPA-combined cycle for small SUVs.

The fuel consumption of electrified powertrains decreases steadily over time, with the most significant reductions occurring in BEVs and PHEVs. For example, the fuel consumption of small SUV PHEVs with a 20-mile AER (PHEV20) decreases by 62–64% by 2050 compared with conventional gasoline vehicles [14]. The higher vehicle weight of

premium category models explains the higher fuel consumption in comparison with base models, but this difference diminishes over time as lightweighting technologies advance.

Figure 7 illustrates the adjusted electrical energy consumption (utility-weighted for PHEVs) for small SUV electrified powertrains. Similar to fuel consumption, electrical energy consumption also declines significantly by 2050, particularly for BEVs with higher ranges.

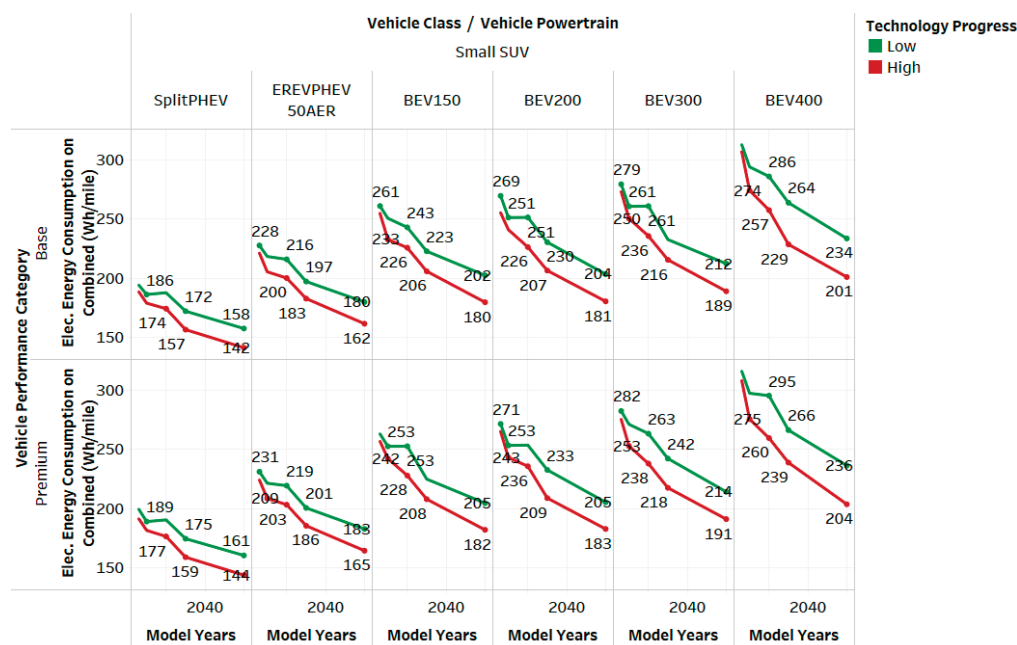


Figure 7. Adjusted DC electrical energy consumption on the combined label (Wh/mile) for small SUVs.

The reduction in energy consumption is driven by advancements in battery energy density, electric machine efficiency, and lightweighting. These reductions, combined with steady improvements in conventional engine efficiency, paint a positive picture of the future trajectory of vehicle energy consumption, particularly for electrified powertrains [14,15].

Table 3 summarizes the energy consumption improvements for various powertrain types across the simulation timeframes, highlighting the significant efficiency gains achieved through advancements in powertrain technologies.

Table 3. Energy consumption improvements across powertrain configurations and timeframes summary.

Powertrain Type	2023	2030	2050	% Improvement (2023–2050)
Conventional	6.6 L/100 km	5.8 L/100 km	3.4 L/100 km	48%
HEV	4.6 L/100 km	4.0 L/100 km	2.6 L/100 km	43%
PHEV (Split PHEV)	1.7 L/100 km	1.6 L/100 km	1.0 L/100 km	41%
BEV (400)	322 Wh/mile	265.3 Wh/mile	208.6 Wh/mile	35%

4. Cost Analysis

The cost of manufacturing battery packs, motors, and other components is projected to decline significantly over time. While innovations in battery chemistry and energy density initially increase development costs, advancements in manufacturing processes, economies of scale, and supply chain optimizations offset these costs. For example, the cost of batteries is expected to decrease from 200 USD/kWh in 2023 to 60 USD/kWh in

2050, driven by higher production volumes and improvements in cathode and anode materials. Similarly, motor costs are projected to decline by over 80%, reflecting increased manufacturing efficiency and material utilization.

4.1. Component Cost

Electric motor costs are expected to decrease significantly over time, as shown in Figure 8. By 2050, the manufacturing cost of electric motors for small SUVs is projected to be 75–82% lower than in 2023, thanks to improvements in manufacturing processes, economies of scale, and material efficiency [11,12]. This trend is consistent across all electrified powertrains, although higher-performance models in the premium category tend to have slightly higher costs due to their more aggressive performance targets.

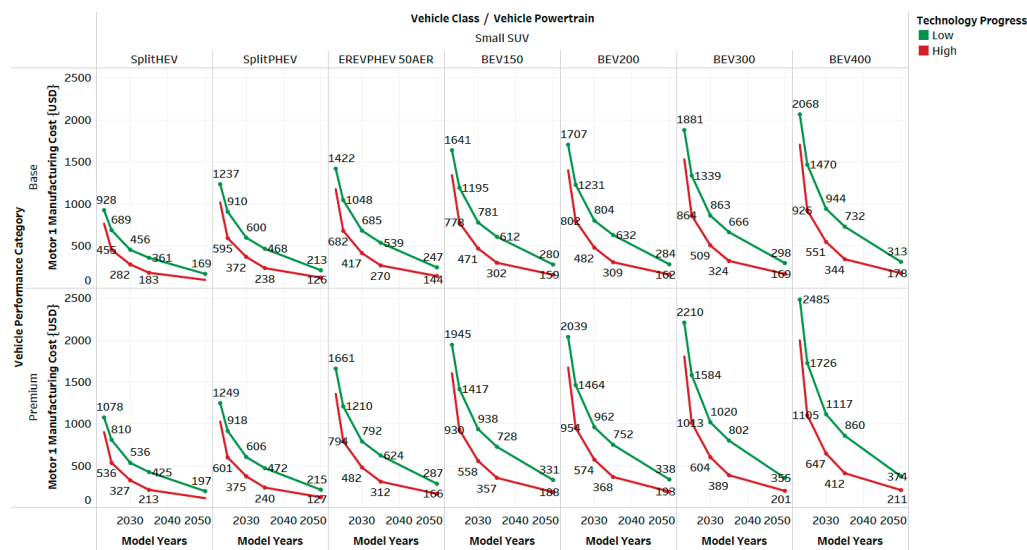


Figure 8. Motor cost of small SUVs.

Similarly, battery pack costs exhibit a sharp decline over the simulation timeframe. Figure 9 shows the cost trajectory for high-voltage battery packs across various powertrains. Battery costs for HEVs, PHEVs, and BEVs decline by 21–44%, 44–79%, and 76–87%, respectively, over the period ranging from 2023 to 2050. This decrease in battery costs is attributed to advances in battery chemistry, improvements in manufacturing processes, and increased energy density, which allows for smaller and more efficient battery packs [9].

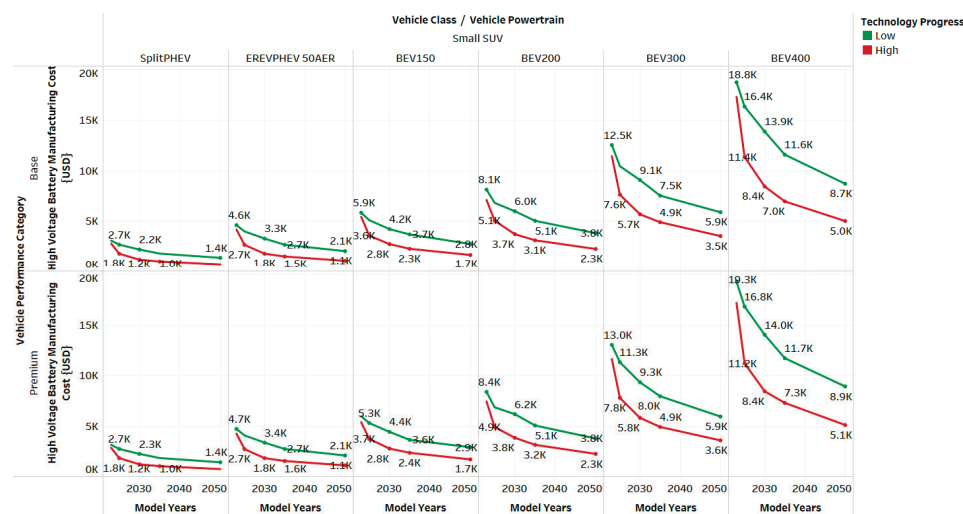


Figure 9. Battery cost for small SUVs.

The reduction in battery size and cost is particularly impactful for BEVs with higher ranges. For instance, BEVs with a 400-mile range experience a greater reduction in manufacturing costs due to the combined effects of battery energy density improvements and lightweighting [10].

4.2. Vehicle Manufacturer Suggested Retail Price (MSRP)

The reduction in component costs translates into lower vehicle manufacturing costs and, by extension, lower manufacturer suggested retail prices (MSRPs). Figure 10 shows the projected MSRPs for small SUVs across different powertrain types, reflecting the impact of technology progress on vehicle cost. The MSRPs for BEVs, which are initially 50–150% higher than conventional gasoline vehicles in 2023, are expected to become cost-competitive by 2050 [6,14].

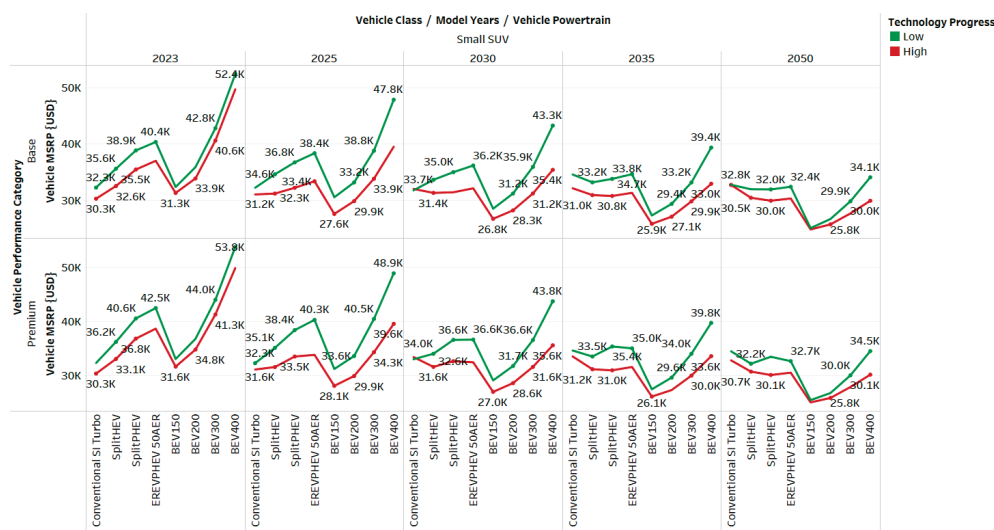


Figure 10. Vehicle MSRPs of small SUVs.

The cost reductions are driven by declining battery and electric machine costs as well as improvements in vehicle design and manufacturing efficiency. By 2050, BEVs are projected to have a 10–20% lower MSRP than conventional gasoline vehicles, marking a significant milestone for the adoption of electrified powertrains [14,15]. These cost reductions are expected to accelerate the market penetration of BEVs, particularly in vehicle segments like small SUVs, where fuel economy and cost savings are critical factors for consumers.

Table 4 summarizes the motor, battery cost, and vehicle MSRP improvements for BEV400 AERs across the simulation timeframes for small SUVs, achieved through advancements in powertrain technologies.

Table 4. Projected cost reductions for batteries, motors, and vehicle MSRP for BEV 400 for small SUVs.

Cost Component	2023	2030	2050	% Improvement (2023–2050)
Battery	18,751	13,882	5036	73%
Motor	2068	944	178	91%
Vehicle MSRP	52,382	43,265	29,955	43%

4.3. Energy Consumption vs. Vehicle Manufacturing Cost

In this section, we explore the relationship between energy consumption and vehicle manufacturing costs across different powertrains. The objective is to assess how advancements in vehicle technologies influence both the fuel consumption and the overall cost of

production. The results from this analysis highlight the trade-offs between cost reductions and fuel economy improvements as technology progresses.

Figure 11 illustrates the manufacturing cost versus fuel consumption for conventional vehicles across various vehicle classes, including compact cars, midsize vehicles, and SUVs. The different-colored lines represent trend lines for each class, showing how these relationships evolve over time. One notable observation is that diesel vehicles tend to have higher manufacturing costs compared with gasoline-powered vehicles, primarily due to the increased cost of diesel engines and after-treatment systems [1,9].

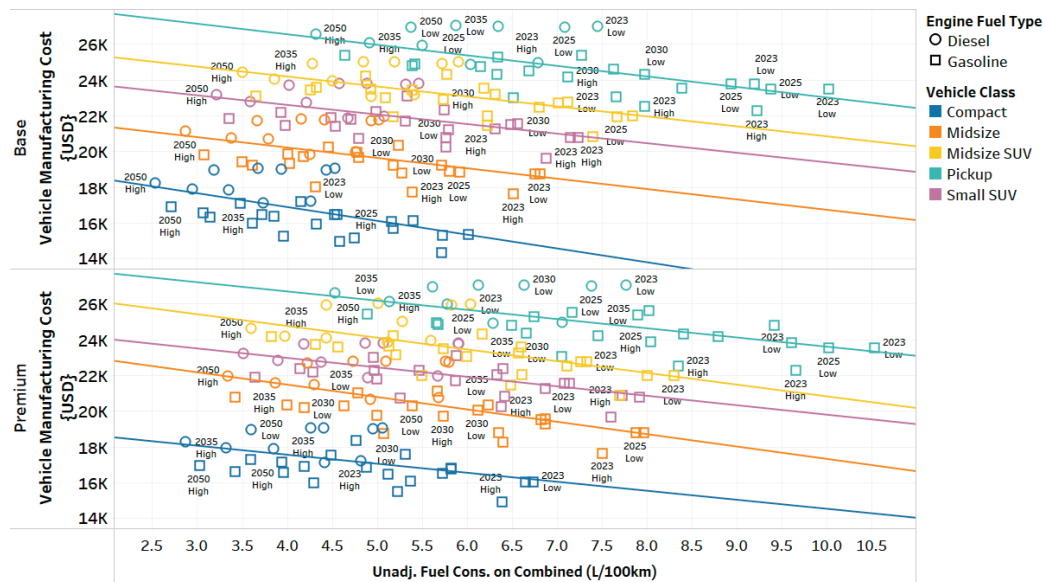


Figure 11. Manufacturing cost vs. fuel consumption of conventional vehicles.

By contrast, hybrid electric vehicles (HEVs) show a different trend. As illustrated in Figure 12, the manufacturing costs for HEVs decrease over time due to cost reductions in battery packs, electric machines, and other components. Despite the higher initial cost of HEVs, fuel consumption is significantly lower than that of conventional vehicles, making HEVs more cost-effective in the long run [2,6].

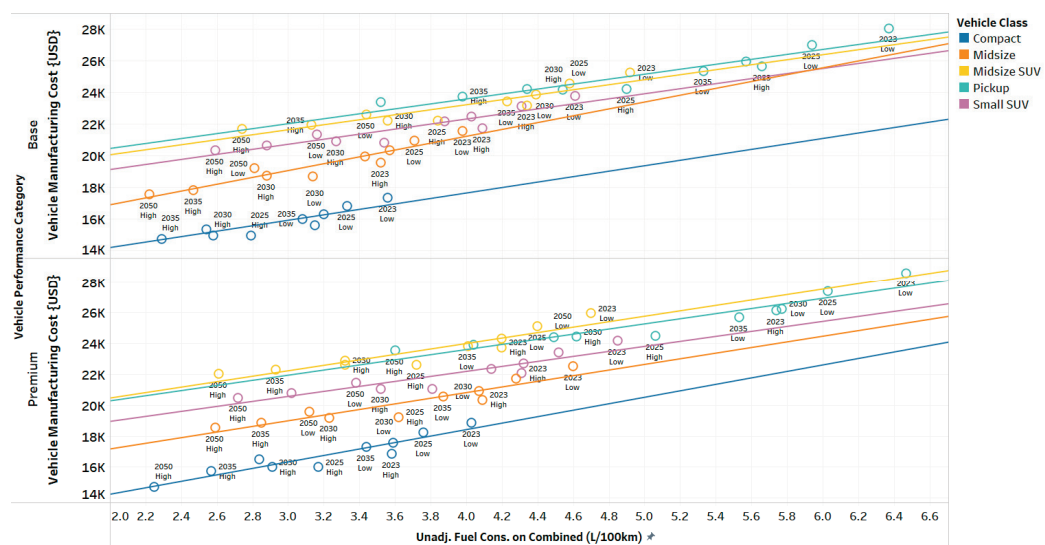


Figure 12. Manufacturing cost vs. fuel consumption of split HEVs.

For plug-in hybrid electric vehicles (PHEVs), the analysis shows a sharp reduction in both fuel consumption and manufacturing costs over time. As shown in Figure 13,

the improvements in component efficiency, particularly in electric machines and batteries, contribute to this reduction. PHEVs with higher all-electric ranges (AERs) exhibit a more significant drop in fuel consumption, but this comes at the expense of higher initial manufacturing costs due to larger battery packs. However, these costs are expected to decline substantially by 2050, owing to continued advancements in battery technology [18,23].

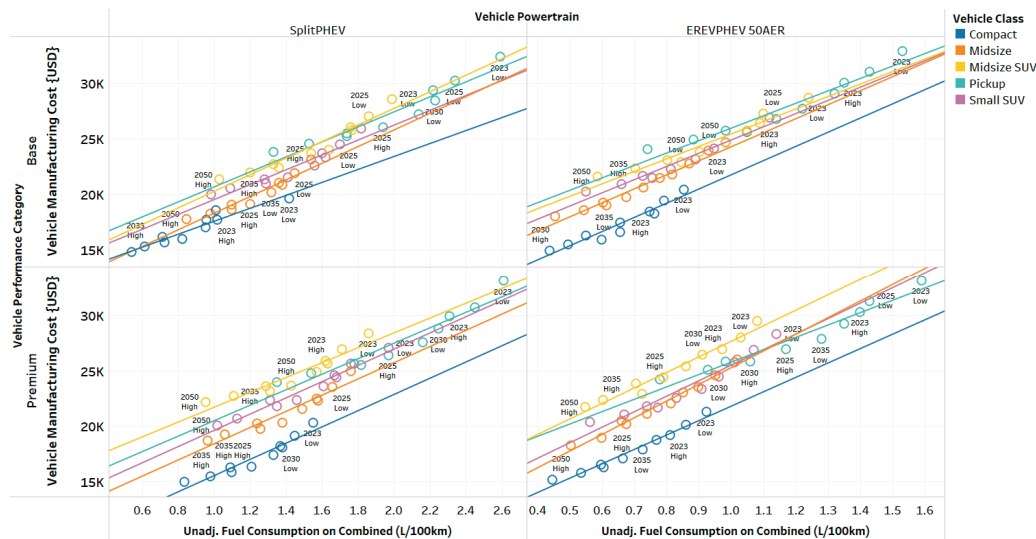


Figure 13. Manufacturing cost vs. fuel consumption of PHEVs.

Battery electric vehicles (BEVs) follow a similar pattern, as demonstrated in Figure 14. The manufacturing costs for BEVs are initially much higher than for conventional vehicles, mainly due to the cost of battery packs. However, as battery technology continues to improve and economies of scale are realized, manufacturing costs for BEVs decrease significantly, particularly for vehicles with higher AERs [8,9]. The figure also highlights the aggressive decline in fuel consumption for BEVs, which is a result of ongoing advancements in battery energy density and vehicle lightweighting.

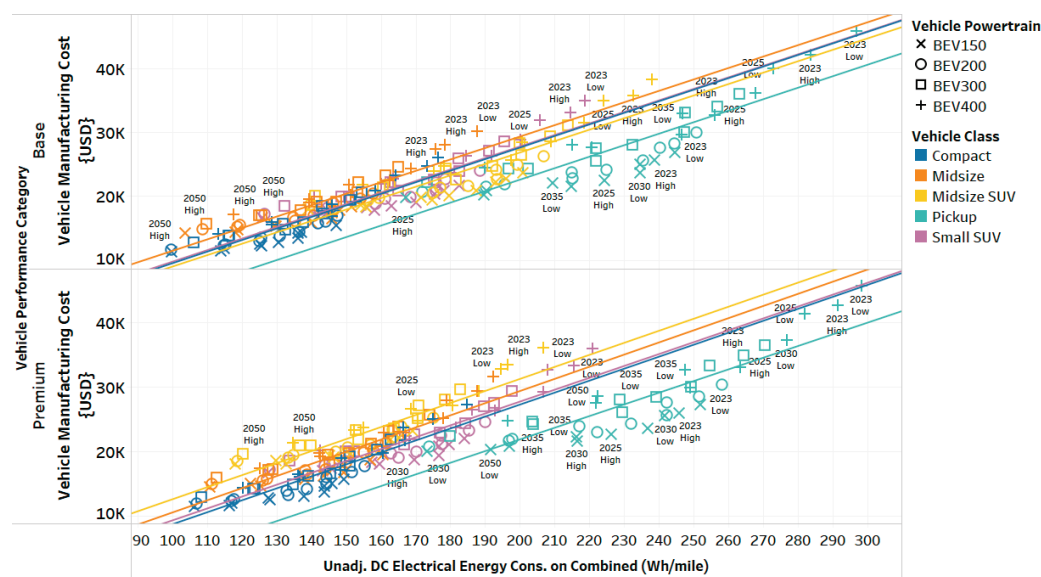


Figure 14. BEV manufacturing cost vs. electrical energy consumption.

By comparing the energy consumption and manufacturing costs across different vehicle powertrains, we observe that while electrified powertrains initially incur higher costs, these are offset by substantial reductions in energy consumption over time. This trend

suggests that BEVs, in particular, will become increasingly cost-competitive as technology continues to advance, reinforcing their role in reducing overall vehicle emissions and energy use [9].

The analysis of technological potential highlights advancements in lightweighting, manufacturing processes, and efficiency improvements. Compared with current lithium-ion battery technologies, future solid-state batteries are expected to achieve higher energy densities (400 Wh/kg vs. 250 Wh/kg) and improved safety profiles, enabling further weight reductions and increased vehicle range. Lightweight composite materials, such as carbon fiber-reinforced polymers, are projected to reduce vehicle weight by an additional 10–15% compared with today's aluminum and steel composites. These advancements ensure that future vehicles achieve superior energy efficiency and performance while maintaining cost effectiveness [25].

4.4. Levelized Cost of Driving

The levelized cost of driving (LCD) provides a comprehensive measure of the total cost per mile driven, incorporating both vehicle purchase costs and fuel or energy costs. This section presents an analysis of LCD for different powertrain types, focusing on small SUVs. The results highlight the long-term cost implications of adopting electrified powertrains, particularly as battery costs continue to decrease.

Figure 15 illustrates the levelized cost of driving across various powertrains, including conventional gasoline vehicles, split HEVs, PHEVs, and BEVs. The analysis covers both base and premium performance categories.

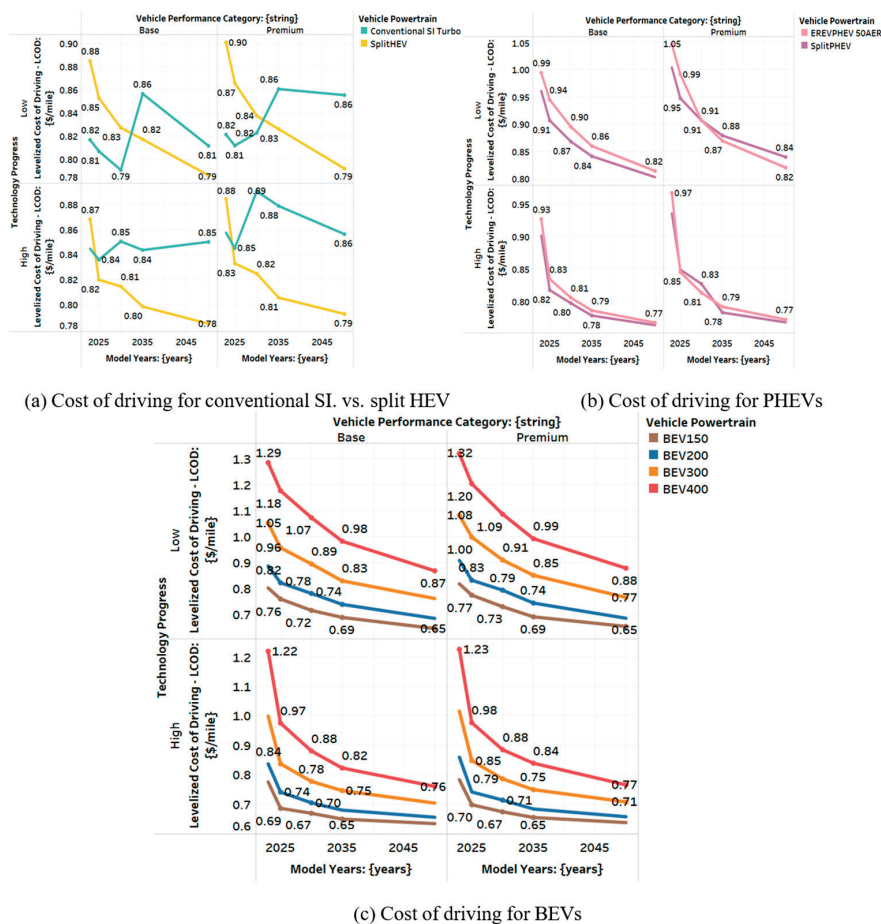


Figure 15. Levelized cost of driving cost comparisons across different powertrains.

For conventional gasoline vehicles, the LCD remains relatively stable over time, with only minor reductions in fuel consumption driving down the total cost per mile. However, for hybrid electric vehicles (HEVs), the LCD shows a significant decline, particularly after 2030. This is primarily due to reductions in battery costs and improvements in engine efficiency, which lower both the upfront cost and the fuel consumption of HEVs [5].

Plug-in hybrid electric vehicles (PHEVs) also exhibit a declining LCD, with the most substantial reductions occurring in models with higher AERs. For instance, PHEVs with a 50-mile AER experience a 30–40% reduction in the cost per mile driven by 2050 compared with 2023. This reduction is driven by the lower cost of electricity and the decreased reliance on gasoline as battery technology improves [6,8].

For battery electric vehicles (BEVs), the LCD decreases dramatically over the simulation period. By 2050, BEVs with a 200-mile range are expected to have a 50–70% lower LCD compared with conventional gasoline vehicles, making them one of the most cost-effective options for consumers. This decline is largely driven by reductions in battery costs and the lower cost of electricity relative to gasoline [5,9]. The LCD for BEVs with higher ranges, such as BEV400 models, is even lower, reinforcing the economic viability of BEVs in the long term.

5. Comparison Cost Analysis

This section compares the total cost of ownership (TCO) across different powertrains, focusing on how advancements in vehicle technology and cost reductions influence overall affordability. The analysis covers the period from 2023 to 2050, highlighting key trends in both base and premium performance categories.

Figure 16 presents the TCO for small SUVs across various powertrain types, including conventional gasoline vehicles, HEVs, PHEVs, and BEVs. The figure shows the point at which BEVs achieve cost parity with conventional vehicles under both low and high technology progress scenarios.

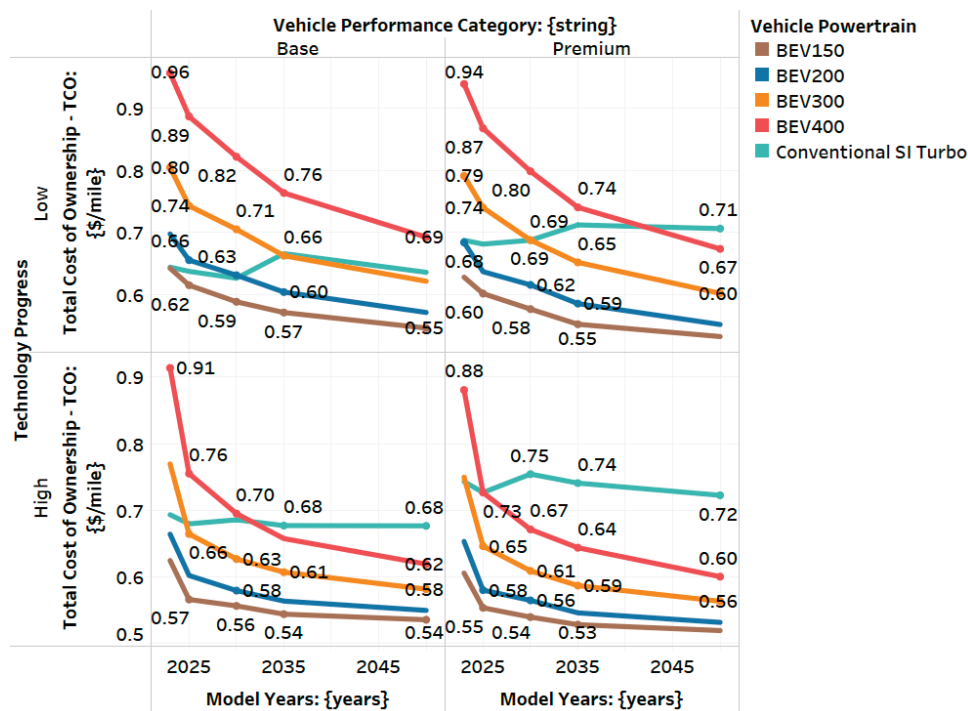


Figure 16. Total cost of ownership comparison across powertrains for small SUVs.

Under the low technology progress scenario, BEVs with a 200-mile range are expected to reach cost parity with conventional vehicles around 2025, while BEVs with a 400-mile range achieve parity closer to 2040. However, under the high technology progress scenario, BEVs achieve cost parity approximately five years earlier, with BEVs becoming cost-competitive by 2020 for 200-mile range vehicles and by 2035 for 400-mile range vehicles [9].

This cost parity is driven by two key factors: the declining cost of battery packs and the lower operational costs of BEVs. Battery costs are projected to decrease by 70–80% by 2050, making BEVs not only more affordable upfront but also more cost-effective in terms of total cost of ownership. Additionally, the lower cost of electricity compared with gasoline further reduces the operational costs of BEVs, making them a financially attractive option for consumers [8,9].

The analysis shows that while conventional gasoline vehicles remain competitive in the short term, the rapid advancements in battery technology and the declining cost of electrified powertrains will make BEVs the most cost-effective option in the long run, particularly for consumers who prioritize fuel economy and lower operational costs.

6. Summary and Conclusions

This article presents a comprehensive simulation-based analysis of the potential benefits of vehicle electrification, focusing on fuel consumption, energy consumption, and cost implications. The results suggest that significant reductions in fuel consumption and manufacturing costs can be achieved by 2050, particularly for electrified powertrains such as HEVs, PHEVs, and BEVs.

Key findings include:

- Engine, electric machine, and battery sizes decrease significantly from model year 2020 to 2050 due to improvements in component efficiencies, lightweighting technologies, and advancements in battery energy density. Engine peak power for conventional vehicles decreases by 14–23%, while battery energy requirements for BEVs decrease by 26–40% [14].
- The fuel consumption of conventional and hybrid electric vehicles (HEVs) declines steadily, with HEVs consuming 33% less fuel than conventional vehicles in 2023 and 22% less by 2050. PHEVs and BEVs exhibit even greater reductions, with BEVs reducing energy consumption by up to 44% by 2050 [5,6].
- Manufacturing costs for BEVs and PHEVs decrease significantly, driven by reductions in battery and electric machine costs. By 2050, BEVs are expected to be 10–20% less expensive than conventional vehicles, making them the most cost-competitive option in the small SUV class [14].
- The total cost of ownership for BEVs becomes competitive with conventional gasoline vehicles between 2025 and 2040, depending on the technology progress scenario. This cost parity, combined with lower operational costs, suggests that BEVs will play a critical role in the future of transportation, particularly as consumers seek more energy-efficient and environmentally sustainable options [10].

In conclusion, the article demonstrates the transformative potential of vehicle electrification, highlighting the significant benefits in terms of fuel economy, energy consumption, and cost. These findings underscore the importance of continued investment in powertrain technology advancements and the need for policies that support the transition to electrified vehicles.

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Article

Adaptive Path-Tracking Control Algorithm for Autonomous Mobility Based on Recursive Least Squares with External Condition and Covariance Self-Tuning

Hanbyeol La and Kwangseok Oh *

School of ICT, Robotics & Mechanical Engineering, Hankyong National University,
Anseong-si 17579, Republic of Korea; byeol0515@hknu.ac.kr

* Correspondence: oks@hknu.ac.kr; Tel.: +82-31-670-5117

Abstract: This paper introduces an adaptive path-tracking control algorithm for autonomous mobility based on recursive least squares (RLS) with external conditions and covariance self-tuning. The advancement and commercialization of autonomous driving necessitate universal path-tracking control technologies. In this study, we propose a path-tracking control algorithm that does not rely on vehicle parameters and leverages RLS with self-tuning mechanisms for external conditions and covariance. We designed an integrated error for effective path tracking that combines the lateral preview distance and yaw angle errors. The controller design employs a first-order derivative error dynamics model with the coefficients of the error dynamics estimated through the RLS using a forgetting factor. To ensure stability, we applied the Lyapunov direct method with injection terms and finite convergence conditions. Each regression process incorporates external conditions, and the self-tuning of the injection terms utilizes residuals. The performance of the proposed control algorithm was evaluated using MATLAB®/Simulink® and CarMaker under various path-tracking scenarios. The evaluation demonstrated that the algorithm effectively controlled the front steering angle for autonomous path tracking without vehicle-specific parameters. This controller is expected to provide a versatile and robust path-tracking solution in diverse autonomous driving applications.

Keywords: recursive least squares; self-tuning; path tracking; autonomous mobility; external condition

1. Introduction

Autonomous driving control requires a controller that improves convenience for users and ensures robust performance for path tracking. Therefore, prominent universities and research institutes have developed a variety of parameter-independent adaptive control algorithms. Recent studies have employed a range of methodologies to estimate the parameters of system models. Scholars have estimated vehicle mass, road gradient, longitudinal and lateral velocity, etc., based on nonlinear vehicle dynamics models using the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) [1–3]. Both filters can estimate the state even when the system is nonlinear, but the linearization process of a nonlinear system involves mathematical complexity when it comes to calculating the Jacobian or performing stochastic sampling. Alternatively, studies have been conducted to investigate methods to estimate longitudinal and lateral tire forces using artificial neural networks [4,5]. They can achieve high performance in complex nonlinear systems but a large amount of training data are required to train the neural network. If the training data are insufficient, overfitting may occur and the data may not be suitable for real-time estimation. In studies considering linear systems, other scholars have used the recursive least squares (RLS) method to estimate vehicle mass, vehicle center height, and cornering stiffness coefficient [6–9]. In linear systems, RLS guarantees fast convergence speed and operates relatively accurately and efficiently. Ref. [10] used an adaptive sliding mode observer to estimate the lateral tire force of each wheel. The adaptive sliding mode observer is robust to noise and can handle

nonlinear systems. However, due to the nature of the sliding mode, it may cause shaking problems and its design may be more complex than the estimators mentioned above. A review of existing research reveals that various methods, such as Kalman Filters, Extended Kalman Filters, Unscented Kalman Filters, and recursive least squares (RLS), have been employed to estimate the parameters of mathematical models. In this paper, we do not consider nonlinearity because it does not require the mathematical information of the system, and we adopt the recursive least squares method because it has low computational complexity and can estimate real-time parameters. In this case, we utilize an RLS approach with a forgetting factor to account for the individual weights of the estimated parameters.

In addition, various studies are being conducted with regard to control parameters or model independence. Refs. [11–14] proposed a methodology for self-tuning PID gains. An adaptive learning methodology was proposed based on the particle swarm optimization technique, Lyapunov stability theorem, and a gain self-tuning methodology applying fuzzy logic theory. Ref. [15] proposed a model-free adaptive integral sliding mode control based on a data-driven technique for identifying object models for parking systems of autonomous four-wheel vehicles. In addition, ref. [16] proposed a model-free control method using an artificial neural network-based data-driven approach for tracking output model references for unknown systems. The authors of [17,18] proposed a model-free adaptive control to address the challenge of constructing an accurate mathematical model for nonlinear four-wheel steering vehicles or the strong nonlinearity and uncertainty of six-wheel independent drive and four-wheel independent steering vehicles with variable wheelbases. The authors of [19] proposed a model-free control approach for position control of uncertain modeled DC motors.

A commonly used control algorithm is model predictive control. Self-tuning and model-free control algorithms are being developed for general control of unknown systems, and in this study, a mathematical model that does not require system parameters is designed for path-tracking control without information about the system. The authors of [20–25] propose an MPC controller for path following. In the case of the model predictive controller designed in previous studies, dynamic models such as side slips are considered. Since these dynamic models, especially the standard bicycle model, do not accurately describe the vehicles' behavior, there are problems with inaccurate motion prediction when these models are used for MPC [24]. Another control method is the sliding mode controller [26–29]. It has the advantage of being robust to internal/external disturbances, but this control methodology also requires a dynamic model of the system.

In this study, we propose an adaptive path-tracking control algorithm for autonomous mobility based on RLS with external conditions and a covariance self-tuning method. The proposed adaptive control algorithm only needs to know some of the parameters, such as the forgetting factor, initial values, constants for finite convergence, and external conditions for path tracking of autonomous mobility. For reasonable performance evaluation, the proposed control algorithm was evaluated using CarMaker software under various driving scenarios. The remainder of this paper is organized as follows. Section 2 describes the adaptive path tracking control algorithm for autonomous mobility using RLS with external conditions and covariance self-tuning. Section 3 discusses evaluation results obtained from the Matlab®/Simulink® and CarMaker co-simulation. Finally, Section 4 presents the conclusions and an analysis of the limitations and future works.

2. Adaptive Path Tracking Control Algorithm

Figure 1 shows a schematic of the proposed path-tracking control algorithm. The controller consists of four blocks: error derivation, scaling factor calculation, recursive least squares (RLS) with forgetting, and control input derivation. In sequence, it receives the vehicle's position, attitude-related state variables, and current target path data to calculate the error. The calculated error was used in the remaining three blocks, and it was recommended that the first step should be to obtain and verify the scaling factor S to update the covariance of the RLS. Using the derived scaling factor, the RLS estimates the

coefficients of the designed first-order error dynamics. The control input is derived using the Lyapunov direct method based on the estimated coefficients. In this process, a sliding mode approach was applied, and the magnitude of the injection term was self-tuned using the residuals of the RLS. The developed method uses adaptive recursive least squares (RLS) filtering. Thus, the proposed algorithm adaptively tracks the target path using the RLS estimated in real time.

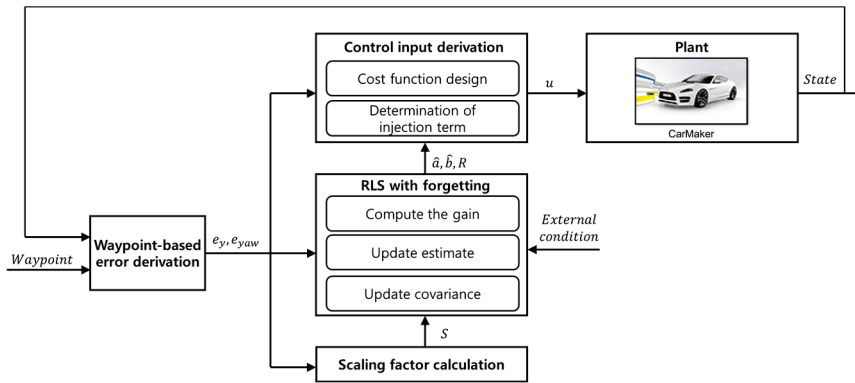


Figure 1. Schematic of the proposed path-tracking control algorithm.

In Figure 1, e_y and e_{yaw} are the lateral and yaw angle errors derived from the waypoints, respectively. Scale factor S calculated using the absolute value of the error derivative was used for covariance self-tuning. The coefficients a and b were estimated using RLS with the forgetting factor. The residual R from the RLS algorithm was used for injection term self-tuning. Finally, control input u was derived using errors, estimated coefficients, and the residual. Equation (1) represents the integrated error designed by applying weights to the lateral and yaw angle errors. Weights (w_1, w_2) were set at 1. Based on the above equation, simplified error dynamics were designed, as shown in Equation (2).

$$e = w_1 e_y + w_2 e_{yaw} \quad (1)$$

$$\dot{e} + ae + b = u \quad (2)$$

2.1. RLS-Based Coefficient Estimation with External Condition and Covariance Self-Tuning

In this study, coefficients a and b were estimated using the RLS with forgetting factors. A relational function was designed for parameter estimation, as shown in Equation (3). Equation (4) presents the following RLS equations: in the virtual relational function, y , ϕ , and θ represent the output, regressor, and estimated value, respectively.

$$y = \phi^T \theta \quad (3)$$

$$y = \dot{e} - u, \phi = [e \ 1]^T, \theta = [a \ b]^T \quad (4)$$

In this study, the cost function V was defined as following Equation (5) to design an RLS algorithm with multiple forgetting factors λ ranging from zero to one. As the forgetting factor approaches 1, a greater weight is assigned to past data, resulting in more gradual changes in the parameter estimation. In least squares estimation, unknown parameters are chosen in such a way that the sum of the squares of the difference between the actually observed and the computed values is a minimum at each time instance k . The RLS method with multiple forgetting factors was designed based on a previous study [30].

$$V(\hat{\theta}_1(k), \hat{\theta}_2(k), k) = \frac{1}{2} \sum_{i=1}^k \lambda_1^{k-i} (y(i) - \phi_1(i) \hat{\theta}_1(k) - \phi_2(i) \hat{\theta}_2(k))^2 + \frac{1}{2} \sum_{i=1}^k \lambda_2^{k-i} (y(i) - \phi_1(i) \hat{\theta}_1(k) - \phi_2(i) \hat{\theta}_2(k))^2 \quad (5)$$

The estimated values that minimize the cost function of the recursive least squares method defined in Equation (5) are computed using the regressor described in Equation (4). The calculation process is shown in Equation (6):

$$\begin{bmatrix} \hat{\theta}_1(k) \\ \hat{\theta}_2(k) \end{bmatrix} = \begin{bmatrix} 1 & L_1(k)\phi_2(k) \\ L_2(k)\phi_1(k) & 1 \end{bmatrix}^{-1} \times \begin{bmatrix} \hat{\theta}_1(k-1) + L_1(k)(y(k) - \phi_1(k)\hat{\theta}_1(k-1)) \\ \hat{\theta}_2(k-1) + L_2(k)(y(k) - \phi_2(k)\hat{\theta}_2(k-1)) \end{bmatrix} \quad (6)$$

In Equation (6), the optimal gain $L(k)$ for the estimation and the covariance matrix $P(k)$, which remains positive definite, are updated at each sampling instance using the forgetting and covariance update factors, as described in Equation (7) [30].

$$\begin{aligned} L(k) &= P(k-1)\phi(k)(\lambda + \phi^T(k)P(k-1)\phi(k))^{-1} \\ P(k) &= S(I - L(k)\phi^T(k))P(k-1)/\lambda \end{aligned} \quad (7)$$

The equation of the scaling factor calculation used for covariance self-tuning is as follows. The scaling factor is computed based on the designed function using the absolute value of the time derivative of the error and certain parameters. Equation (8) describes the scaling factor function for covariance self-tuning. The threshold value of the time derivative of error was taken as an appropriate value through evaluation, with the upper threshold $\dot{e}_{up,th}$ being 0.1 and the lower threshold $\dot{e}_{low,th}$ being 0.03. The minimum s_{min} value of the scale factor was set to 1, and the maximum value s_{max} was set to 1.1.

$$S = \begin{cases} s_{min}, & |\dot{e}| < \dot{e}_{low,th} \\ \frac{s_{max}-s_{min}}{\dot{e}_{up,th}-\dot{e}_{low,th}}, & \dot{e}_{low,th} \leq |\dot{e}| < \dot{e}_{up,th} \\ s_{max}, & \dot{e}_{up,th} \leq |\dot{e}| \end{cases} \quad (8)$$

In addition, an evaluation was conducted by applying external constraints to analyze the influence of the coefficients estimated by the RLS. External constraints were placed such that the estimated a and b parameters did not change, and an analysis was conducted to determine whether the control inputs were reasonably derived. The related content is explained in more detail in Section 3.

2.2. Derivation of Control Input Based on the Lyapunov Direct Method

In this study, the direct Lyapunov method was used to ensure the stability of the control algorithm. The Lyapunov function V is defined to ensure that the error converges to zero within a finite time, and finite stability conditions are applied, as in Equation (9).

$$\begin{aligned} V &= \frac{1}{2}e^2 \\ \text{Condition 1 : } \lim_{e \rightarrow \infty} V &= \infty \\ \text{Condition 2 : } \dot{V} &\leq -\alpha V^{1/2}, \alpha > 0 \end{aligned} \quad (9)$$

Suppose the rate of change in the Lyapunov candidate function with respect to time is negatively definite. In that case, the equilibrium is guaranteed to be asymptotically stable. Therefore, the Lyapunov candidate function must always be negative, and the defined function must be differentiated with respect to time, as shown in Equation (10).

$$\dot{V} = e\dot{e} = e(-ae - b + u) \quad (10)$$

To derive a control input that can converge the error to zero, the control input of Equation (10) is defined using the estimation coefficients $\hat{a}$ and $\hat{b}$ discussed in Section 2.1.

At this time, the injection term v based on sliding mode method is applied to ensure control stability with the magnitude of the injection term ρ as follows.

$$\begin{aligned} u &= (\hat{a}e + \hat{b} + v) \\ v &= -\rho \operatorname{sign}(e) \end{aligned} \quad (11)$$

The time derivative of the cost function in Equation (10) can be rewritten as Equation (12) using the control input in Equation (11). This can then be rewritten using the residual R between the current and estimated values, as shown in Equation (13).

$$\dot{V} = e\dot{e} = e\left((\hat{a} - a)e + (\hat{b} - b) - \rho \operatorname{sign}(e)\right) \quad (12)$$

$$\dot{V} = e(R - \rho \operatorname{sign}(e)) \text{ where } R = (\hat{a} - a)e + (\hat{b} - b) \quad (13)$$

The disturbance boundary range L_b can be determined using the reachability factor η and is expressed as an inequality condition, as shown in Equation (15). Equation (16) describes the substitution of Equation (15) into Equation (13). If convergence condition 1 is applied within finite time, it can be reformulated as Equation (17).

$$|R| + \eta = L_b \quad (14)$$

$$|R| \leq L_b \quad (15)$$

$$\dot{V} = e(R - \rho \operatorname{sign}(e)) \leq (|e|L_b - |e|\rho) = -|e|(\rho - L_b) \quad (16)$$

$$\dot{V} \leq -\alpha V^{\frac{1}{2}} = -\frac{\alpha}{\sqrt{2}}|e| \quad (17)$$

Because the right-hand sides of Equations (16) and (17) can be assumed to be the same because they are the time-varying quantities of the same cost function, the magnitude of the injection term ρ is determined accordingly.

$$\rho = L_b + \frac{\alpha}{\sqrt{2}} = |R| + \eta + \frac{\alpha}{\sqrt{2}} \quad (18)$$

Equation (10) can be expressed as Equation (19) by using the magnitude of the injection term derived in Equation (18). The control input u may cause unrealistic chattering when the sign function of the error is applied, similarly to the conventional sliding-mode technique. Therefore, as shown in Equation (20), the sign function is replaced by a sigmoid function with error and sigmoid function gradient m . The final adaptive control input is given by Equation (21).

$$u = \hat{a}e + \hat{b} - \left(\left(|R| + \eta + \frac{\alpha}{\sqrt{2}} \right) f(e, m) \right) \quad (19)$$

$$\frac{me}{1 + m|e|} = \text{sigmoid function} = f(e, m) \quad (20)$$

$$u = \hat{a}e + \hat{b} - \left(\left(|R| + \eta + \frac{\alpha}{\sqrt{2}} \right) \frac{me}{1 + m|e|} \right) \quad (21)$$

3. Performance Evaluation

The proposed path-tracking control algorithm was evaluated using the MATLAB® / Simulink® (2019a version) and CarMaker (8.1.1 version) software environment. The evaluation was conducted for four scenarios: an S-curved road with a large radius of 100 m and a small radius of 65 m, low-speed driving at 30 km/h, and high-speed driving at 50 km/h.

Table 1 lists the vehicle parameters used for the performance evaluation. Table 2 lists the control parameters used to derive the control inputs. The control parameters

of the algorithm were determined through an iterative trial and error method. When the control inputs were excessive relative to the target trajectory, the covariance values were adjusted to reduce their magnitude, and when the inputs were insufficient, the values were increased accordingly. Furthermore, the decay rate of the Lyapunov function was adjusted to prevent excessive chattering at points where curved and straight roads transitioned. The control parameters were determined through trial and error and the same values were applied for all four driving scenarios. The critical parameters that required adjustment to achieve reasonable control performance were, as mentioned, the covariance and the decay rate of the Lyapunov function. Through trial and error, it was confirmed that adjusting these two parameters could potentially enhance transferability, even when the vehicle to which the controller is applied changes. As mentioned in Section 2.1, this study derives the control inputs using the estimated coefficients; therefore, unreasonable control parameters can affect the control performance. Therefore, we assumed a situation in which one of the coefficients, a or b , could not be reasonably estimated because the control parameters were not set appropriately by applying external constraints to each coefficient. We evaluated whether the other coefficients could compensate for this and estimated reasonable parameters, even when external constraints were applied.

Table 1. Vehicle parameters for proposed controller.

Parameter	Unit	Value
Mass (m)	kg	2108
Wheelbase (l)	m	2.97
Distance between CG * and front/rear axle (l_f, l_r)	m	1.47, 1.5
Z-axis rotational inertia (I_z)	kg·m ²	3170.6
Estimated cornering stiffness of front/rear wheels (C_f, C_r)	N/rad	118,270, 117,990

* CG is the center of gravity.

Table 2. Design parameters for front-wheel steering vehicle adaptive steering control.

Parameter	Unit	Value
Decay rate of the Lyapunov function (α)	-	1
Reachability factor (η)	-	0.01
Initial value of estimated states ($\hat{a}, \hat{b}$)	-	$\begin{bmatrix} 0 & 0 \end{bmatrix}$
Initial value of covariance (P_1, P_2)	-	$\begin{bmatrix} 0.1 \times 10^{-15} & 0.1 \times 10^{-15} \end{bmatrix}$
Forgetting factor ($\lambda_{11}, \lambda_{12}$)	-	$\begin{bmatrix} 0.999999 & 0.999999 \end{bmatrix}$
Lower-scale factor threshold ($\dot{e}_{low,th}$)	-	0.03
Upper-scale factor threshold ($\dot{e}_{up,th}$)	-	0.1
Normalized threshold (s_{max})	-	1.1

3.1. Large Radius of Curvature Scenarios

As shown in Figure 2, the path-trajectory tracking performance was evaluated at a relatively low speed of 30 km/h and high speed of 50 km/h on an S-curved road with a relatively large curvature radius of 100 m. In the previous study [31], under these driving conditions with relatively low speed and large curvature, where control is comparatively reasonable, the vehicle was able to track the target path without lane departure. The control input derived for path tracking was applied identically to the front wheels of the CarMaker vehicle model.

Figure 3 shows the longitudinal velocity and yaw rate of the dynamic behavior of the vehicle. And even when external constraints are applied, the results are not significantly different from those obtained without constraints, indicating that the vehicle can reasonably follow the target path. When comparing driving results according to speed, the yaw rate increases by approximately 3°/s. Figure 4 shows the control input and the magnitude of the injection term. While the absolute value of the steering angle is similar at both speeds,

it oscillates more at the higher speed of 50 km/h. And the magnitude of the injection term is greater at higher speeds, with a larger amplitude.

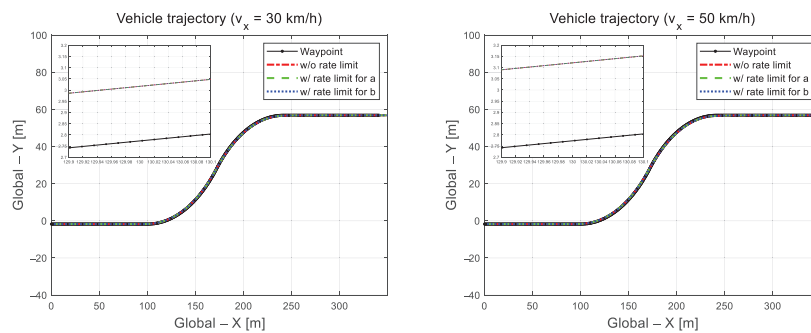


Figure 2. Driving trajectories at 30 km/h (left) and 50 km/h (right).

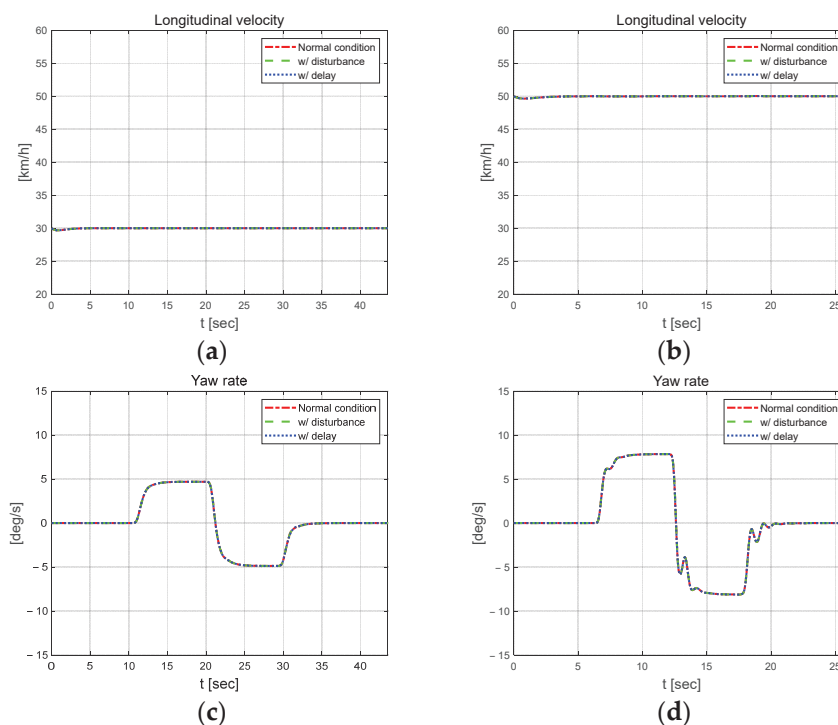


Figure 3. Vehicle dynamic behavior at 30 km/h (left) and 50 km/h (right). Longitudinal velocity at 30 km/h (a) and km/h (b), yaw rate in at 30 km/h (c) and 50 km/h (d).

Figure 5 shows the lateral and yaw angle errors. The black dash-dotted line indicates the width of the road. The upper 1.75 m and lower -1.75 m lines are the positions of the lanes. The width of the vehicle is 1.662 m. Therefore, if the error magnitude is greater than about 0.9 m, the vehicle will deviate from the lane. The lateral error shows relatively different results when applying external constraints to parameter b at 30 km/h. At both speeds, it shows a symmetrical shape around the inflection point of the S-curve. The lateral error is within about 0.3 m at 30 km/h. At 50 km/h, it is a little larger, within 0.4 m. The yaw angle error increases in absolute value when changing from a straight to a curved section, from a curve to a straight section, and at the inflection point of the S-curve. In addition, this error is about 0.5 to 1° larger in the high-speed scenario.

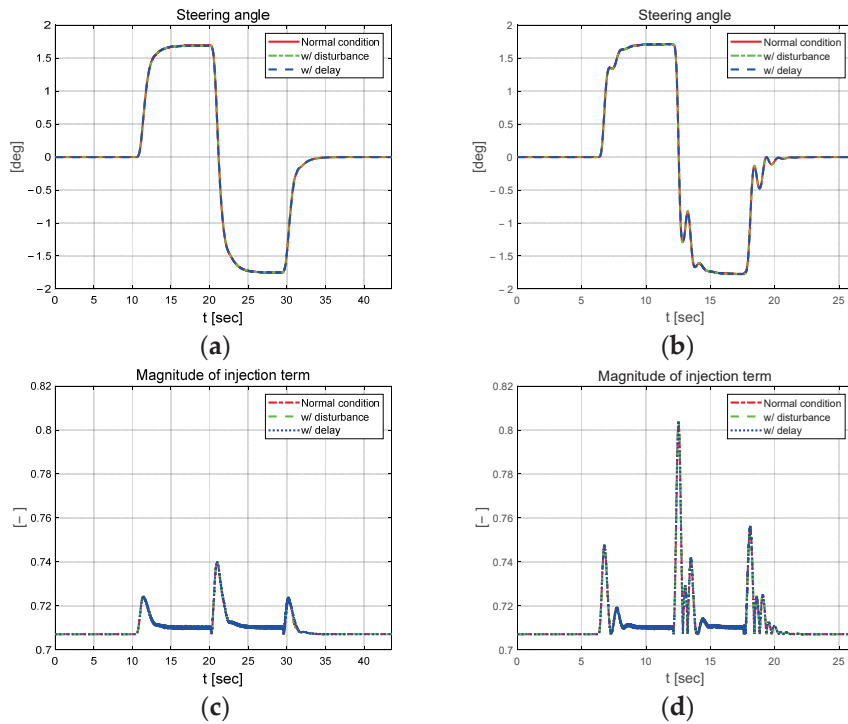


Figure 4. Control parameters at km/h (left) and 50 km/h (right). Steering angle at 30 km/h (a) and 50 km/h (b). Magnitude of injection term at 30 km/h (c) and 50 km/h (d).

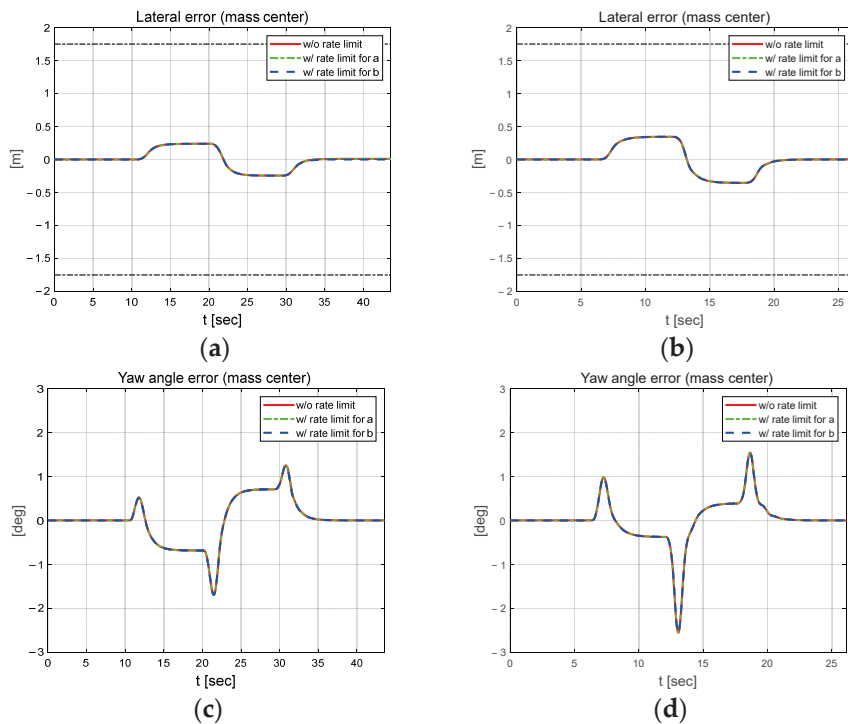


Figure 5. Control errors at 30 km/h (left) and 50 km/h (right). Lateral error at 30 km/h (a) and 50 km/h (b). Yaw angle error at 30 km/h (c) and 50 km/h (d).

Figures 6 and 7 present the coefficients estimated using the designed RLS. External constraints were applied to each regression process, in which coefficients a and b were estimated using the rate-limit condition. Compared to the case without the rate limit constraint, when the rate limit constraint is applied to a , it can be seen that b changes significantly, and when the constraint is applied to b , it also changes significantly. When

rate constraints were applied to each individual parameter, it was observed that the other parameter was adjusted to maintain control performance. This result suggests that even if one parameter is inaccurately estimated due to external disturbance during the control algorithm's operation, the other parameter can adapt and be estimated in such a method that allows the vehicle to complete the driving task reasonably. In the low-speed scenario, a parameter has a relatively large difference when external constraints are applied, and the absolute magnitude of the estimated parameter is also large.

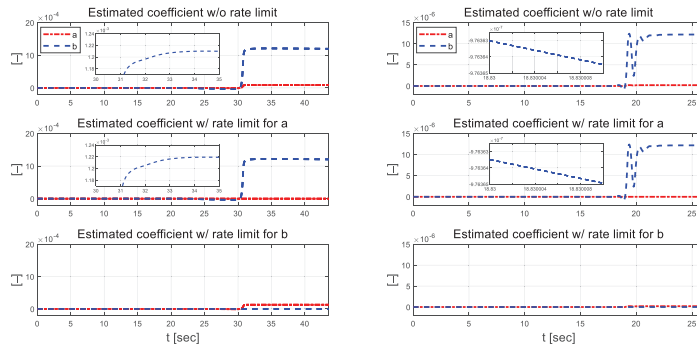


Figure 6. Estimated coefficients for each scenario at 30 km/h (left) and 50 km/h (right).

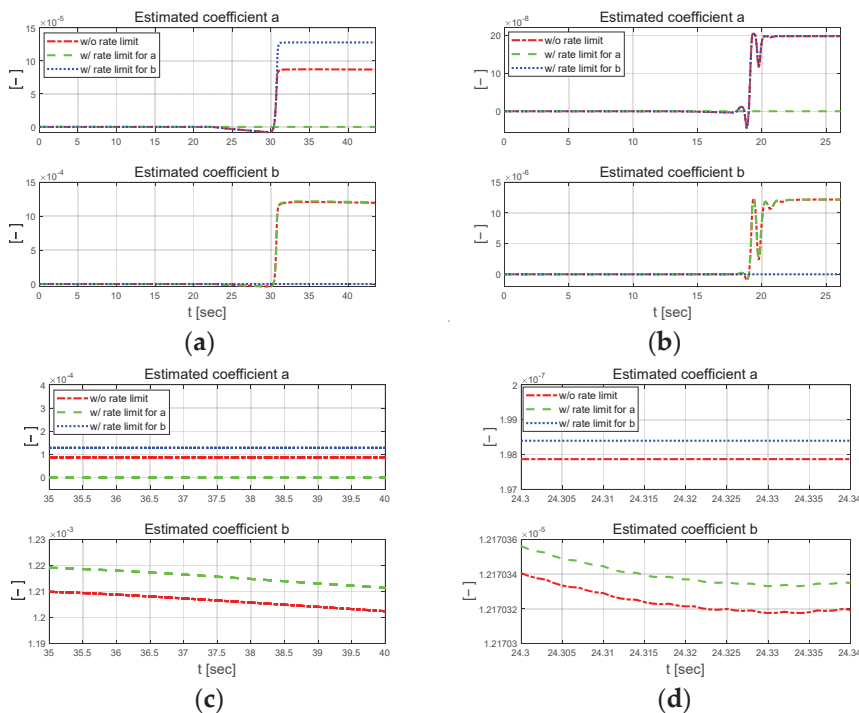


Figure 7. Comparison of estimated coefficients at 30 km/h (left) and 50 km/h (right). Full at 30 km/h (a) and 50 km/h (b). Zoomed in at 30 km/h (c) and 50 km/h (d).

3.2. Comparison of APTA and LQR-Based Path-Tracking Performance

To compare the model-free method-based path-tracking control performance proposed Adaptive Path-Tracking Algorithm (APTA) in this study with another controller, a conventional linear quadratic regulator (LQR) was used to conduct performance evaluation under the extra-high-speed path-tracking scenario with a large-curvature-radius road. The mathematical model of LQR used the bicycle dynamic model in terms of error. As shown in Figure 8, the path tracking performance of the LQR algorithm for comparison with the proposed algorithm was evaluated at a road curvature radius of 100 m.

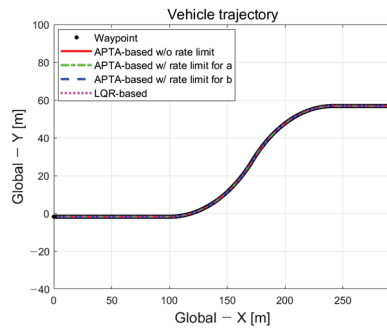


Figure 8. Driving trajectory.

The longitudinal velocity was set to 70 km/h, which is faster than 50 km/h, which was previously set as a high speed. In Figure 9, the velocity was set to 70 km/h, but it decreased to approximately 69.6 km/h around the 10 s inflection point of the curve. The proposed model-free adaptive control results in the yaw rate tended to oscillate around the 5, 9 and 13 s regardless of whether external constraints were applied. Compared to the yaw rate in the previous high-speed scenario, the amplitude increased by a maximum of about $2^\circ/\text{s}$. However, there was little oscillation in the yaw rate behavior for the LQR control.

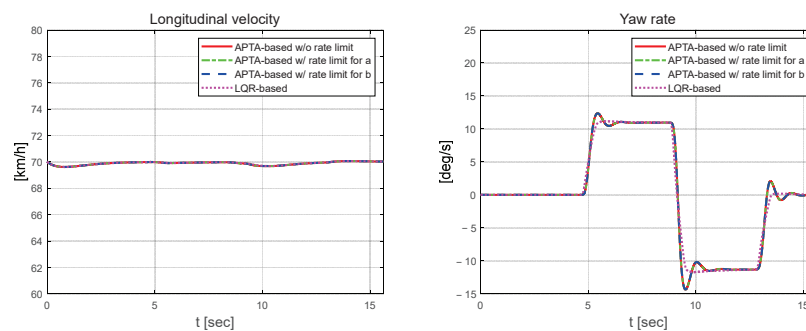


Figure 9. Longitudinal velocity (left) and yaw rate (right).

Figure 10 shows the steering angle of the vehicle, which is the control input, and the magnitude of the injection term, which is a component of the control input. The magnitude of the injection term is calculated using the residual of RLS and oscillates in the section where the road environment changes. The control input affected by the magnitude of the injection term also oscillates in a similar section. The steering angle, which is the control input of the LQR controller, does not have oscillations like the proposed algorithm, but shows the chattering in the S-curve road.

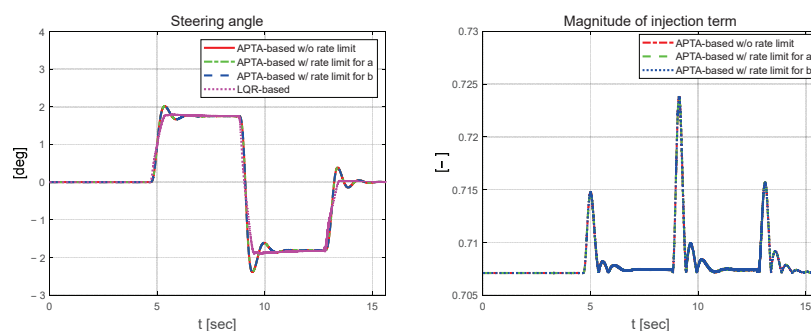


Figure 10. Front-wheel angle (left) and magnitude of injection term (right).

In Figure 11, the lateral error for the proposed algorithm remains below approximately 0.03 m, regardless of the application of external constraints during driving, whereas the LQR control exhibits an error of around 0.3 m. The magnitude of the lateral error, which can

be analyzed as lane departure, is smaller than 0.9 m. For the yaw angle error, the proposed algorithm shows a maximum value of about 0.4° , while the LQR used as a comparative controller has a maximum error of approximately 1.7° . This difference was because the cornering stiffness coefficient and vertical axis rotational inertia were treated as constants in the bicycle model, which is a system model, but in actual driving, they change due to dynamic factors such as curved driving, which causes differences from the mathematical model. Figure 12 shows the estimated parameters using RLS for each scenario.

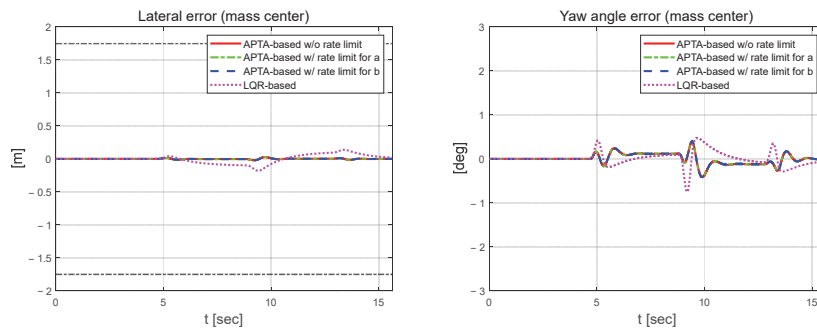


Figure 11. Lateral error (left) and yaw angle error (right).

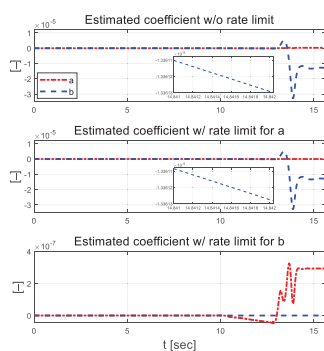


Figure 12. Estimated coefficients for each scenario.

3.3. Small Radius of Curvature Scenarios

This section examines the results of driving on an S-curved road with a relatively small curvature radius of 65 m at a low speed of 30 km/h and a high speed of 50 km/h. Even if we assume an unreasonable application of the control parameters and impose external constraints on the RLS estimation coefficients, the vehicle can explore the target path without lane departure, as the vehicle trajectory can be seen in Figure 13. Even in the most challenging scenarios with a curvature radius of 65 m and relatively high speed, the target path was reasonably tracked in all cases, where external constraints were imposed on the RLS estimation coefficients.

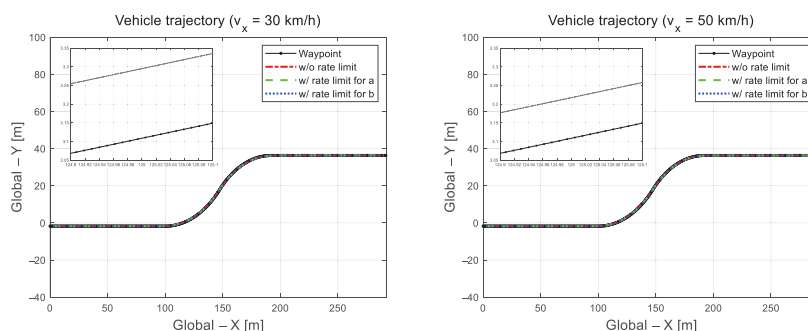


Figure 13. Driving trajectories at 30 km/h (left) and 50 km/h (right).

Figure 14 shows the longitudinal velocities and yaw rate at 30 km/h and 50 km/h. The longitudinal velocities for all scenarios were observed, and there was no relatively large variation without an accompanying decrease or oscillations. This indicates that the steering input produced by the controller does not have a significant influence on the vehicle's longitudinal behavior, and even in the high speed and small radius scenario. The yaw rate is the highest among all the scenarios, reaching approximately $12^\circ/\text{s}$.

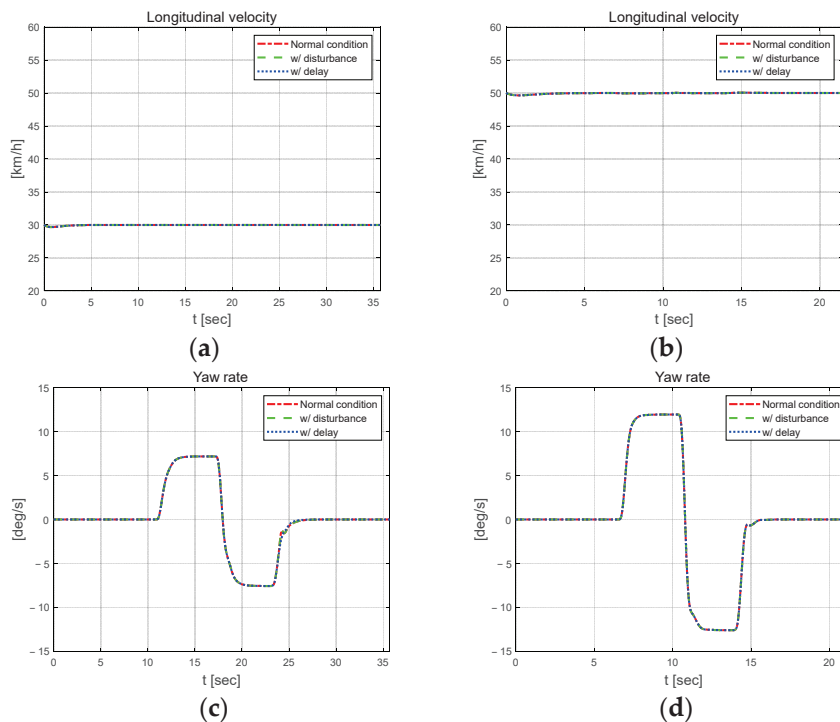


Figure 14. Vehicle dynamic behavior at 30 km/h (left) and 50 km/h (right). Longitudinal velocity at 30 km/h (a) and 50 km/h (b), yaw rate in at 30 km/h (c) and 50 km/h (d).

The driving results for the steering angle of 50 km/h Figure 15b are not significantly different from those at 30 km/h. The steering angle is approximately 2.5° , which is 0.8° greater than the approximately 1.7° angle mentioned in Section 3.1, owing to the reduced radius of curvature. The magnitude of the injection term is reduced compared to that described in Section 3.1.

In Figure 16, the lateral error in (a), which is the result of driving at 30 km/h, slightly increases to about 0.2 m on the curve, and the yaw error is about 2° . In particular, when no external constraints are applied (red dash-dotted line) and when an external constraint is applied to the estimated coefficient a (green dotted line), the vehicle drives while maintaining an error of about 0.02 m at the exit point of the S-curve. Furthermore, the yaw angle error (c) is approximately 2° . In the results obtained for high-speed 50 km/h driving, the lateral error is about 0.1 m, which is smaller than that of 30 km/h driving. The yaw angle error is also small and is not greatly affected by the application of external constraints.

As shown in Figure 17(left), which depicts the results of driving at 30 km/h, the estimated coefficient magnitude increased compared with the previous driving scenarios. There are relatively large changes in the estimated coefficients around 24 s into the simulation time. When external constraints are applied to parameters a and b , the other parameters are estimated to be larger than when no constraints are applied. The estimated coefficients in Figure 17(right) are smaller than those estimated when driving at 30 km/h. They changed at the exit point in an S-curve for approximately 14 s and converged to a constant value in the straight section. When comparing the results for relatively low velocity (30 km/h) with the same curvature radius for the relatively high-velocity (50 km/h)

scenario, as shown in Figure 18, the vehicle can track the target path reasonably well, although there are individual rate limit constraints on parameters a and b .

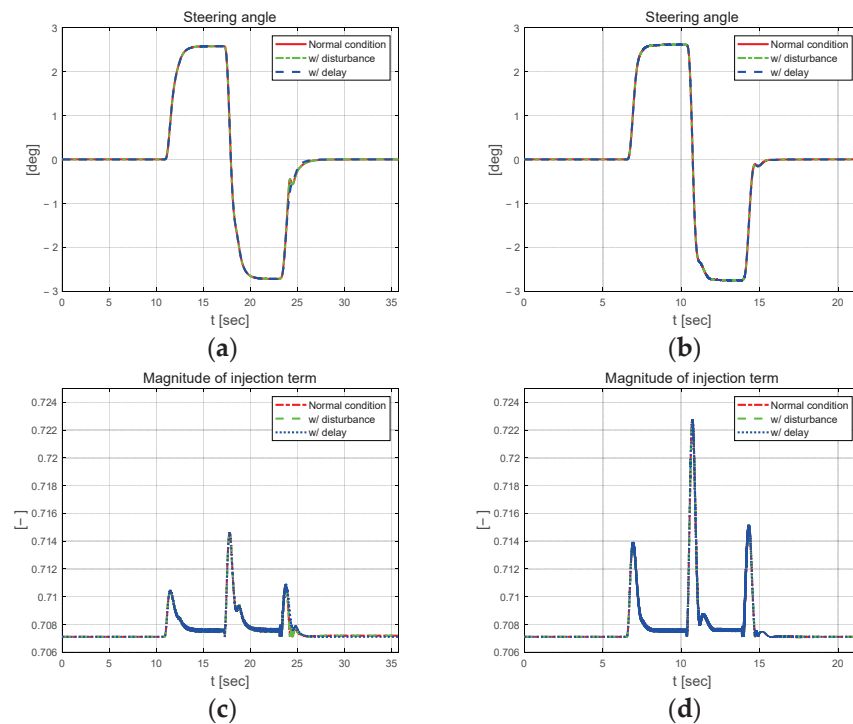


Figure 15. Control parameters at 30 km/h (left) and 50 km/h (right). Steering angle at 30 km/h (a) and 50 km/h (b). Magnitude of injection term at 30 km/h (c) and 50 km/h (d).

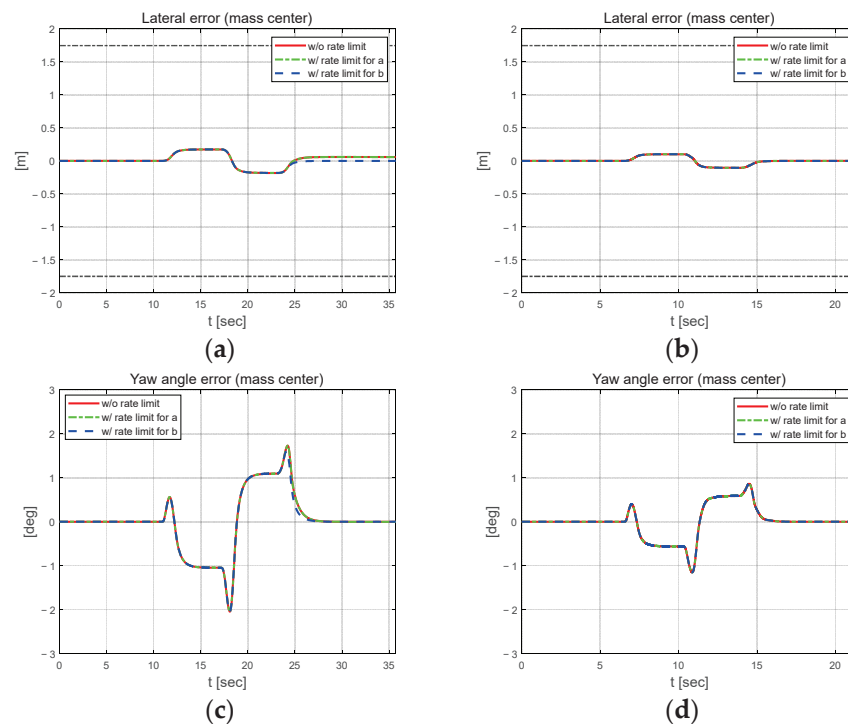


Figure 16. Control errors at 30 km/h (left) and 50 km/h (right). Lateral error at 30 km/h (a) and 50 km/h (b). Yaw angle error at 30 km/h (c) and 50 km/h (d).

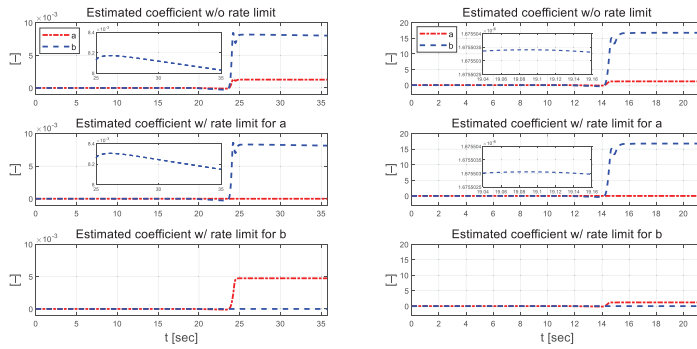


Figure 17. Estimated coefficients for each scenario at 30 km/h (left) and 50 km/h (right).

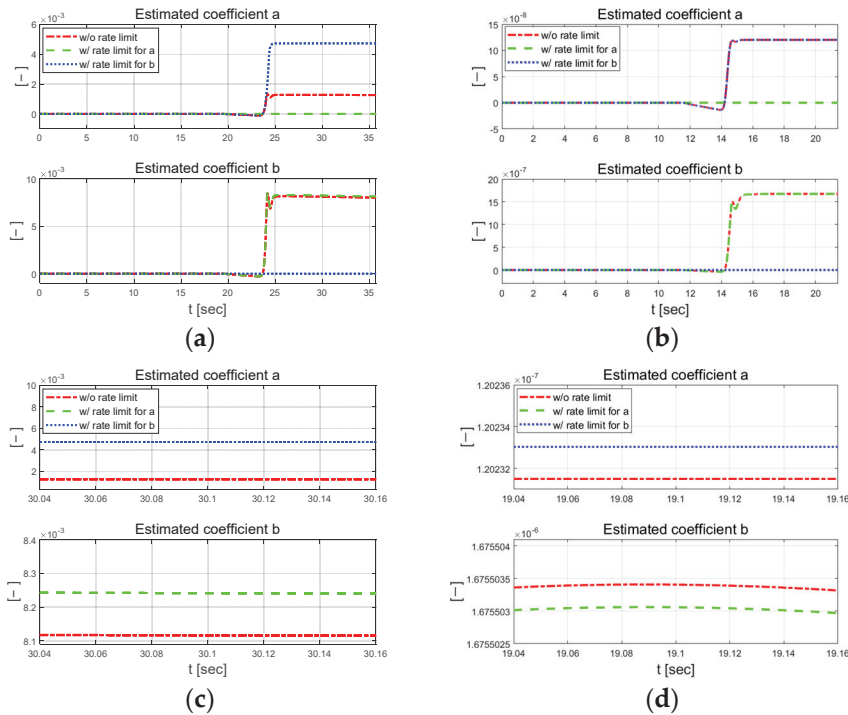


Figure 18. Comparison of estimated coefficients at 30 km/h (left) and 50 km/h (right). Full at 30 km/h (a) and 50 km/h (b). Zoomed in at 30 km/h (c) and 50 km/h (d).

3.4. System Disturbance and Measurement Delay Scenario

This section describes the results of applying disturbances or delayed input signals during driving. The performance was evaluated in a driving scenario on a 100 m road with a large curvature radius. The disturbance during driving was applied to a situation where a mass load of 500 kg was applied to the vehicle at 10 s, and the delay of the input signal was applied by applying a time delay constant of 0.5 s to the input signal error in order to calculate the control input. As shown in Figure 19, the proposed control algorithm can guarantee a certain level of reasonable control performance even when system disturbances or measurement signal delays occur.

Figure 20 shows the longitudinal velocity and yaw rate. At 10 s, the mass load is applied and the yaw rate oscillates, and the results for all scenarios oscillate at the inflection point of the curve.

Figure 21 shows the steering angle and the magnitude of the injection term. The steering angle exhibits the most vibration when a mass load disturbance is applied compared to the normal driving results. It is a control input for driving a vehicle that shakes when a large mass load of 500 kg is applied in stages. The magnitude of the injection term is the largest at approximately 1.2 when the input signal is delayed.

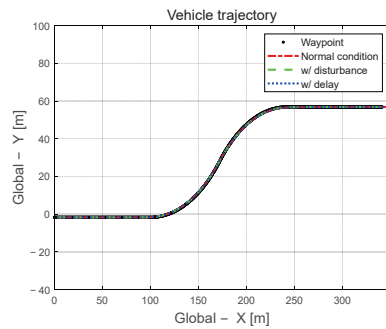


Figure 19. Driving trajectory.

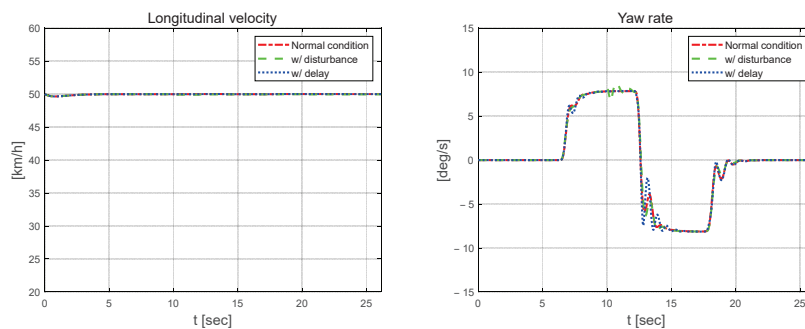


Figure 20. Longitudinal velocity (left) and yaw rate (right).

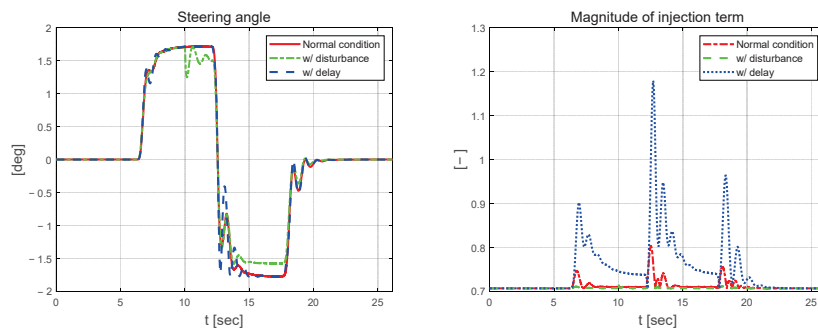


Figure 21. Front-wheel angle (left) and magnitude of injection term (right).

Figure 22 shows the control error. The control error is about 0.01 m larger in the lateral direction and about 0.2° larger for the yaw angle when there is a delay in the measurement signal compared to the normal state. When the disturbance is applied, the result is the smallest in terms of error, although there is some fluctuation. However, the disturbance case has the largest error among all the scenarios performed, and the proposed algorithm does not achieve a reasonable performance when disturbance and delay are applied. Figure 23 shows the estimated coefficients of each scenario from RLS. The estimated coefficients a and b are largest in the normal state and smallest in the scenario in which a delay is applied to the measurement signal.

Table 3 lists the RMSE of APTA- and LQR-based derived integrated error in Equation (1). In driving scenarios with the same curvature radius and driving speed, the RMSE value of APTA is similar even when external constraints are applied. However, there is an exception; when driving at 30 km/h with a curvature radius of 65 m, the results of applying external constraints to parameter b are approximately 0.33 smaller than those achieved by applying or not applying said constraints to parameter a . As shown in the tables, when calculating the RMSE value, it was confirmed that the integrated error of LQR compared to APTA was approximately 24% larger for the same scenario. The error did not increase even when disturbance and delays were applied. In the scenario with high speed and a small

curvature radius, the error increased. In the scenario with a small curvature radius and high speed, the error is the largest among the cases where the proposed methodology is applied. However, it is smaller than the error in the scenario with model-based LQR control.

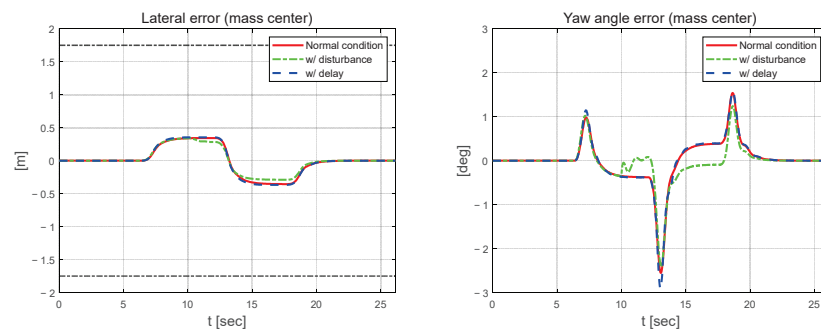


Figure 22. Lateral error (left) and yaw angle error (right).

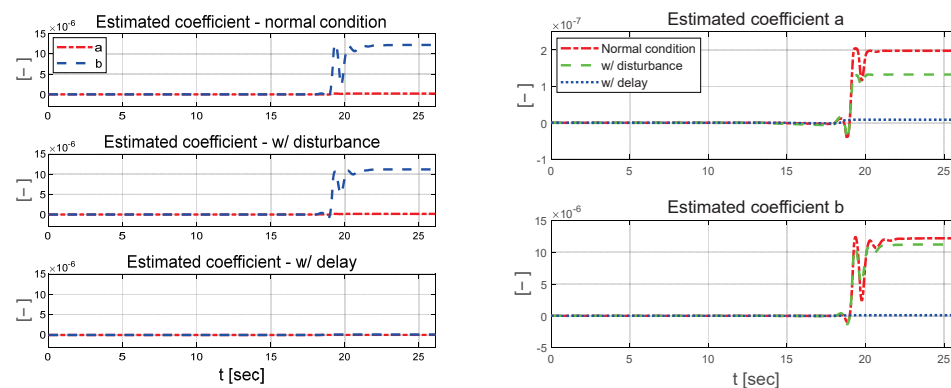


Figure 23. Estimated coefficients for each scenario (left) and comparison (right).

Table 3. RMSE error for each scenario.

Radius of Curvature	Velocity	Controller	External Constraints	Evaluation Environment	RMSE
100	30	APTA	-	-	0.1347
100	30	APTA	<i>a</i>	-	0.1347
100	30	APTA	<i>b</i>	-	0.1346
100	50	APTA	-	-	0.1355
100	50	APTA	<i>a</i>	-	0.1355
100	50	APTA	<i>b</i>	-	0.1355
100	50	APTA	-	Disturbance	0.1263
100	50	APTA	-	Delay	0.1197
100	70	APTA	-	-	0.1648
100	70	APTA	<i>a</i>	-	0.1648
100	70	APTA	<i>b</i>	-	0.1648
100	70	LQR	-	-	0.2046
65	30	APTA	-	-	0.1908
65	30	APTA	<i>a</i>	-	0.1909
65	30	APTA	<i>b</i>	-	0.1876
65	50	APTA	-	-	0.1949
65	50	APTA	<i>a</i>	-	0.1949
65	50	APTA	<i>b</i>	-	0.1949

a and *b* are coefficients in Equation (2).

When applying disturbance and delay at a curvature radius 100 m and a longitudinal velocity 50 km/h, it was observed that the RMSE value is decreased. The RMSE value is influenced by the initial RLS values, covariance, and estimates in the control input

derivation process using the RLS. The control input can have an impact on the path tracking performance. Therefore, analysis of relationship between RLS values and control input is considered as a future work to improve the proposed control algorithm.

4. Discussion with Future Work

The performance of the adaptive path-tracking control algorithm for RLS-based autonomous driving under external conditions and covariance self-tuning was evaluated using MATLAB®/Simulink® and CarMaker. The evaluations performed for the four scenarios based on the curvature radius and driving speed simulated a universally applicable environment for user convenience. Target-value tracking does not require system information. Only a few control parameters, such as initial values and forgetting factors, are required for the RLS-based coefficient estimation and control input derivation. The injection terms were self-tuned in the control input using RLS estimation residuals. The evaluation results confirmed that the adaptive control input using the RLS-based real-time estimated coefficients could reasonably track the target path. The RLS-based coefficient estimation is sensitive to the initial parameter setting.

In this study, the same parameters were applied to all scenarios. Therefore, it can be concluded that the estimation performance did not react sensitively to the initial values. However, unreasonable control parameters or an unstable estimation performance can have a negative impact on coefficient estimation performance, and the control performance may deteriorate. This can be addressed by applying external constraints to each estimated coefficient, and in our study, the control input for tracking the target path was reasonably derived by compensating and adapting other parameters, even when constraints were applied to each parameter. However, vibrations were confirmed in the control input, and the oscillation in the road section was aggravated when driving at high speeds. The vibration that appears as a vehicle state quantity has a relatively small value; however, it can affect the target value tracking when driving at higher speeds. In the future, an enhancement of the proposed control and estimation algorithms using a stabilization approach with the improved external constraint method will be considered to address the aforementioned issue.

5. Conclusions

In this study, we estimated the coefficients of a first-order differential error equation using RLS with multiple forgetting factors for path tracking. The error is designed as an integrated error using the lateral error and yaw angle error of the target path and current vehicle. The control input was derived by applying the Lyapunov direct method with injection terms and finite-time convergence conditions. The sizes of the injection terms were self-tuned using the residual of the RLS. Therefore, the proposed adaptive control algorithm only needs to know constants, such as forgetting factors, initial conditions, and external and finite convergence conditions. Because it does not require information about the system parameters, it can be applied as a general-purpose control algorithm. The control input was calculated using the coefficients of the error dynamics estimated from the RLS. In the case of the RLS, if the control parameters are unreasonable, they can affect the estimated coefficients. Therefore, when the control parameters are assumed to be set incorrectly, and external constraints are applied to each estimated coefficient, we evaluate whether the other parameters compensate and adapt reasonably. A scaling factor is applied to the RLS covariance update process to adjust the adaptability of the coefficient estimation according to the amount of error change. In the MATLAB®/Simulink® and CarMaker environments, the performance was evaluated in four scenarios according to the curvature radius of the S-curved road and driving speed. The performance evaluation results showed a reasonable path-tracking performance for the autonomous vehicle. Even when external constraints were applied, the proposed algorithm drove the target path without lane departure in all situations. The current control algorithm has limitations in single-input and single-output systems, and the results indicate small vibrations under high-speed conditions. In

future studies, we plan to investigate the application methodology in an extended system considering a multi-input/output system. We plan to improve the algorithm by developing the self-tuning of the initial value of covariance based on rules through sensitivity analysis of control parameters. In this study, the proposed algorithm achieved path-tracking control without requiring system parameters, relying only on a few control parameters. However, initial control parameter settings were determined through a trial-and-error approach. In future work, we plan to develop a learning-based controller that automatically determines initial control values, allowing these control parameters to operate freely. In addition, along with performance evaluations in various driving scenarios, improving the control algorithm to generate the desired yaw rate stably even under high-speed conditions is being considered as a future research subject.

Author Contributions: Conceptualization, K.O.; methodology, H.L. and K.O.; software, H.L.; validation, H.L.; formal analysis, H.L. and K.O.; investigation, H.L.; resources, H.L.; data curation, H.L.; writing—original draft preparation, H.L.; writing—review and editing, H.L. and K.O.; visualization, H.L.; supervision, K.O.; project administration, K.O.; funding acquisition, K.O. All authors have read and agreed to the published version of the manuscript.

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Article

Development of a New Electric Vehicle Post-Crash Fire Safety Test in Korea (Proposed for the Korean New Car Assessment Program)

Jeongmin In *, Jaehong Ma and Hongik Kim

Korea Transportation Safety Authority, 200 Samjon-ro, Songsan-myun, Hwaseong-si 18247, Gyeonggi-do, Republic of Korea; mjh1409@kotsa.or.kr (J.M.); hongeik@kotsa.or.kr (H.K.)

* Correspondence: ijm2000@kotsa.or.kr; Tel.: +82-313690309

Abstract: Recent fire incidents following electric vehicle (EV) collisions have been increasing rapidly in Korea, corresponding to the growing distribution of EVs. While the overall number of EV fires is lower compared to those involving internal combustion engine (ICE) vehicles, EV fires can lead to more severe outcomes. Current regulations for post-crash fuel system integrity evaluation do not differentiate between EVs and ICE vehicles. However, the causes of fires in these vehicles differ due to variations in the design and construction of their fuel systems. This study analyzed seventeen cases of EV post-crash fires in Korea to derive two representative risk scenarios for EV post-crash fires. The first scenario involves significant intrusion into the EV front-end structure resulting from high-speed frontal collisions, while the second scenario involves direct impacts to the battery pack mounted under the vehicle from road curbs at low speeds (30–40 km/h). Based on these scenarios, we conducted tests to assess battery damage severity under two crash test modes, simulating both high-speed frontal collisions and low-speed curb impacts. The test results led to the development of a draft crash test concept to evaluate EV post-crash fire risks. Furthermore, we assessed the reproducibility of these test modes in relation to actual EV post-crash fires. Our findings indicate that square-shaped impactors provide higher reproducibility in simulating real EV post-crash fire incidents compared to hemisphere-shaped impactors. Additionally, a fire occurred 31 days after the storage of a crash-evaluated battery test specimen, which was determined to be caused by moisture invasion during post-crash storage, accelerating a micro-short circuit. This study aims to contribute to the development of new evaluation methods for the Korean New Car Assessment Program (KNCAP) to enhance EV post-crash fire safety by utilizing these test results to refine collision severity evaluation methods.

Keywords: electric vehicle; post-crash fire; high-speed frontal collision; direct impact to battery pack by road curbs at low speed

1. Introduction

The global supply of electric vehicles (EVs) is rapidly increasing due to government policies aimed at expanding the adoption of eco-friendly vehicles [1]. As the volume of EVs grows, the number of EV-related fires has also risen. These fires can occur for a variety of reasons, including collision accidents, defects in the battery control system, or issues with individual cells [2–4]. Although fires following EV collisions account for less than approximately 10% of all EV fires in Korea, their frequency is steadily increasing. In Korea, a total of 17 EV fires have occurred from the first incident in December 2020 to July 2024.

Since 2023, the share of post-collision fires in total EV fires has consistently risen ('23 to '24.7). The number of casualties resulting from these post-collision fires is increasing, likely due to the difficulty in extinguishing fires once they occur (see Figure 1).

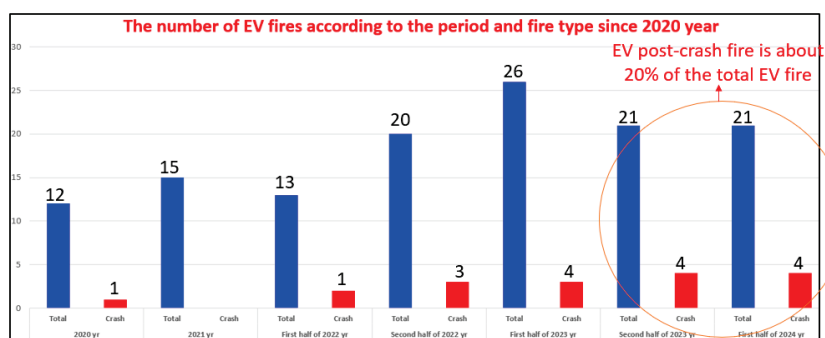


Figure 1. Number of EV fires by period and fire type from '23 to '24.7 in Korea.

Current crash safety regulations for EVs are the same as those for vehicles using other fuels [5–7]. Additionally, EVs do not appear to be more vulnerable than vehicles using conventional fuels, according to the results of the Self-Certification Compliance Investigation and the New Car Assessment Program (KNCAP) conducted in Korea. However, the vulnerability of the battery has been highlighted in the undercarriage test, which simulates bottom collisions, as evidenced by data from the EVERS SAFE European project [8]. Furthermore, there is a need for further research on post-collision fires in EVs, particularly concerning the direction of impact. Current crash test methods are limited in evaluating collision severity, as the impact location of the EV battery pack significantly influences the potential for fire and explosion [9–13].

Therefore, the objective of this study is to derive crash test modes that reflect vulnerable situations, such as fire or explosion, based on real-world post-collision fire scenarios involving EVs. This study aims to develop test protocols and standards to evaluate the likelihood and mechanisms of fire occurrence following an EV collision, utilizing the derived crash test modes in Korea.

2. Representative Crash Scenario of Post-Collision Fires in Electric Vehicles in Korea

Since the first EV fire accident following a collision occurred in December 2020 in Korea, a total of 17 post-collision EV fire accidents have been recorded. Among these, 13 fires were initiated by the EV battery, while the other 4 cases had initial fires originating from the electrical room or high-voltage connectors. Notably, the majority of these fires occurred due to collisions with road infrastructure or building walls, with only one instance involving a vehicle-to-vehicle collision (see Table 1).

Table 1. Impact types and number of fires/explosions from batteries after EV crashes.

Crash Types of EV Fires	Number	Crash Types of EV Fires	Number
Building Wall/Pole	4	Road Infrastructure	3
Road Curb	4	Road Debris	1
Vehicle Collision	1		

This study confirmed that physical damage, such as excessive deformation or penetration of the battery pack, was present in all post-crash EV fires. These damages were primarily caused by direct impacts to the battery pack from road infrastructure, such as curbs, or by deformed vehicle structures. Of the 13 cases, 9 involved frontal collisions.

This study analyzed these incidents and found that high-speed frontal collisions caused significant deformation of the front body structure, which led to the destruction of the battery pack. This damage subsequently resulted in direct impacts to the internal modules and/or cells of the battery.

Three of the thirteen cases confirmed that the battery pack, mounted on the bottom of the EV, was directly impacted by road debris or curbs, leading to penetration and deformation of the battery pack. These cases demonstrated that EV fires can occur even in low-speed collisions (approximately 20 km/h or less) when the battery pack is directly impacted by road curbs or other road infrastructure.

In all post-crash fire cases, fires or explosions occurred immediately following the collision.

In conclusion, post-crash fires in EVs in Korea can be categorized into two primary scenarios: high-speed frontal collisions and low-speed bottom impacts. Interestingly, in both types of collisions, the battery pack was primarily impacted at the front end of the vehicle, as illustrated in Figures 2 and 3. Representative post-crash fire scenarios for EVs were derived from data on EV fire accidents in Korea, as shown in Figure 4.



Figure 2. Damage shapes of vehicle structures and battery packs in post-collision fires following high-speed frontal collisions in EVs. (Red and yellow cycles are battery impact points).



Figure 3. Damage shapes of vehicle structures and battery packs in post-collision fires from direct impacts to the battery pack located at the bottom of EVs. (Yellow cycle is battery impact point).

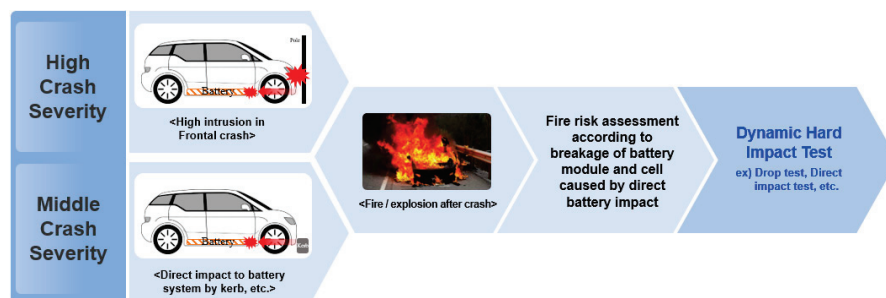


Figure 4. Two representative fire scenarios after EV collisions in Korea.

3. Evaluation of Battery Damage Severity According to Crash Modes Reflecting Two Post-Crash Fire Scenarios in Electric Vehicles

3.1. Crash Mode 1: Battery Damage Severity in High-Speed Frontal Collisions with Road Infrastructure (e.g., Impact Attenuators and Street Trees)

High-speed frontal collisions result in significant deformation of the vehicle's front structure. To simulate such collisions, this test mode was designed as the frontal center-pole impact mode, reflecting one of the most severe crash types encountered in real road conditions, which can cause extensive deformation of the front structure. The impact speed was set at 56 km/h, a velocity derived from GIDAS data that encompass the severity of most real-world road collisions, as shown in Figure 5.

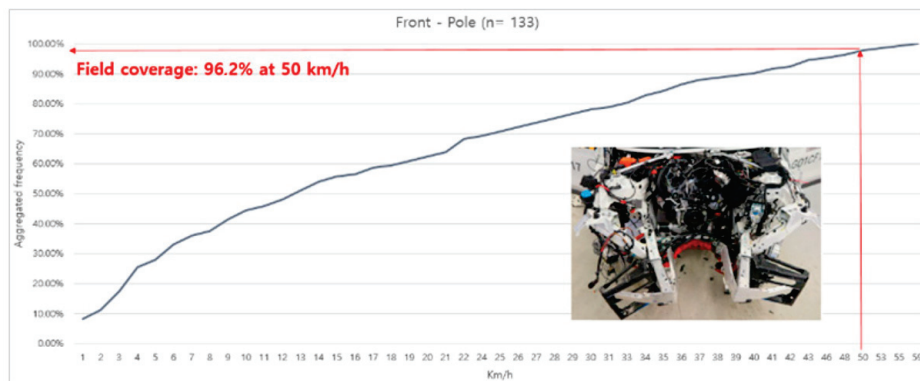


Figure 5. Impact velocity reflecting field accident coverage for frontal pole collisions based on German accident research (GIDAS).

This study analyzed the impact of crash severity on batteries by comparing the front structure of electric vehicles (EVs) and internal combustion engine (ICE) vehicles in the above-mentioned crash test modes. The EVs in this study were equipped with pouch-type lithium-ion polymer batteries. To minimize the risk of fire or explosion, the batteries were set to a low state of charge (SOC) of approximately 30% or lower during the indoor crash test evaluations.

The evaluation of the 56 km/h frontal center-pole impact mode revealed the following key findings:

First, despite most real-world EV post-crash fires in Korea occurring in high-speed frontal collisions, the 56 km/h frontal center-pole test did not trigger any fire or explosion risks from the battery pack. This indicates that fire or explosion in high-speed frontal collisions involving EVs is likely to be a rare edge case.

Second, it was observed that the amount of front intrusion in EVs was greater than that in ICE vehicles. In this test, although the rigid pole (used as an external barrier) did not directly impact the EV battery, the greater depth of intrusion of the EV's front structure increased the risk of direct battery collisions compared to ICE vehicles (see Figure 6).

However, although the EV showed substantial intrusion into the front section, the damage to the battery pack was minimal, consisting only of minor scratches and dents (see Figure 7). In contrast, the relatively smaller deformation in the ICE vehicle's front section was predicted to result in more significant impacts to the battery pack due to the presence of engine and transmission components in the front section.

Third, no deformation or penetration of the battery pack was observed, and there was no direct damage to the battery modules or cells. CT scans confirmed that there was no damage to the cells within the modules adjacent to the impact zone (see Figure 8).

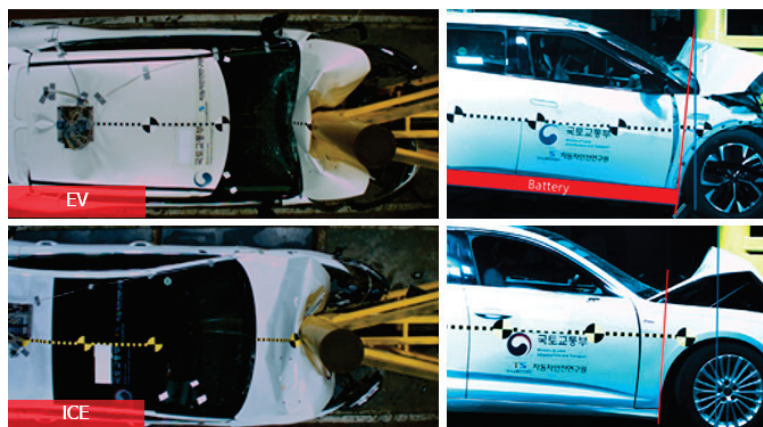


Figure 6. Comparison of front-end intrusion between EVs and ICEVs following a 56 km/h frontal center-pole impact test. (The red line is the foremost position of the battery and the blue line is the intrusion depth of the vehicle front structure).

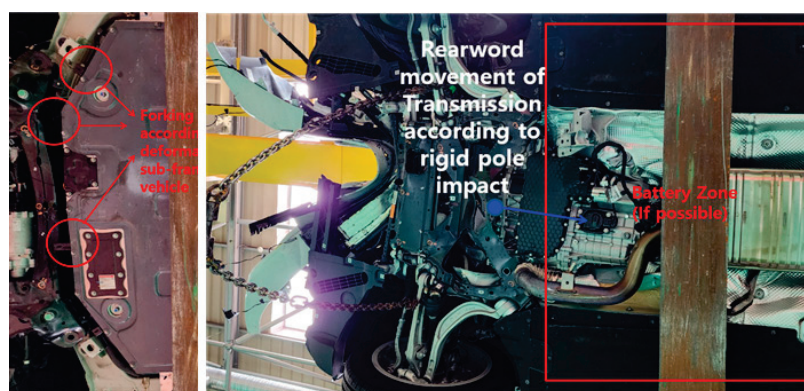


Figure 7. Comparison of battery pack damage between EVs and ICEVs following a 56 km/h frontal center-pole impact test.

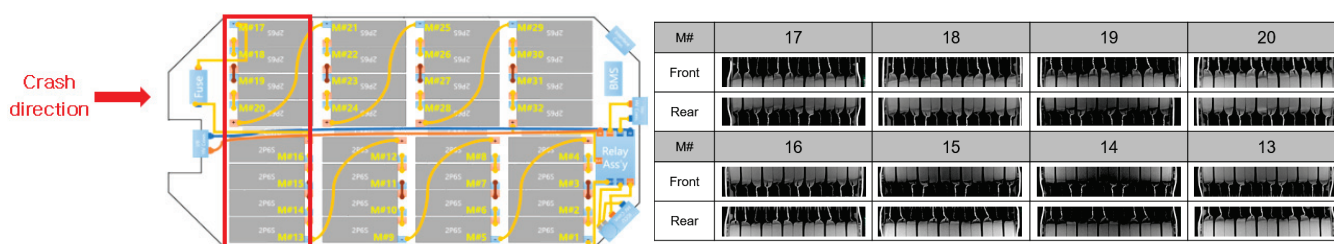


Figure 8. CT scan of battery modules after a 56 km/h frontal center-pole test.

As a result, the fire risk due to battery damage is considered low for electric vehicles, such as the tested vehicle, in most frontal collisions that may occur under real-world road conditions. Additionally, it is believed that minimizing battery damage during crash tests at speeds that reflect the severity of real-world roadway conditions would reduce the risk of fire from the battery in the event of an actual road crash.

3.2. Crash Mode 2: Battery Damage Severity Due to Impact on Batteries Mounted on the Bottom of EVs by Road Curbs, etc., at Low Speed

Crash Mode 2 was designed to evaluate the risk of fire or explosion when the battery pack mounted on the bottom of an EV is directly impacted by a road curb. Initially, both full-scale vehicle tests and trolley-mounted battery tests were considered; however, further evaluation of reproducibility and repeatability was necessary. Consequently, the crash evaluation was performed by simulating impact energy equivalent to that of a 2000 kg EV

impacting a road curb at approximately 17–18 km/h. The representative impact object, derived from Korea's road curb specifications, was used to simulate this impact. The battery used in the evaluation test is a lithium-ion polymer pouch-type battery. The SOC of the battery was 90%.

This test was conducted outdoors to account for the risk of fire or explosion resulting from the direct impact of the battery pack on an impactor simulating the road curb structure. The battery drop test was carried out in the test mode shown in Figure 9, during which kinetic energy was converted into potential energy, replicating the impact during an EV crash. Considering both the lowest ground clearance of the vehicle and the curb height on the road, the impact height between the battery and the impactor was determined, with a maximum overlap of 5 cm expected between the front end of the battery and the road curb.

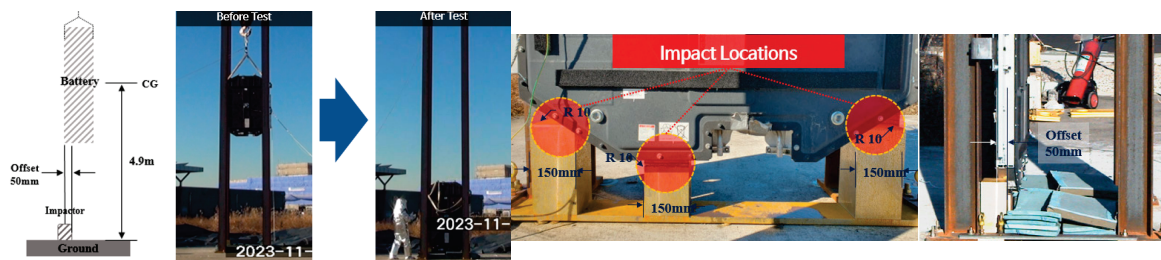


Figure 9. Battery drop test to reflect crash energy equivalent to the bottom impact (17–18 km/h) of EVs at the curb.

First, deformation and penetration of the battery pack occurred at all three impact points, as shown in Figure 10. It was observed that direct impact to the EV battery by the curb at low impact speeds (approximately 20 km/h or less) caused more damage to the battery located at the bottom of the vehicle than a high-speed frontal crash (approximately 56 km/h or more).

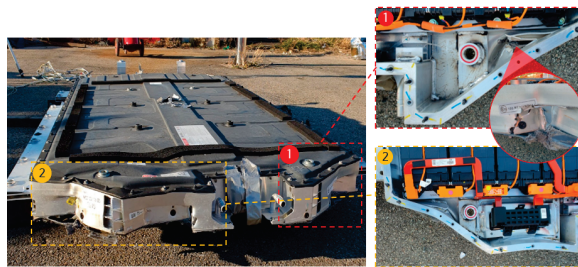


Figure 10. Damage and penetration of battery packs in the 4.9 m battery drop test.

Second, a fire ignited in the tested battery approximately 2 h after the drop test, with only the eight battery modules adjacent to the impact area burning, as shown in Figure 11. This confirmed that the most vulnerable area of the battery in a direct impact is the location closest to the impact zone.

Third, a CT scan was performed on the fully burned modules adjacent to the impact surface of the battery pack, as shown in Figure 12. The CT scan revealed that the cells within the battery pack were damaged due to the fracture of the pack. It was confirmed that the cell in contact with the lateral support bar inside the battery pack also experienced movement or local compression deformation due to the impactor penetrating the pack. Based on the battery fire analysis, it was confirmed that the first fire occurred in battery module No. 16 in the front row, where the impactor collided. The impact was transmitted directly to the battery module through the penetration of the battery pack. The fire was

likely caused by the anode material tearing first, followed by damage to the separator due to the tensile deformation of the cell during compressive deformation.

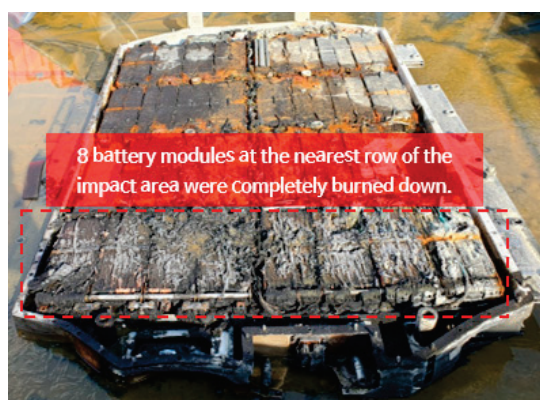


Figure 11. Burned battery after 4.9 m battery drop test.

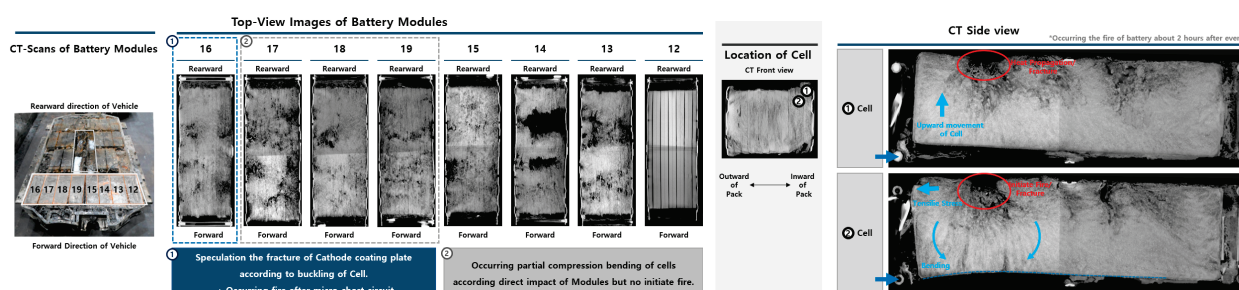


Figure 12. CT scan analysis of the burned battery following the 4.9 m battery drop test.

4. Development of New Draft EV Post-Crash Fire Safety Protocol Concepts for KNCAP

This study analyzed both the battery fire occurrence mechanisms and the associated risks by examining fire scenarios from representative EV crash accidents in Korea. Based on this analysis, it was determined that the new EV post-crash fire safety protocol should prioritize protecting the battery from deformation in high-speed frontal collisions and mitigating fire risks arising from low-speed, direct bottom impacts. As discussed in Sections 2 and 3, it was confirmed that direct impacts to the EV battery pack are the primary cause of post-crash fires, according to both the fire incident data in Korea and the evaluation tests reflecting representative EV crash scenarios. However, it was concluded that evaluating both fire risk mechanisms simultaneously would be challenging.

The fire mechanism in high-speed frontal collisions is attributed to direct damage to the battery. As outlined in the conclusion of Section 3.1, it is believed that EV fires can be prevented by minimizing damage to the battery during collision conditions typical of domestic roads. The frontal crash test: Given that domestic safety regulations (KMVSS) and the Korean New Car Assessment Program (KNCAP) already address most real-world crash scenarios, it is assumed that most fires in high-speed frontal collisions can be prevented by minimizing damage to battery cases in such crash conditions.

However, it is challenging to address low-speed direct collisions with existing collision evaluation methods, necessitating the development of a new evaluation approach. Since the battery, which is mounted at the center of the vehicle, will first impact the front-end structure of the vehicle, rather than directly impacting the battery when hitting objects like curbs, ensuring reproducibility and repeatability under full vehicle crash conditions becomes difficult. Therefore, trolley tests that reflect full-scale vehicle conditions are

considered more appropriate for evaluating battery damage severity in the event of an electric vehicle collision.

In this context, we developed new draft EV post-crash fire safety protocol concepts, as shown in Figure 13, based on the following considerations:

- **Impact Speed:** Reflecting the representative crash speed of low-speed direct bottom impacts, impact speed is derived from domestic and international literature research.
- **Impactor:** The hemispherical type applies the existing impactor for undercarriage vehicle tests, and the square type applies the domestic standard curb size in Korea.

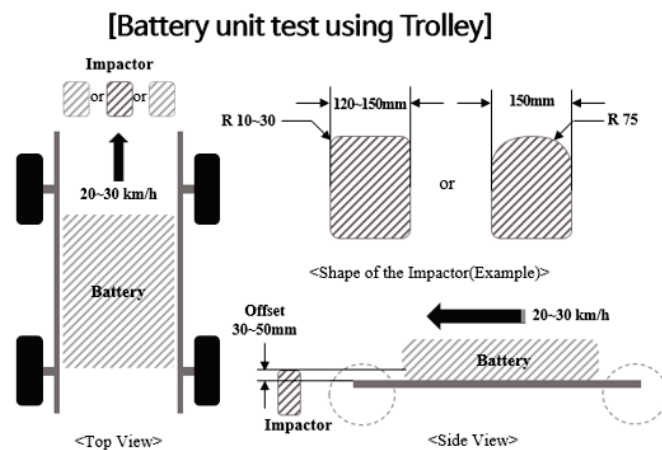


Figure 13. Initial draft of new EV post-crash fire safety protocol concepts for direct impact on the batteries mounted at the bottom of EVs by road curbs or similar road debris at low speeds, derived from this research.

The draft concepts will undergo further investigation to develop detailed protocols, including collision speed and impact location, among others.

5. Evaluation of Battery Damage Severity Based on Initial Draft of New EV Post-Crash Fire Safety Protocol Concepts (Low-Speed, Direct-Impact Test on the Battery)

In order to evaluate the reproducibility of the new draft EV post-crash fire safety protocol in real EV fire accidents, tests were first conducted to analyze the effect of two impactor types, as shown in Figure 13, since the shape of the impactor can significantly influence the EV post-crash fire mechanism [14]. A trolley mounted with the battery was used to replicate the same curb weight conditions as a full-scale vehicle, ensuring similar reproducibility to real electric vehicle crash scenarios. The overlap height between the front face of the battery and the impactor was set to 50 mm, and the state of charge (SOC) of the battery was maintained above 95% (see Table 2).

Table 2. Comparison between full-scale vehicle and trolley with test battery.

	Front Axle	Rear Axle	Total Curb Weight
Full-Scale Vehicle	935 kg	1040 kg	1975 kg
Trolley w/Battery	942 kg	1032 kg	1974 kg

5.1. Crash Mode 3: 30 km/h Trolley Test Using a Hemispherical Impactor

The hemispherical impactor used in this test is of the same specification type employed in the bottom-scraping test in the 2024 C-NCAP [15]. As a result of the 30 km/h trolley impact test with the hemispherical impactor, the following main characteristics were observed:

A crash mechanism similar to the bottom-scraping test condition occurred, despite the impact being directed at the frontal face of the battery pack, as shown in Figures 14 and 15. The front face of the battery pack showed minimal deformation following the crash impact.

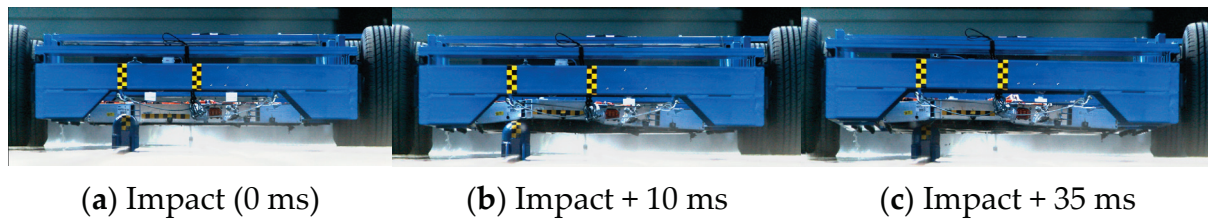


Figure 14. Frontal view of 30 km/h trolley test using a hemispherical impactor.

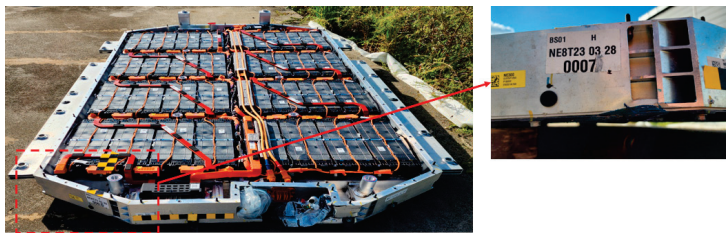


Figure 15. Minor damage to the bottom of the battery packs following 30 km/h trolley test using a hemispherical impactor.

As shown in Figure 16, no damage was observed to the battery cells or modules as a result of tensile or compressive forces, due to the minimal movement of the battery modules during the crash.

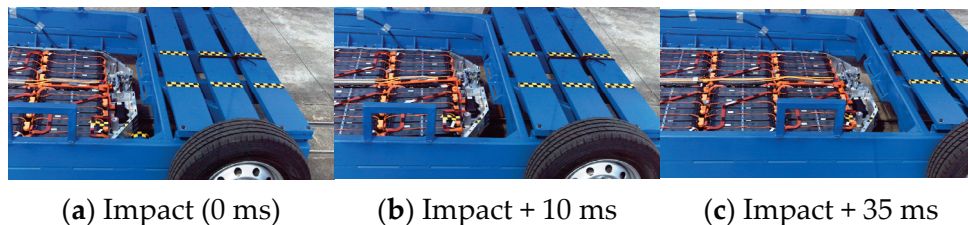


Figure 16. Frontal view of 30 km/h trolley test using a hemispherical impactor.

Post-crash monitoring over 12 h revealed no drop in battery voltage, nor were there any instances of fire or explosion.

5.2. Crash Mode 4: 30 km/h Trolley Test Using a Square Impactor

The square impactor reflects the standard road curb shape in Korea. As a result of the 30 km/h trolley impact test using the square impactor, the following key characteristics were identified:

The crash mechanism of Crash Mode 4 was observed to resemble aspects of both Crash Modes 2 and 3. The first characteristic noted was the fracture and deformation of the front face of the battery pack, which caused the lateral support bar to impact the battery modules adjacent to the impact location, similar to Crash Mode 2. As a result, the deformation geometry of the frame inside the battery pack was found to be similar to or more severe than that observed in Crash Mode 2. The second characteristic was a bottom-scraping mechanism similar to Crash Mode 3, although it was more severe (see Figures 17 and 18).

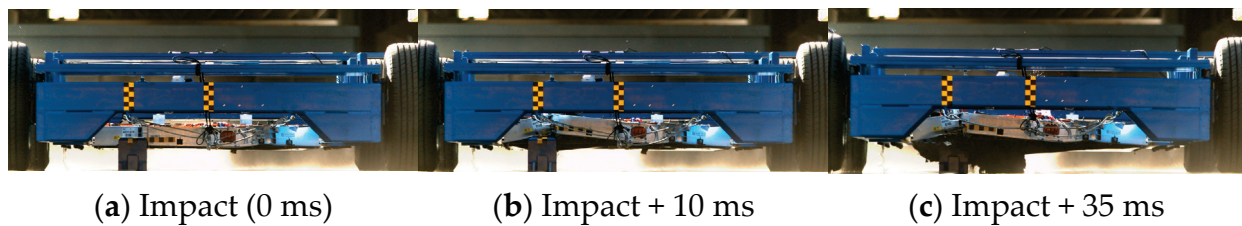


Figure 17. Frontal view of 30 km/h trolley test using a square impactor.



Figure 18. Excessive damage to the front face and internal frame of the battery packs following 30 km/h trolley test using a square impactor.

As shown in Figure 19, the battery cells and modules were impacted by the internal frame of the battery pack due to the large deformation and fracture of the pack. Despite the severe damage, no fire or explosion occurred during the 12 h of post-crash monitoring, in contrast to Crash Mode 2.

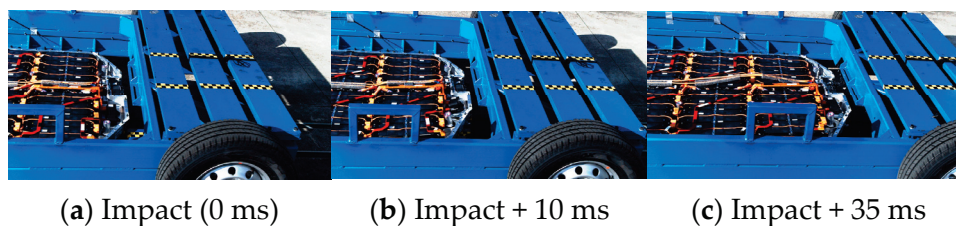


Figure 19. Frontal view of 30 km/h trolley test using a square impactor.

However, after storing the two tested batteries, one battery (used in the hemispherical impactor crash test) caught fire after 31 days, while the other battery, which did not catch fire (used in the square impactor for crash testing), was disassembled and found to have moisture in the internal modules.

6. Conclusions

This study confirmed the fire occurrence mechanisms following electric vehicle (EV) crashes through both crash evaluation tests and an analysis of 13 accident datasets from Korea between 2021 and 2024. 7. Based on the analysis of EV post-crash fire accident data, crash test results reflecting the severity of EV fire accidents, and draft concepts for EV post-crash fire safety protocols, the following conclusions can be drawn:

1. Post-crash fires in EVs in Korea primarily occurred in high-speed frontal collisions and low-speed direct impacts to the battery mounted at the bottom of the vehicle. Additionally, these fires were caused by direct damage to the battery pack (e.g., excessive deformation and penetration) resulting from direct impacts to the cells and modules within the battery pack.
2. This study confirmed that the mechanisms causing direct impact to the battery differ in high-speed frontal collisions between EVs and internal combustion engine (ICE)

vehicles. In the case of EVs, the battery pack can be damaged due to intrusion from external structures resulting from excessive deformation of the front structure. Conversely, for ICE vehicles, the front structure can cause damage to the battery pack by moving the front drive components or rigid parts into the battery zone, thereby impacting the battery pack.

3. The fire mechanisms caused by the breakage of modules and/or cells within the battery pack were identified. It was confirmed that battery fires can occur not only from direct cell breakage due to impact but also from cell fractures induced by tensile deformation during the impact event.
4. Regarding the impactor geometry, it was found that the square impactor type exhibited better reproducibility of the battery damage observed in real-world EV post-crash fire accidents in Korea compared to the hemispherical type.
5. In real-world road crashes in Korea, EV fires typically occurred immediately after the crash. However, in the evaluation tests, fires were observed to occur as long as 2 h or even 31 days after the crash. This discrepancy is attributed to the lower severity of battery damage in the evaluation tests compared to real-world accidents, which resulted in micro-short circuits during the evaluation tests, as opposed to the large short circuits typically seen in real-world collisions. As mentioned in Chapter 4, the battery that caught fire 31 days after the crash test indicated the potential for moisture invasion into the micro-short-circuited battery. Therefore, it is recommended to include an additional evaluation, such as an immersion test (according to KMVSS), to assess the waterproof performance of the battery.
6. This study has derived EV post-crash fire safety assessment concepts that can be applied to future NCAP regulations, with the following considerations:
 - The new EV post-crash fire safety test concept should accurately represent the fire mechanisms observed in real EV crash accidents.
 - It is reasonable to develop separate evaluation methods for high-speed frontal collisions and low-speed bottom impacts, as the mechanisms causing damage to the battery differ between these two crash types.
7. Although further modifications and improvements will be made before NCAP is implemented in 2026, this research has established new test protocols aimed at minimizing post-crash fires in electric vehicles, as shown in Figure 20.

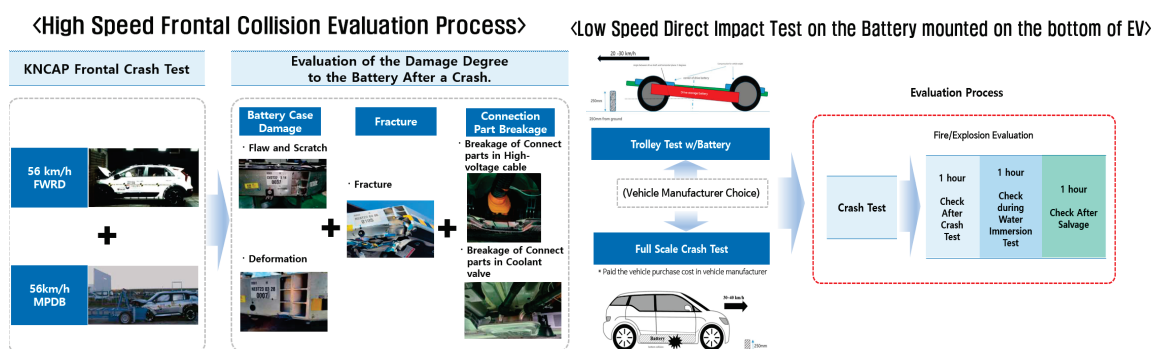


Figure 20. New draft EV post-crash fire safety protocol concepts for future NCAP ('26) derived from this research.

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Article

Driving Control Strategy and Specification Optimization for All-Wheel-Drive Electric Vehicle System with a Two-Speed Transmission

Jeonghyuk Kim ¹, Jihyeok Ahn ¹, Seyoung Jeong ¹, Young-Geun Park ¹, Hyobin Kim ¹, Dongwook Cho ² and Sung-Ho Hwang ^{1,*}

¹ Department of Mechanical Engineering, Sungkyunkwan University, 2066 Seobu-ro, Suwon 16419, Republic of Korea; jungjjang44@naver.com (J.K.); ahnkevin0@g.skku.edu (J.A.); nasy960@skku.edu (S.J.); biee00m@naver.com (Y.-G.P.); illusosmile@naver.com (H.K.)

² Department of Intelligent Robotics, Sungkyunkwan University, 2066 Seobu-ro, Suwon 16419, Republic of Korea; dw0313@g.skku.edu

* Correspondence: hsh0818@skku.edu

Abstract: Equipping electric vehicles with a two-speed gearbox allows for achieving high torque and maximum speed through appropriate gear ratio adjustments. Additionally, tuning motor operating points to efficient zones, considering energy efficiency, significantly enhances the vehicle's overall performance. This paper presents an AWD system configuration method, integrating a two-speed transmission to improve energy efficiency and driving performance through front and rear motor torque distribution and powertrain specification optimization. Based on vehicle simulations conducted using MATLAB/Simulink, a strategy for torque distribution between the front/rear axles was established using fuzzy logic, considering energy efficiency and driving stability. Furthermore, a multi-objective optimization was performed using a surrogate model trained through MATLAB parallel simulations. When the optimization results were applied to various vehicle specifications, it was observed that energy efficiency was improved, and acceleration performance was increased compared to a baseline vehicle without optimization.

Keywords: AWD electric vehicle; two-speed transmission; torque distribution; surrogate model; multi-objective optimization

1. Introduction

Due to global environmental regulations, countries are strengthening regulations on internal combustion engine vehicles, and there is a notable trend towards the transition to electric vehicles (EVs). Consequently, various existing internal combustion vehicles are converted to electric vehicles [1–3]. However, electric vehicles face issues of short driving ranges due to low energy density, and recently, consumers have had higher expectations for the driving performance of electric vehicles. Against this backdrop, many automobile manufacturers focus their research and development efforts on meeting these dual demands [4].

A recent solution to these problems proposes the integration of a two-speed transmission in the EV layout. Typically, the fixed-ratio gear reducer installed in electric vehicles provides sufficient acceleration performance even at low speeds due to the torque characteristics of electric motors, and it is widely used due to its simple design and highly efficient operation within a specific rotational speed range of the motor. However, fixed-ratio gear reducers limit the dynamic performance of electric vehicles and reduce the utilization of the motor's high-efficiency range, thus hindering efficient driving [5]. A two-speed transmission can satisfy both high initial drive torque and high top speeds. An appropriate shifting strategy allows for controlling motor operation points, enhancing motor driving

efficiency [6,7]. For instance, Huang et al. [8] demonstrated the advantages of a two-speed transmission by comparing motor operation points with a fixed-ratio reducer and changes in vehicle driving performance according to the gear ratio under the European New Driving Cycle (NEDC). Janulin et al. [9] reduced the energy consumption of a vehicle by optimizing the gear ratio parameters in actual traffic cycles.

The All-Wheel-Drive (AWD) layout can be utilized to enhance the driving performance of electric vehicles. The AWD system delivers power to all wheels, providing superior driving performance on slippery roads and rough terrains, thereby improving driving stability and traction capabilities [10]. The multi-motor configuration of this system allows for appropriate torque distribution to the front and rear motors, which enhances driving performance and energy efficiency. In this context, Dizqah et al. [11] proposed a rapid and parameterized torque distribution strategy for four-wheel drive electric vehicles to increase energy efficiency. Cao et al. [12] suggested a method to improve vehicle energy consumption and wheel slip ratio performance through multi-purpose optimal torque distribution in four-wheel drive electric vehicles.

Therefore, the new structure equipped with a two-speed gearbox in the AWD layout has the advantage of satisfying electric vehicle driving efficiency, vehicle power performance, and driving stability through appropriate shift strategies and torque distribution. Currently, many studies are being conducted related to this. However, as the layout becomes more complex, it is necessary to consider that the design time can increase due to the many powertrain specification variables that must be considered during the vehicle design phase. To address this, researchers have recently presented methods to optimize various powertrain structures and pre-select component specifications to reduce design time. For example, Kim et al. [13] presented a method to determine the optimal gear ratio that satisfies the dynamic performance of hybrid electric vehicles while minimizing energy consumption. Nguyen et al. [14] proposed an energy management strategy through gear shift scheduling using a dual-loop optimization algorithm to explore motor capacity and gear ratios.

Related prior studies primarily focus on optimizing gear ratios to improve the performance of electric vehicles, and there are few studies on the simultaneous optimization of motor specifications and shift maps. Individually optimizing the gear ratio, motor specifications, and shift maps has the advantage of simplifying the optimization process. However, this method does not reflect the interaction between these elements. Therefore, it cannot guarantee the system's optimal performance. Additionally, the design of objective functions is crucial when performing multi-objective optimization. However, designing objective functions based on formulas can result in a lack of credibility in the solutions derived from optimization, as they fail to fully reflect vehicle modeling. Therefore, to address these issues, the main contributions of this paper are summarized as follows:

- (i) A method is presented for the simultaneous optimization of motor specifications, reduction ratios, and shift maps, considering torque distribution strategies for both front and rear wheels, which is expected to maximize vehicle performance;
- (ii) An objective function was designed by training electric vehicle simulation data using deep learning for application in multi-objective optimization. This approach enhances the credibility of selecting optimal specifications for the AWD EV powertrain.

Firstly, the paper proposes a method that integrates motor torque distribution strategies with optimization techniques to fully utilize the characteristics of AWD EVs equipped with two-speed gearboxes. Changes in component specifications, such as motor specifications and reduction ratios, result in variations in the torque distribution ratio map to maximize energy efficiency. Consequently, a variable torque distribution ratio 2D Look-up Table, adjusted for various input parameters (maximum motor torque and power, front and rear reduction ratios, shifting speeds), is applied in the simulator. The simulation outputs, such as State of Charge (SOC) variations and acceleration times, are then used for optimization. This method offers the advantage of producing solutions close to the system's optimal performance by considering major powertrain component specifications

simultaneously. An additional consideration is that focusing the torque distribution strategy solely on energy efficiency often concentrates torque on one motor, which can reduce vehicle stability in special situations like rapid acceleration or deceleration. In response, the paper presents an integrated torque distribution methodology that can adjust between a torque distribution strategy focused on energy efficiency and one focused on straight driving stability based on Fuzzy Control.

Additionally, the objective functions used in this study for multi-objective optimization are energy consumption and acceleration performance. However, setting up objective functions based on formulas to predict energy consumption and acceleration performance for complex vehicle structures with a transmission in the AWD layout is quite challenging. This is due to elements like motor efficiency maps, which have nonlinear solid characteristics, making output prediction difficult. Therefore, in this paper, we use deep learning to create a surrogate model that emulates electric vehicle simulations. Through this model, two objective functions—one for energy consumption (SOC variations) and another for acceleration performance (0–96 kph acceleration time)—are designed and applied to multi-objective optimization.

The structure of this paper is as follows: Section 2 describes the methodology for modeling AWD vehicles based on MATLAB/Simulink (<https://www.mathworks.com/>), including explanations and result graphs for shift logic to prevent torque holes and shift shocks. Section 3 discusses the motor torque distribution strategies required for optimization and explains how energy efficiency and driving stability were simultaneously considered using Fuzzy Control. Section 4 focuses on the main content of this paper, explaining the method of using an Artificial Neural Network (ANN) to emulate electric vehicle simulations with torque distribution strategies and the approach for deriving optimal solutions through multi-objective optimization based on the Non-Sorted Genetic Algorithm-II (NSGA-II). Section 5 presents and discusses the simulation results. Finally, Section 6 summarizes the key conclusions.

2. AWD Vehicle Modeling with Two-Speed Transmission

As shown in Figure 1, an AWD electric vehicle equipped with one motor on each front and rear axle was developed using MATLAB/Simulink. The powertrain consists of a battery, Vehicle Control Unit (VCU), two motors, gears connected to the front axle motor, and a two-speed transmission connected to the rear axle motor. Section 2.2 provides detailed descriptions of each module.

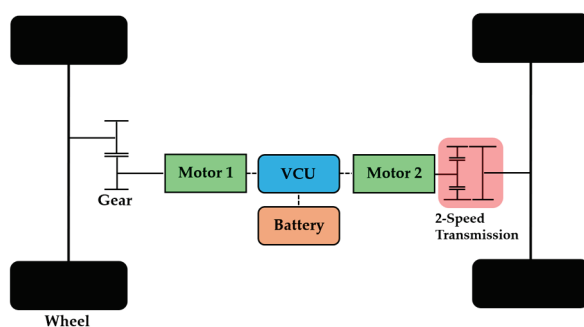


Figure 1. Schematic Diagram of 2-Speed Transmission AWD Vehicle Powertrain Structure.

2.1. Parameters of the Target Vehicle

The paper considers three types of vehicle specifications: Sedan, SUV (Sport Utility Vehicle), and SUV equipped with a trailer. Table 1 displays the key parameters used in the system and the optimization parameters. Moreover, Table 2 displays the vehicle performance indicators.

Table 1. Target vehicle key parameters.

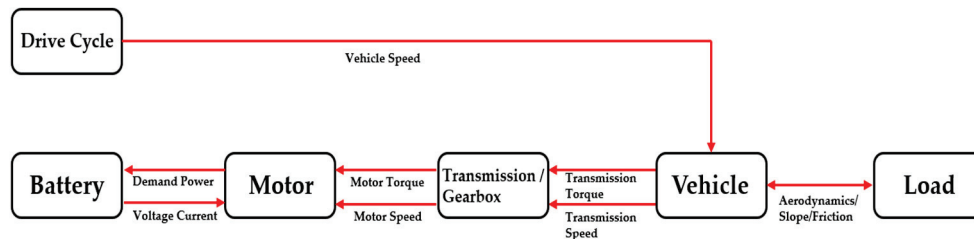
Item	Value [Unit]
Vehicle mass (Sedan/SUV/SUV-Trailer), m	2265/2728/5803 [kg]
Base motor power, P /Maximum torque, T	92 [kW]/230 [Nm]
Base motor max speed, ω_{max} /motor base speed, ω_{base}	20,000 [RPM]/3820 [RPM]
Battery capacity, Q_n	77.4 [kWh]
Initial front gear ratio, i_f	10.65 [-]
Initial rear 1st/2nd gear ratio, i_{r1}/i_{r2}	14 [-]/6 [-]

Table 2. Electric vehicle performance indicators.

Indicators	Value [Unit]
Maximum vehicle speed (Sedan/SUV/SUV-Trailer)	225/170/128 [km/h]
Maximum climbing grade	60 [%]
Acceleration time (0~96 km/h)	4.1/5.0/20.0 [s]

2.2. AWD Electric Vehicle Model-Based Simulation

The backward simulation was selected to optimize electric vehicle components and system specifications. This approach calculates the required power of the vehicle from a speed profile, not dynamic state variables. It allows for establishing optimal energy management strategies among various components while shortening simulation time [15]. Additionally, it enables rapid iterative simulations, contributing to time savings in the optimization process. The structure of the backward simulation is shown in Figure 2.

**Figure 2.** Backward simulation structure.

The backward simulation comprises several subsystems, and the description of each subsystem is as follows:

- (1) Driving Cycle and Vehicle: Vehicle speed is calculated based on the driving cycle, and from this speed, driving resistance is computed to determine the vehicle-level output force. The calculation for vehicle-level output force is as follows [16].

$$F = m \cdot \frac{dv}{dt} = \frac{T}{r_D} - \left(\mu_r mg \cos \theta + \frac{1}{2} C_D \rho_a A v^2 + mg \sin \theta \right) \quad (1)$$

where F is the vehicle-level output force; v is the vehicle speed; T is the total (front/rear) wheel torque; r_D is the tire radius; μ_r is the rolling resistance coefficient; C_D is the air drag coefficient; ρ_a is the air density; A is the windward area; and θ is the climbing gradient.

- (2) VCU: Based on the vehicle-level required torque, values for Accel Pedal (AP) and Brake Pedal (BP) are calculated. Then, the torque distribution logic derives the required torque levels for the front and rear motors. Estimating vertical forces for the front and rear axles is also conducted simultaneously. The formula for estimating vertical forces is as follows.

$$F_{zf} = mg \cdot \left(\frac{l_r}{L} - \frac{h}{L} \cdot \frac{a}{g} \right) \quad (2)$$

$$F_{zr} = mg \cdot \left(\frac{l_f}{L} + \frac{h}{L} \cdot \frac{a}{g} \right) \quad (3)$$

where F_{zf} , F_{zr} are normal force of front/rear wheel; l_f , l_r are the front/rear distance from the center of gravity; L is the total wheelbase; h is the height of the center of gravity; and a is the vehicle acceleration.

- (3) Motor: Motor efficiency is determined based on the required motor torque and speed calculated by the VCU. The motor efficiency map was adapted by transforming the x - and y -axis scale of the reference motor's efficiency map. Section 4 discusses the efficiency map scaling method in detail. Then, considering the motor efficiency and the battery's Open Circuit Voltage (OCV), the battery current is calculated. The speed of the rear motor is inputted, considering the transmission's first and second-gear ratios. The calculation for the battery current during motor charge and discharge, considering motor torque, speed, and efficiency, is as follows.

$$I_d = \left(\frac{T_1 \omega_1}{\eta_1} + \frac{T_2 \omega_2}{\eta_2} \right) \cdot \frac{1}{V_t} \quad (4)$$

$$I_c = (T_1 \omega_1 \eta_1 + T_2 \omega_2 \eta_2) \cdot \frac{1}{V_t} \quad (5)$$

where I_d , I_c are the battery current during motor(charge/discharge); ω is the motor speed; η is the motor efficiency; and V_t is the voltage applied to the motor.

- (4) Battery: The SOC is calculated using the Open Circuit Voltage and the required battery current. Then, the voltage applied to the motor is computed using the SOC and the circuit voltage values. The battery model utilizes a first-order R equivalent circuit model, as shown in Figure 3. The formulas for calculating the motor applied voltage and SOC are as follows:

$$V_t = I \cdot R_{int} - V_{oc}(SOC) \quad (6)$$

$$SOC(t) = SOC(t-1) + \frac{I(t)}{Q_n} \Delta t \quad (7)$$

where R_{int} ($= R_0$) is the battery's internal resistance; SOC is the state of charge of battery; $V_{oc}(SOC)$ is the open circuit voltage based on SOC; and $I(t)$ is the battery current.

- (5) Transmission: Unlike internal combustion engine vehicles, electric cars benefit from the torque-speed characteristics of electric motors, which provide high torque at low speeds and maintain constant power across an extended speed range. Due to these characteristics, electric vehicles can achieve the necessary performance with fewer gears [17]. Transmission modeling can consider various structures, and in this paper, a dog clutch-type transmission system was selected. The dog clutch is simple in structure and excellent in power transmission efficiency, making it suitable for electrified transmission systems. Due to these characteristics, it can be utilized in two-speed transmission systems.

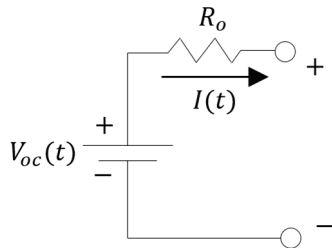


Figure 3. Equivalent circuit of internal resistance model.

2.3. Gear Shift Mechanism

Due to simulation time constraints, a detailed transmission dynamic model was not implemented. Instead, the system was structured to shift gears based on different states aligned with the gear change process. To minimize shift shocks, a 'speed synchronization' process was included where the motor speed in neutral matches the gear's speed to be engaged next [17]. Below is the gear change process divided by states.

- State 1. Torque Phase and Gear Neutral: When a gear shift command is issued, the torque of the rear motor is controlled to zero. Simultaneously, the torque of the front motor is compensated to maintain maximum total torque [18]. After the torque phase, the control shifts to neutral in the transmission.
- State 2. Speed Synchronization: Control the motor to the target speed range to mitigate shocks during the clutch engagement due to speed changes in the dog clutch gear when shifting. The speed synchronization phase ends when the difference between the target and motor speeds is less than or equal to 1 rad/s. The formula to calculate the motor speed when in neutral is as follows.

$$\omega = \int \dot{\omega} dt = \int \frac{T}{J} dt \quad (8)$$

where ω is the rear motor speed in a neutral state; T is the rear motor torque in a neutral state; and J is the moment of inertia of the motor, shaft, and clutch.

- State 3. Gear Engagement and Torque Phase: Engage the dog clutch actuator and normalize the torque distribution between the front and rear motors.

Figure 4 illustrates the speed synchronization process of the rear motor in a neutral state. First, the target reference speed for the rear motor shift is calculated using the vehicle speed and the current rear gear ratio (first/second gear). Then, motor torque is output through the speed synchronization process based on a PI controller in the neutral state. The motor torque is converted to speed using Equation (8) and fed back into the PI controller. When the difference between the reference speed and the rear motor speed in neutral falls below 1 rad/s, the shift end signal changes, and the speed synchronization process ends.

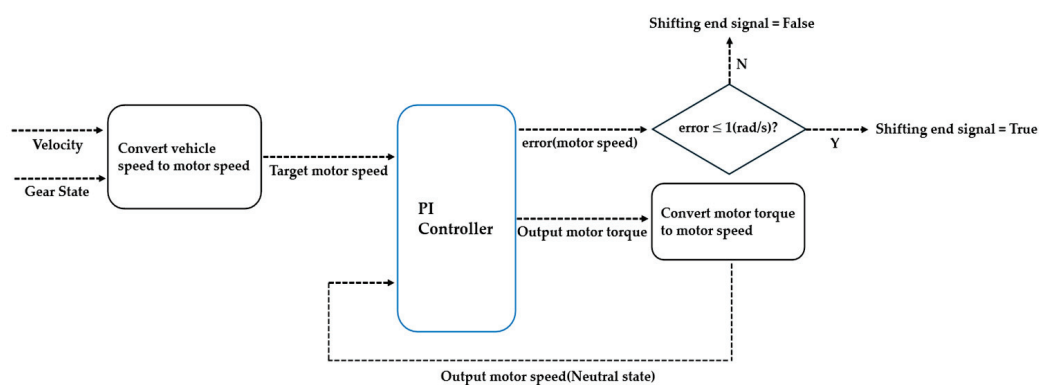


Figure 4. Schematic Diagram of Neutral State Speed Control Module.

Figure 5 shows the results of rear motor speed control and torque values in neutral state during upshifting and downshifting when a two-speed shift logic is applied. The sky-blue area represents the gear-neutral state in Figure 5.

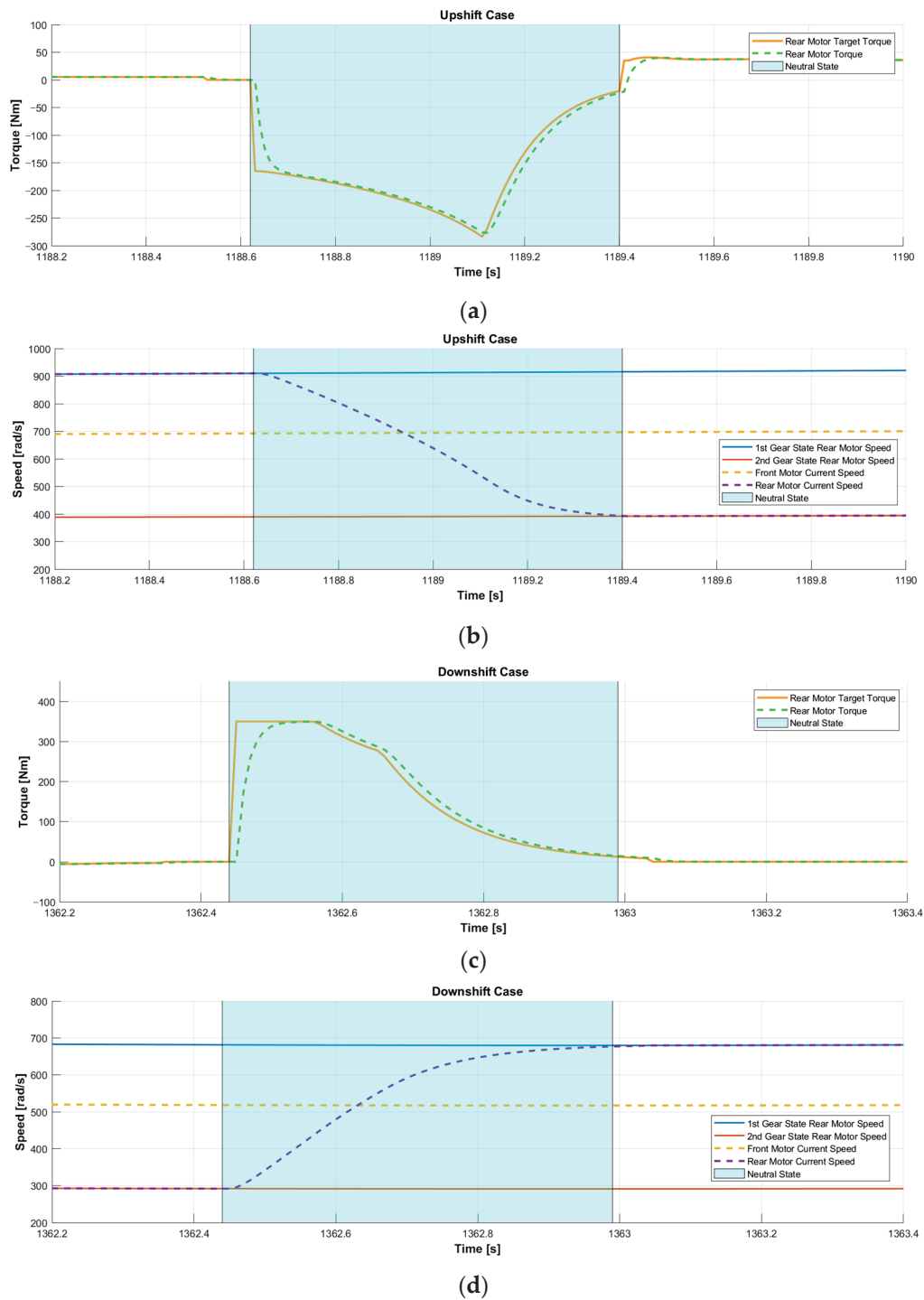


Figure 5. (a,c) Target torque and torque results for the rear motor in a neutral state (Uphift case, Downshift case); (b,d) target motor speeds for each gear and motor speeds of front/rear motor in a neutral state (Uphift case, Downshift case).

3. Integrated Torque Distribution Logic

In AWD systems equipped with front and rear motors, appropriate motor torque distribution can enhance energy efficiency. However, focusing solely on energy efficiency can lead to unstable vehicle behavior. Therefore, a torque distribution strategy based on efficiency maps and vertical force-based optimal braking force has been adopted. This strategy is regulated using Fuzzy Control to adjust the torque distribution dynamically [19].

3.1. Detailed Torque Distribution Logic

3.1.1. Energy Efficiency-Based Torque Distribution Strategy

Once the specifications for the front and rear motors are determined, front and rear motor efficiency maps can be generated based on the baseline motor efficiency map. Once the front and rear motor efficiency maps are established, the combined battery consumption power for the front and rear can be calculated when specific wheel torque and speed are input. To create a 2D Look-up Table focused on energy efficiency for front and rear torque distribution ratios, a global search algorithm was devised to store the distribution ratios that yield the minimum combined battery consumption power within the specified wheel torque and speed range. The corresponding Flow Chart and the 2D Look-up Table derived through the global search algorithm are illustrated in Figures 6 and 7, respectively. In Figure 7, as the color changes from blue to yellow, it indicates that the torque ratio is approaching 1.

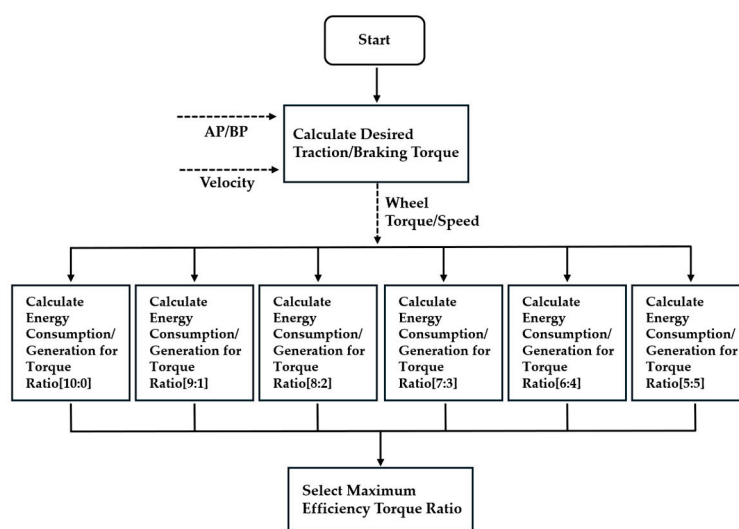


Figure 6. Flow Chart of the Strategy for Optimizing Driving Efficiency (Adapted from Ref. [19]).

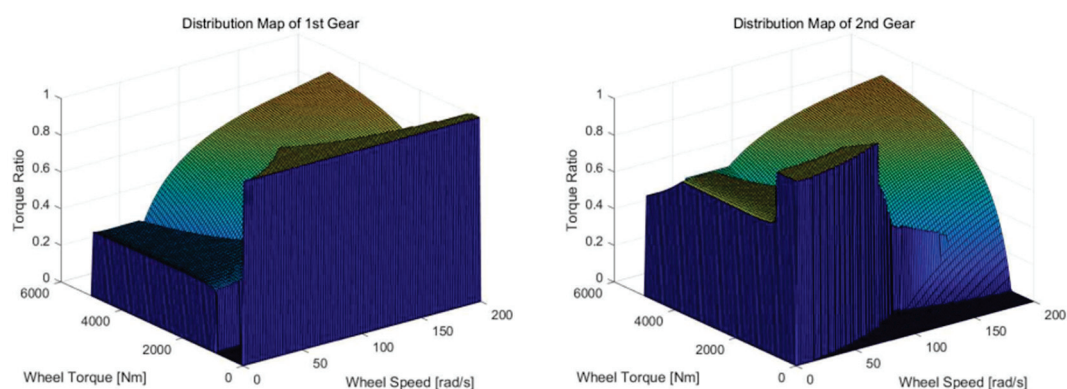


Figure 7. Distribution Map of 1st/2nd Gear.

3.1.2. Vertical Force-Based Torque Distribution Strategy

When a vehicle's torque distribution strategy focuses solely on efficiency, there is a potential to lose driving stability in specific situations, such as rapid acceleration or deceleration. This occurs because the motor's operating points tend to be positioned within high-efficiency areas, causing the required torque to concentrate on the front or rear wheels. Therefore, vertical forces based on the vehicle's acceleration have been calculated and

used to further consider torque distribution. The front wheel torque distribution ratio is expressed using Formulas (2) and (3) as follows.

$$\text{Front Torque Ratio} = \frac{F_{zf}}{F_{zf} + F_{zr}} \quad (9)$$

This formula minimizes tire slip by allocating more torque to the wheels with higher vertical forces. It is intuitively understood.

3.2. Integration of Torque Distribution Based on Fuzzy Logic

An appropriate mix between the two specific torque distribution strategies mentioned earlier is necessary for efficient vehicle operation. Therefore, the two distribution strategies are adjusted based on the driver's acceleration and deceleration demands. To more accurately determine the driver's acceleration and braking requirements, alpha (α) has been defined.

$$\alpha = \frac{v}{AP \text{ or } BP} \quad (10)$$

Alpha represents the value obtained by dividing vehicle speed by the pedal value, and the magnitude of α and vehicle speed can be used to determine the driver's intentions for cruising and acceleration/deceleration. For example, if the vehicle speed is low and the AP value is high, α will decrease, indicating a high demand for acceleration by the driver. Conversely, if the vehicle speed is high and the AP value is low, α will increase, indicating a high demand for cruising by the driver.

Considering this, the driver's driving requirements based on the current vehicle state can be generated into a 2D Look-up Table using Fuzzy Logic. To create the map, the first step was to set up a scenario where the vehicle accelerates from 0 km/h to a predetermined speed and maintains it. Subsequently, this scenario was executed in a simulation environment at various speeds to monitor the changes in α , and α threshold values for acceleration and cruising at specific speeds were derived. Using the speed and α threshold values, an input membership function was designed within the fuzzy logic system to process the input data. This membership function receives input data (speed, α) and outputs a value (ranging from 0 to 1) that indicates how much the data belongs to a logical set. This output value was then used to create a 2D Look-up Table, as shown in Figure 8. Like Figure 7, in Figure 8, as the color changes from blue to yellow, it indicates that the reflection rate approaches 1.

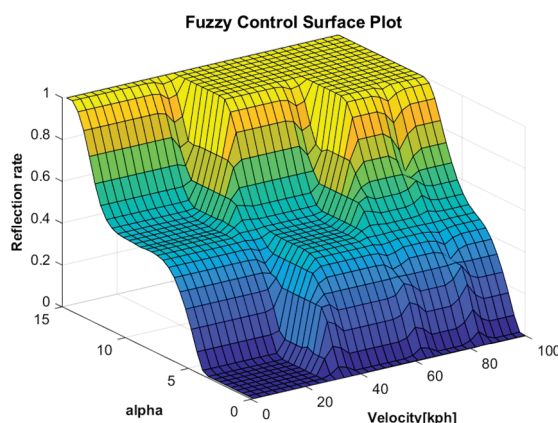


Figure 8. Fuzzy Control Surface Plot.

In the surface plot of Figure 8, the output of the control value represents the ratio of influence between the energy efficiency-based torque distribution strategy and the vertical force-based torque distribution strategy. An output close to 1 indicates a higher preference for cruising, emphasizing the efficiency-centric distribution strategy. Conversely, a value

close to 0 signifies a greater need for acceleration, favoring a strategy that allocates more vertical force to the front and rear wheels. Figure 9 diagrammatically shows the method of adjusting between these two distribution strategies based on the previously described fuzzy logic. In the Fuzzy Control Surface Plot, as the color changes from blue to yellow, it indicates that the reflection rate approaches 1.

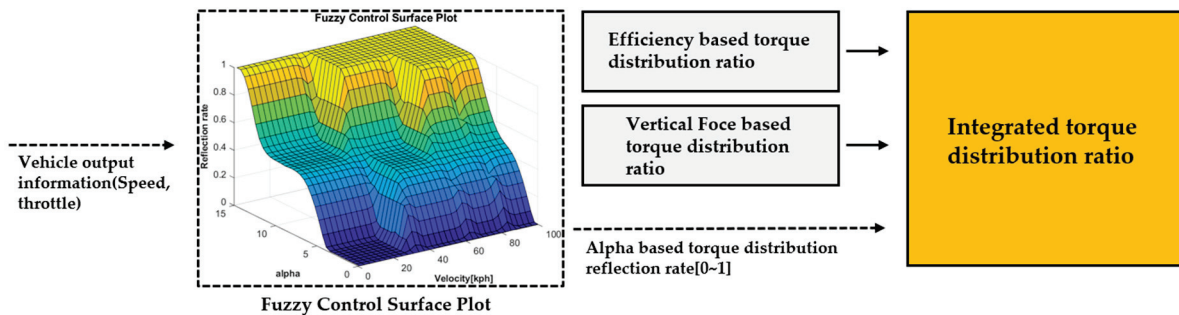


Figure 9. Schematic of torque distribution integration logic.

Unlike driving conditions, friction braking, and regenerative braking are considered simultaneously in braking scenarios, necessitating additional logic to manage the distribution between these two types of braking [20,21]. The general objective is to maximize the use of regenerative braking. When the total braking torque at the front and rear wheels exceeds the regenerative braking torque, the excess torque is transferred to friction braking. Here, Fuzzy Logic is used to adjust between cases that maximize regenerative braking (left side) and those that focus on the ideal braking force for the front and rear wheels (right side), as shown in Figure 10. For instance, if the BP value is high and changes abruptly, the distribution is adjusted closer to the ideal braking force, considering the vertical loads on the front and rear wheels. Conversely, if the vehicle behavior is deemed stable, the distribution shifts towards maximizing regenerative braking. Additionally, using regenerative braking while the vehicle is traveling at low speeds can negatively affect ride comfort. Therefore, the amount of regenerative braking has been linearly reduced in low-speed situations.

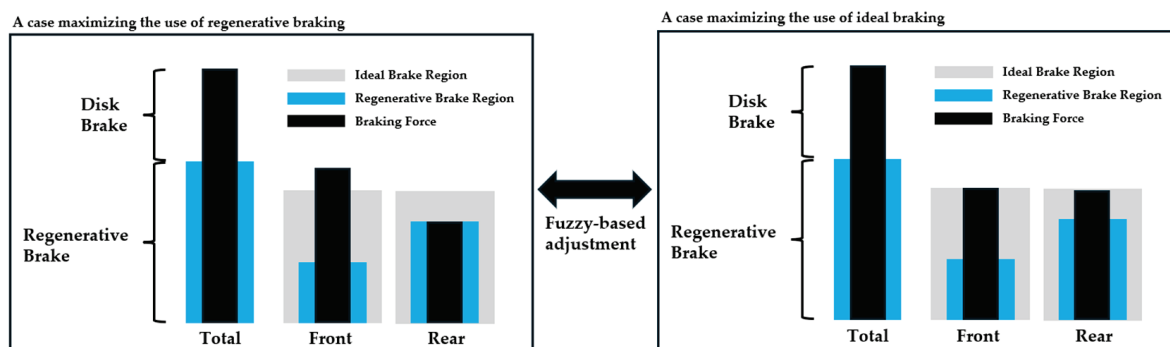


Figure 10. Schematic diagram of braking force distribution logic between friction and regenerative braking.

Figures 11 and 12 display the ideal and actual braking forces for the front and rear wheels during the WLTP (Worldwide Harmonized Light Vehicles Test Procedure) cycle, both with and without applying fuzzy logic. Without fuzzy logic, there was a tendency for braking force to concentrate on the rear wheels. However, after applying fuzzy logic, the ideal and actual braking forces for the front and rear wheels were closely aligned.

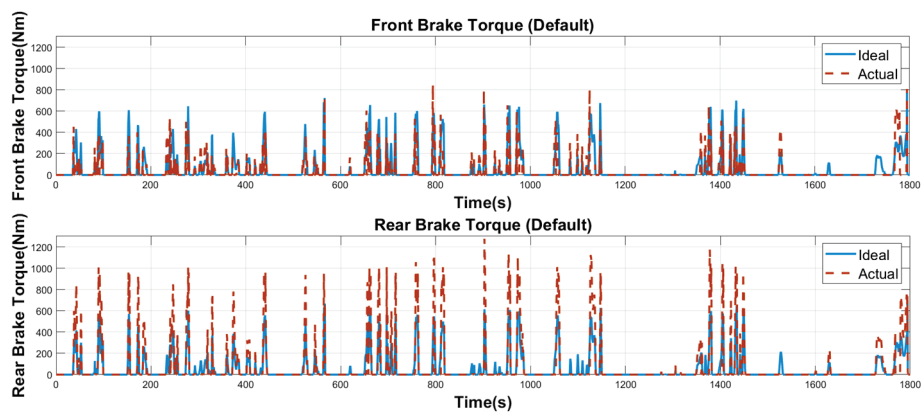


Figure 11. Front/rear ideal braking force (blue) and actual braking force (orange) (before applying Fuzzy Logic).

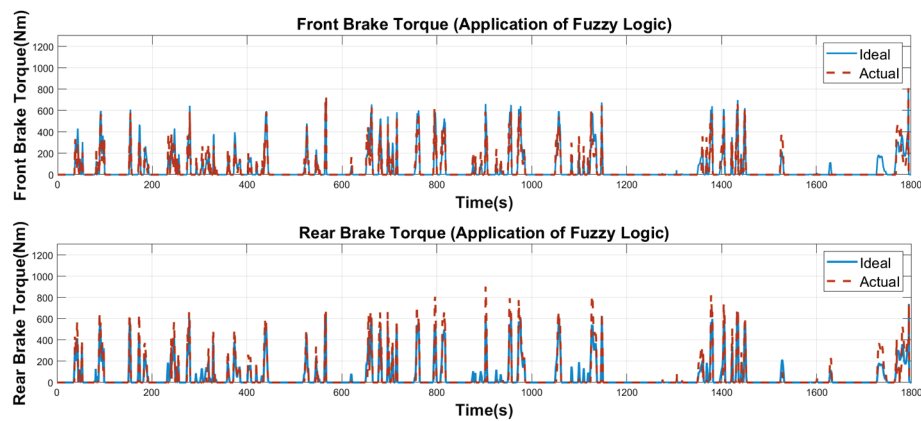


Figure 12. Front/rear ideal braking force (blue) and actual braking force (orange) (after applying Fuzzy Logic).

4. Powertrain Specification Optimization Strategy

The paper adopts a strategy incorporating torque distribution into the powertrain specification optimization strategy to maximize the improvement of vehicle power performance and energy efficiency. Figure 13 shows the flowchart of the overall optimization strategy.

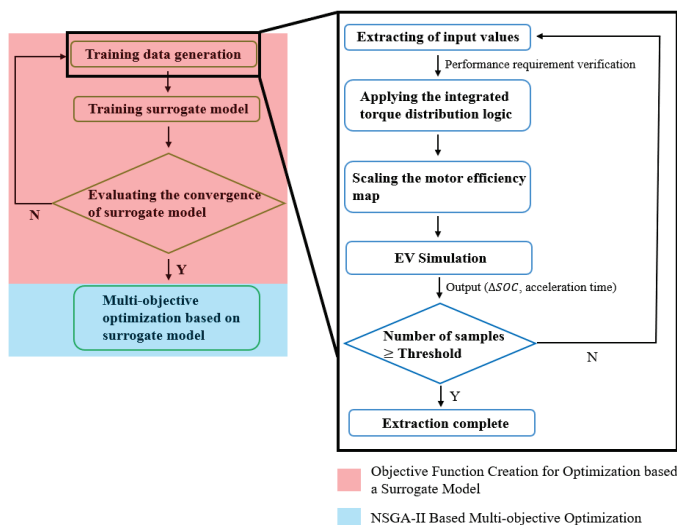


Figure 13. Flowchart of the overall optimization process.

The overall optimization process is divided into two main parts. Section 4.1 discusses the design method of the optimization objective function based on surrogate models, and Section 4.2 covers the extraction of optimal solutions based on multi-objective optimization. This study utilizes the NSGA-II algorithm, which is well known for effectively solving multi-objective optimization problems in various engineering fields [22]. However, this optimization algorithm requires excessive iterative calculations to determine the optimal solutions. An Artificial Neural Network (ANN) model has been trained to emulate a complex EV model to address the computational costs of optimization and is used as a surrogate model for the vehicle simulator [23].

Initially, training data are required to train the surrogate model. The part surrounded by the right black box represents the process of generating training data. Once input variables are extracted through an adaptive sampling process, corresponding torque distribution maps, and motor efficiency maps are created. After these preliminary steps, electric vehicle modeling-based simulations are performed, and outputs such as SOC changes (ΔSOC) and acceleration times (t_{acc}) are extracted. This process is repeated until the data size meets or exceeds a predefined threshold, at which point it transitions to the surrogate model training phase. Subsequently, deep learning is used to train the surrogate model, and convergence is evaluated. Finally, after the convergence assessment, NSGA-II multi-objective optimization is conducted to derive optimal solutions.

4.1. Objective Function Creation for Optimization Based on a Surrogate Model

A surrogate model is a model that can simplify and substitute for costly and complex simulations widely used across various fields [24,25]. The primary purpose of this model is to quickly and cost-effectively predict outputs based on input data. Surrogate models are constructed using statistical or machine learning techniques, such as polynomial regression, artificial neural networks, and Gaussian process regression. Various input variables are fed into backward simulations to build the dataset necessary for model fitting. These simulations consist of multiple subsystems, resulting in solid nonlinearity in the output values. Artificial neural networks, which can effectively learn complex data patterns and capture interactions between input variables, are well suited for modeling nonlinear relationships, making them ideal for constructing surrogate models.

4.1.1. Neural Network Training: Description of Input and Output Variables

In this paper, the input variables for neural network training consist of the maximum torque and power of the front and rear motors, the front axle reduction ratio, the rear axle's first and second reduction ratios, and the shifting speed. The motor efficiency map must also change accordingly as the motor-related variables change. Therefore, a new motor efficiency map was generated by altering the x and y -axis scales based on the reference motor efficiency map matching the altered motor specifications. Figure 14 shows an example of creating a motor efficiency map from the reference motor.

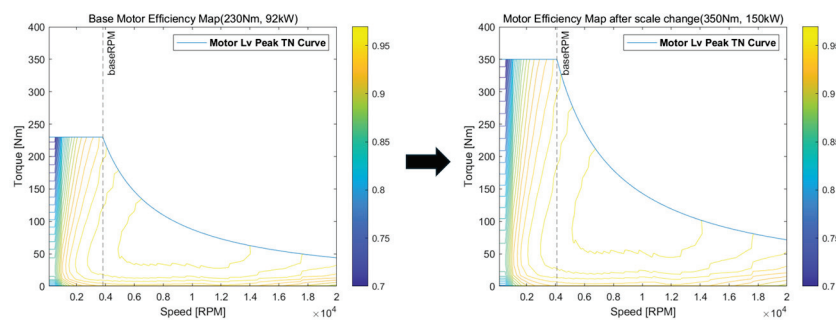


Figure 14. x , y -axis scale change in motor efficiency map.

It is essential to properly select the range of input variables during the training of a Neural Network to improve the quality of training data. In particular, the gear ratio

must be selected within a range that can satisfy the vehicle's required performance. This paper generated a baseline vehicle-level Peak Torque-Speed (T-N) Curve, which minimally satisfies the vehicle's required performance, to analyze whether the vehicle meets the required performance based on the powertrain specification combinations. The creation of the vehicle-level Peak T-N Curve was divided into two stages. First, the vehicle's top speed and maximum torque capable of climbing were calculated considering the driving resistance to reflect climbing performance and maximum speed, and a T-N Curve that meets these criteria was generated. However, the T-N Curve needed to be adjusted because the power required for acceleration performance is more significant than that needed for climbing performance or maximum speed. Therefore, a simple simulation was developed to check the time to reach 0–96 kph, and power was increased until the required acceleration performance was met, ultimately generating the Peak T-N Curve for performance requirement verification, as shown in Figure 15. This curve checks whether the vehicle satisfies the required performance based on different gear ratio combinations.

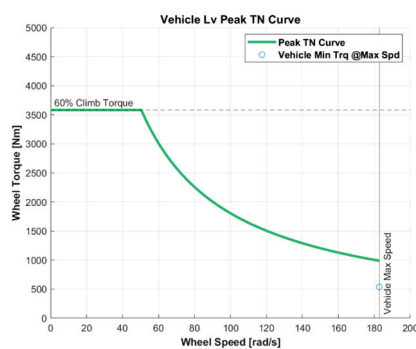


Figure 15. Peak T-N Curve for vehicle performance requirement verification.

4.1.2. Description of Adaptive Sampling Methods and Learning Techniques

The input variables are applied to a vehicle simulation to extract the time it takes to reach 0–96 kph and the change in SOC. The time to reach 96 kph is measured without following a driving cycle, with the accelerator pedal fixed at maximum until the vehicle speed reaches 96 kph. The change in SOC is reported as the final variation after running the driving cycle.

Simulations were conducted on various combinations of input variables to generate data for neural network training. However, if the training data contain only biased data, the model may converge but fail to simulate the entire dataset accurately. To prevent such bias in the training data, the range of each input variable was appropriately divided, and sampling was performed evenly using different combinations each time to avoid data bias. Additionally, the elementary effects method, commonly used to compare the impact of input variables on outputs, was employed. This method involves dividing the range of input variables that significantly impact the output into more segments while dividing those with less impact into fewer segments, thereby efficiently exploring the variable space. Additionally, generating training data requires many samples, and running simulations each time to extract data is time-consuming. Therefore, MATLAB Parallel Computing Toolbox was used to extract samples in parallel, reducing the sampling time.

Once a certain number of samples are collected, the training data are assembled, and training commences. Cross-validation was applied to calculate the model fitting error to prevent overfitting in the neural network and to assess the model's generalization ability more accurately. Initially, samples are divided into training sets and test sets according to a predetermined ratio. The training set is used for neural network training, while the test set compares the error between model estimates and actual values. The training and test sets are varied with each K-Fold split to calculate the fitting error, using the maximum error as the final fitting error. Normalized Root Mean Square Error (NRMSE) is the fitting error

metric used here. Figure 16 illustrates the process of extracting the fitting error through cross-validation.

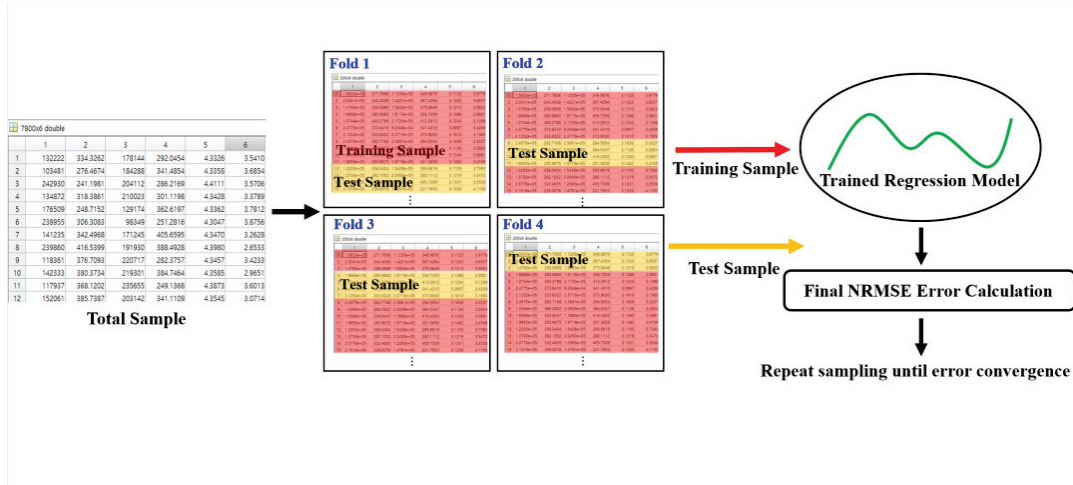


Figure 16. Schematic of model cross-validation and error calculation methods.

4.2. NSGA-II Based Multi-Objective Optimization

After determining the convergence of the neural network, the trained neural network model is used as the objective function for the optimization algorithm. It utilizes two objective functions: the change in SOC and the acceleration time (time to reach 0–96 kph). As there is a trade-off between acceleration performance and SOC change, it is necessary to explore solutions that best satisfy both objectives. NSGA-II is a multi-objective optimization algorithm often used when there is a need to optimize multiple conflicting objectives simultaneously [26]. Using this algorithm, a Pareto Front that maximizes acceleration performance and energy efficiency is explored, and weights are set between the two objectives to extract the optimal set of parameters.

$$\begin{cases} \underset{\Delta SOC}{\text{minimize}} f(M, R, V) \\ \underset{t_{acc}}{\text{minimize}} g(M, R, V) \end{cases} \quad (11)$$

subject to $M, R, V \in \Omega_c$

The objective functions f and g represent fully trained surrogate models, each designed to minimize the change in SOC and the acceleration time, respectively. $M = [T_{max_f}, P_f, T_{max_r}, P_r]$ denotes the set of input variables related to motor specifications, which includes the maximum torque of the front motor (T_{max_f}), power of the front motor (P_f), maximum torque of the rear motor (T_{max_r}), and power of the rear motor (P_r). $R = [r_f, r_{r1}, r_{r2}]$ represents the set of gear ratios, comprising the front gear ratio (r_f), the rear first gear ratio (r_{r1}), and the rear second gear ratio (r_{r2}). $V = [v_{1 \rightarrow 2}, v_{2 \rightarrow 1}]$ refers to the shifting speeds, including both the upshift speed ($v_{1 \rightarrow 2}$) and the downshift speed ($v_{2 \rightarrow 1}$). Finally, all input variables must be determined within the design specification range; therefore, constraints on the input variables (Ω_c) have been set in the optimization problem.

5. Results

Figure 17 shows the distribution of solutions for multi-objective optimization applied to three vehicle types—sedan, SUV, and SUV with trailer—during the WLTP driving cycle. The optimal solution set derived from the optimization algorithm, known as the Pareto Front, is represented by black dots, with specific solutions (A, B, C) indicated by red arrows on the Pareto Front. The optimization results are evaluated by comparing the change in SOC and acceleration performance between the reference vehicle parameter set and

the optimized parameter set under the WLTP driving cycle. Due to the characteristics of multi-objective optimization, the Pareto Front produces no clear superiority between the two objectives, and the optimal solution can vary depending on whether the focus is on energy efficiency or acceleration performance. This paper presents three types of optimal solutions by varying the weights given to acceleration performance or SOC change.

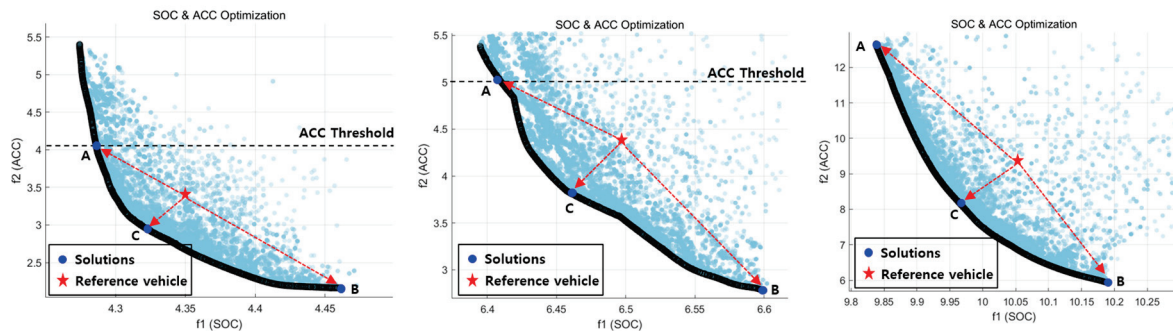


Figure 17. Optimization results for each vehicle specification under the WLTP cycle: Sedan (left), SUV (middle), and SUV with Trailer (right).

Firstly, solution A focuses solely on energy efficiency without considering acceleration performance. Thus, it selects the solution that minimizes the objective on the x -axis (SOC change) among the Pareto Front in Figure 17. Figure 17 displays a critical y -axis line (ACC Threshold) that excludes solutions not meeting the 0–96 km/h acceleration time criteria to reflect the required performance standards. Consequently, the critical value is established, and the solution with the minor SOC change that does not exceed this threshold is chosen as Solution A. Conversely, Solution B focuses on acceleration performance without considering energy efficiency. Hence, it represents the solution with the minimum y -axis (acceleration time) value on the Pareto Front. Solution C equally prioritizes acceleration performance and energy efficiency, carrying equal weight. Therefore, it is located between Solution A and B in the Pareto Front.

Additionally, validation across various driving cycles is necessary to enhance the generality and reliability of optimization results. Thus, results from another driving cycle, the US06 driving cycle, are further presented in Figure 18. Figures 19 and 20 display bar charts comparing the performance (ΔSOC , t_{acc}) of the Reference Vehicle and the optimized Solutions A, B, and C based on the WLTP driving cycle. These charts visually demonstrate the differences in SOC change and acceleration time for each solution, clearly representing the optimization's effectiveness. Additionally, Tables 3 and 4 show the changes in ΔSOC and the rates of change in acceleration performance for the Reference Vehicle when Solutions A, B, and C are applied, based on the WLTP cycle. Subsequently, the results from another driving cycle, the US06, are presented in Figures 21 and 22. Finally, Tables 5 and 6 depict the ΔSOC change and acceleration time change rates for the US06 cycle.

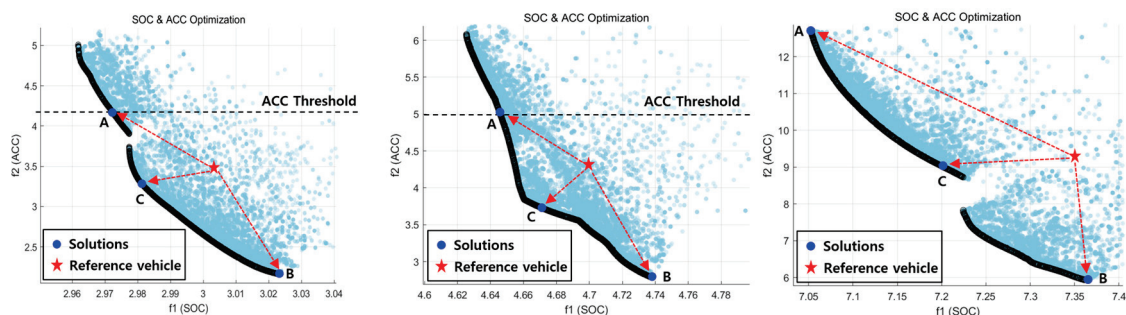


Figure 18. Optimization results for each vehicle specification under the US06 cycle: Sedan (left), SUV (middle), and SUV with Trailer (right).

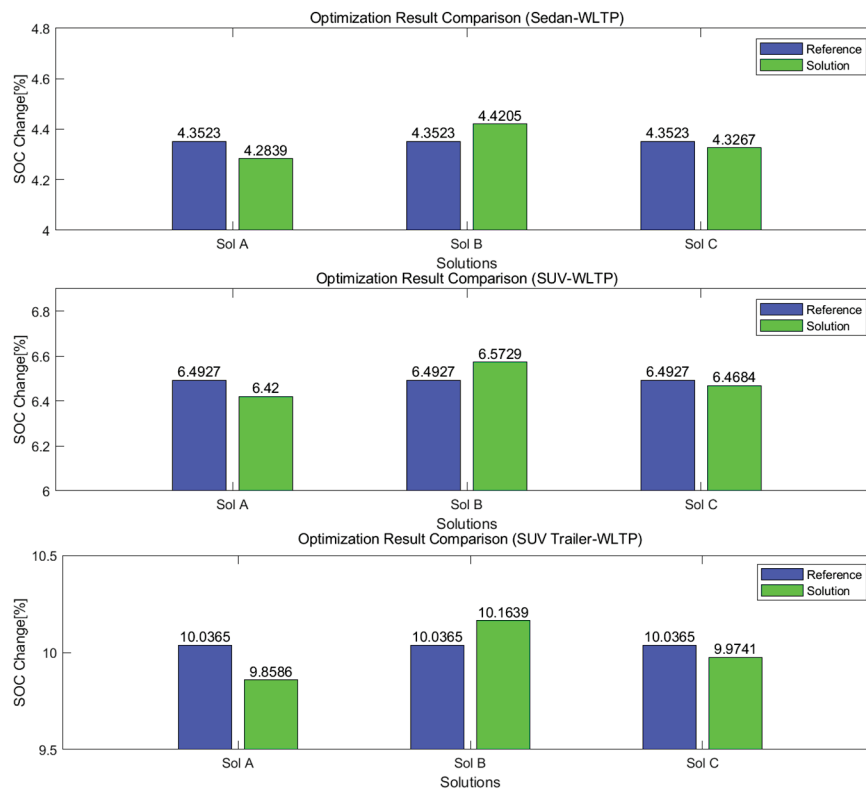


Figure 19. Comparison of SOC changes between the reference and each solution under the WLTP cycle: Sedan (**top**), SUV (**middle**), and SUV with Trailer (**bottom**).

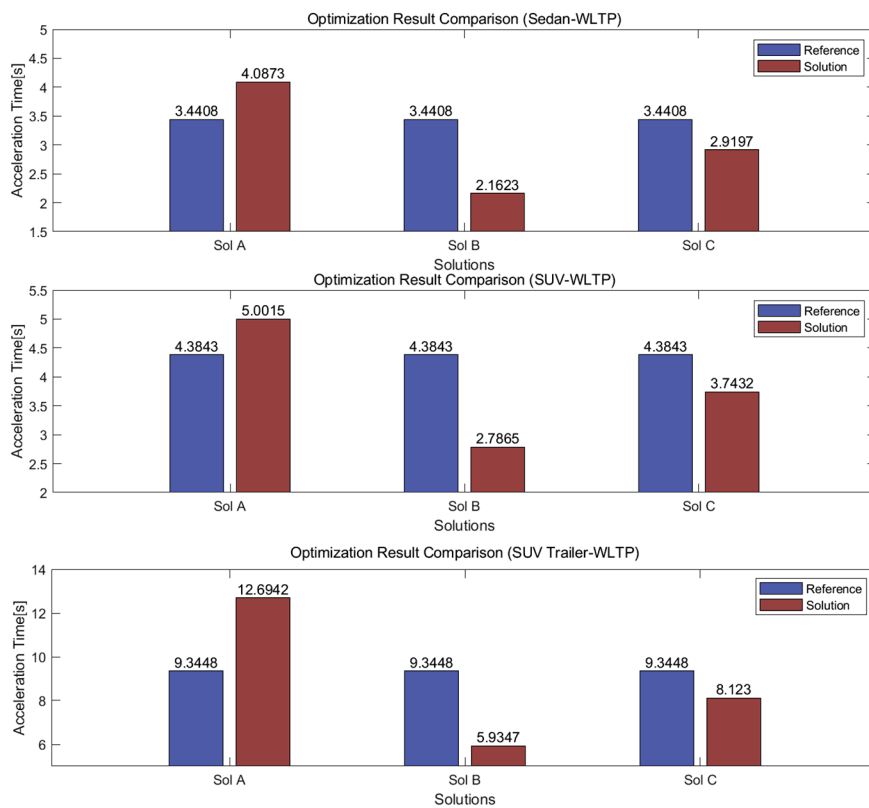


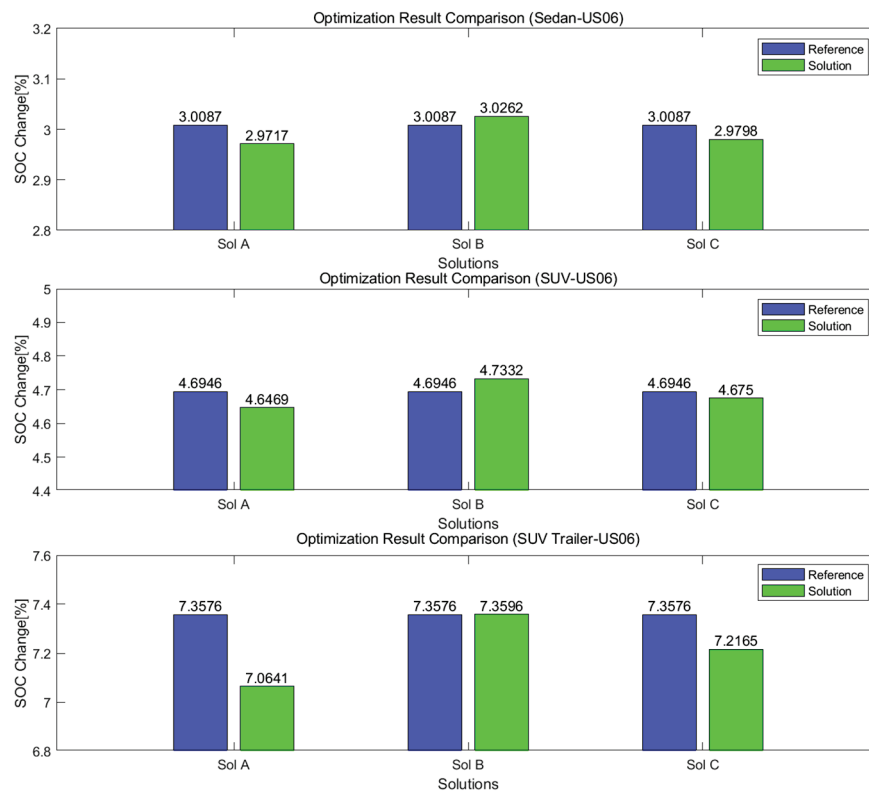
Figure 20. Comparison of acceleration time between the reference and each solution under the WLTP cycle: Sedan (**top**), SUV (**middle**), and SUV with Trailer (**bottom**).

Table 3. Rate of Change in SOC Following Optimization Applied to the Reference Vehicle (WLTP Drive Cycle).

Solution	Sedan	SUV	SUV-Trailer
A	−1.57%	−1.12%	−1.79%
B	1.56%	1.23%	1.29%
C	−0.58%	−0.37%	−0.56%

Table 4. Rate of Acceleration Time Following Optimization Applied to the Reference Vehicle (WLTP Drive Cycle).

Solution	Sedan	SUV	SUV-Trailer
A	18.8%	14.1%	35.7%
B	−37.2%	−36.4%	−36.5%
C	−15.1%	−14.6%	−13.1%

**Figure 21.** Comparison of SOC changes between the reference and each solution under the US06 cycle: Sedan (**top**), SUV (**middle**), and SUV with Trailer (**bottom**).**Table 5.** Rate of Change in SOC Following Optimization Applied to the Reference Vehicle (US06 Drive Cycle).

Solution	Sedan	SUV	SUV-Trailer
A	−1.22%	−1.01%	−3.98%
B	0.58%	0.82%	0.01%
C	−0.96%	−0.41%	−1.91%

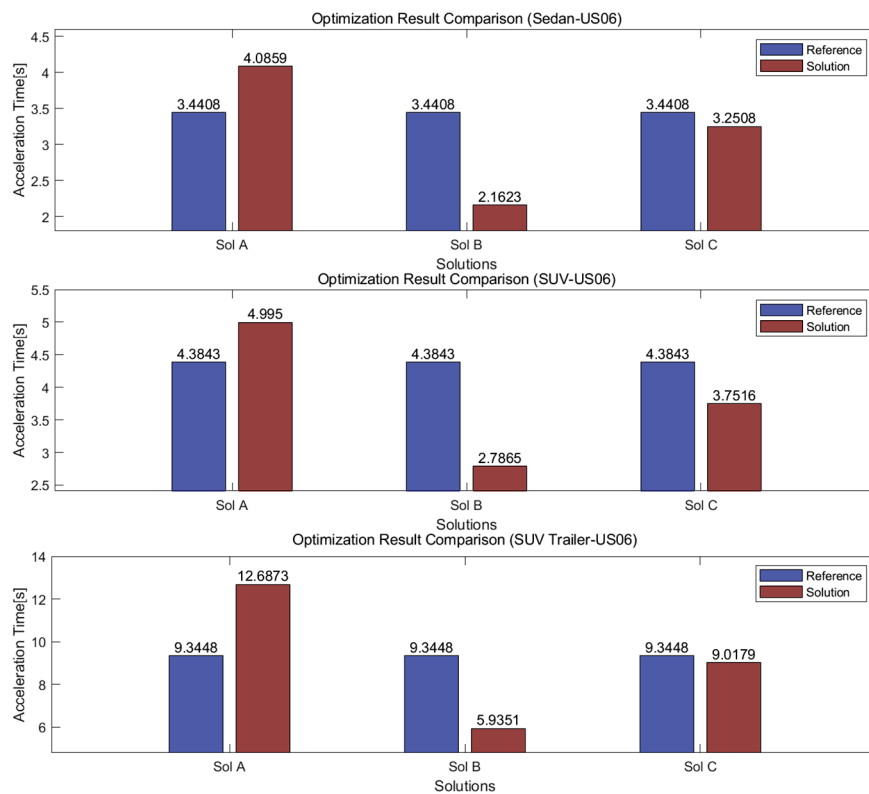


Figure 22. Comparison of acceleration time between the reference and each solution under US06 cycle: Sedan (**top**), SUV (**middle**), and SUV with Trailer (**bottom**).

Table 6. Rate of Acceleration Time Following Optimization Applied to the Reference Vehicle (US06 Drive Cycle).

Solution	Sedan	SUV	SUV-Trailer
A	18.7%	13.9%	35.7%
B	−37.1%	−36.4%	−36.4%
C	−5.52%	−14.4%	−3.49%

Solution A aims to maximize energy efficiency, which, as shown in Table 3, significantly reduces the SOC changes. However, as seen in Table 4, it conversely increases in acceleration time. On the other hand, Solution B focuses on acceleration performance, leading to an increase in SOC changes while significantly decreasing acceleration time. Solution C balances the two objectives, reducing SOC changes and acceleration time compared to the reference vehicle. The application of Solution C results in a decrease in SOC changes by 0.58% (Sedan), 0.37% (SUV), and 0.56% (SUV-Trailer), and a reduction in 0–96 kph acceleration time by 15.1% (Sedan), 14.6% (SUV), and 13.1% (SUV-Trailer). Additionally, as shown in Tables 5 and 6, the US06 driving cycle demonstrates similar patterns of change when the optimization results are applied, comparable to the WLTP driving cycle. Figures 23 and 24 present examples of the results from applying Solutions A, B, and C to vehicle simulations. Each figure compares the SOC change and vehicle speed over time between the Reference Vehicle and Solutions A, B, and C. In terms of energy consumption (Figure 23), Solution A achieved the best results, while Solution B showed the best results in acceleration performance (Figure 24).

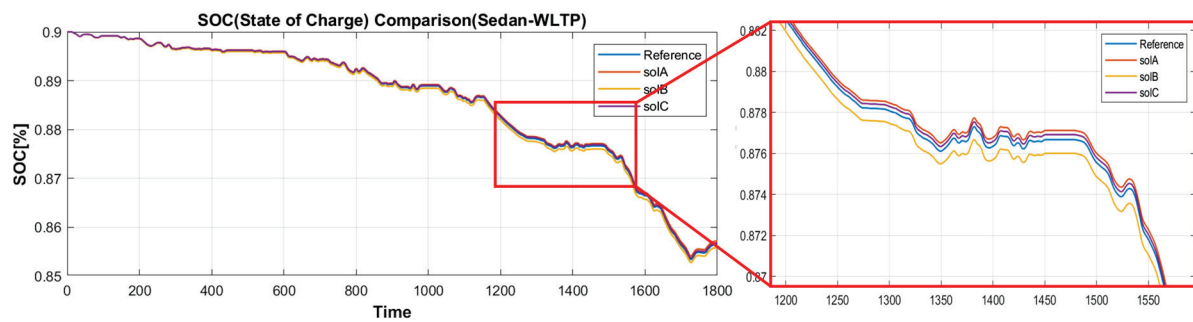


Figure 23. Results from Applying Optimized Solutions to Vehicle Simulations for Comparison: SOC.

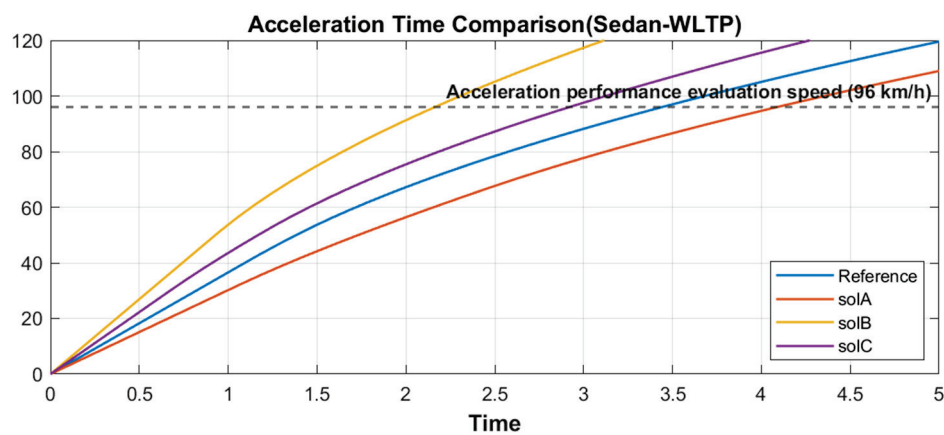


Figure 24. Results from Applying Optimized Solutions to Vehicle Simulations for Comparison: Acceleration Time.

6. Conclusions

This study presented a torque distribution strategy using fuzzy logic and multi-objective optimization based on surrogate models to determine the optimal powertrain component specifications for an AWD powertrain structure with a two-stage gearbox in the rear. Electric vehicle modeling was conducted using MATLAB/Simulink, which included a torque compensation method to prevent torque holes during shifting and a speed synchronization process considering the neutral state of the rear motor.

Additionally, using fuzzy theory, the method proposed an adjustment between the torque distribution strategies based on motor efficiency maps and the distribution strategies considering driving stability in driving and braking situations. Subsequently, a vehicle-level Peak T-N Curve was generated considering performance indicators, and performance was comprehensively reviewed. Neural network training was conducted through MATLAB parallel simulation, and a surrogate model-based optimization objective function was created. Finally, NSGA-II multi-objective optimization was carried out to generate a set of solutions that considered both energy efficiency and acceleration performance. In the solution set, optimal solutions can be derived by setting weights for the two objectives to reflect their importance. This paper presents examples of solutions that consider only energy efficiency, only acceleration performance, and solutions that assign equal weights to both objectives. When equal weights were assigned, SOC change improved by 0.37~0.58%, and acceleration performance improved by 13.1~15.1%.

However, the improvement in SOC change from the optimization results was insignificant, which can be attributed to the main factor determining energy efficiency in the simulation, the baseline motor efficiency map. The efficiency map used in the study showed little difference in motor efficiency outside the low-torque and low-speed areas. Thus, even with changes in the motor operating points within the efficiency map, the efficiency variation was minimal, leading to no significant difference in SOC change. If

there were apparent differences in efficiency with changes in torque and speed in the baseline motor efficiency map, applying the optimization results from this study would result in more significant improvements in energy efficiency.

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Article

Optimized Right-Turn Pedestrian Collision Avoidance System Using Intersection LiDAR

Soo-Yong Park ¹ and Seok-Cheol Kee ^{2,*}

¹ Department of Smart Car Engineering, Chungbuk National University, Cheongju-si 28644, Republic of Korea; adrenalin94@chungbuk.ac.kr

² Department of Intelligent Systems and Robotics, Chungbuk National University, Cheongju-si 28644, Republic of Korea

* Correspondence: sckee@chungbuk.ac.kr

Abstract: The incidence of right-turning pedestrian accidents is increasing in South Korea. Most of the accidents occur when a large vehicle is turning right, and the main cause of the accidents was found to be the driver's limited field of vision. After these accidents, the government implemented a series of institutional measures with the objective of preventing such accidents. However, despite the institutional arrangements in place, pedestrian accidents continue to occur. We focused on the many limitations that autonomous vehicles, like humans, can face in such situations. To address this issue, we propose a right-turn pedestrian collision avoidance system by installing a LiDAR sensor in the center of the intersection to facilitate pedestrian detection. Furthermore, the urban road environment is considered, as this provides the optimal conditions for the model to perform at its best. During this research, we collected data on right-turn accidents using the CARLA simulator and ROS interface and demonstrated the effectiveness of our approach in preventing such incidents. Our results suggest that the implementation of this method can effectively reduce the incidence of right-turn accidents in autonomous vehicles.

Keywords: LiDAR; virtual simulator; pedestrian detection; cooperative perception

1. Introduction

In today's road traffic, intersections and their associated traffic systems are very complex. As intersections are a complex environment with many factors, vehicles and pedestrians in the intersection need to be more careful about their safety. However, as is often reported in the media, right-turning pedestrian accidents are one of the most common types of accident in Korea. In response, the Korea Road Traffic Authority (KRTA) investigated right-turn accidents at all intersections over the past three years, and the results are shown in Figure 1 below.

In Figure 1, we can see the percentage of total accidents and right-turn accidents by vehicle type. As a result, we can note that the ratio of right-turn accidents to total pedestrian accidents is overwhelmingly higher for larger vehicles than for smaller passenger cars. Recognizing the seriousness of right-turn accidents, South Korea implemented the 'Right Turn Pause' law in January 2023. This law requires all vehicles to pause once when turning right to protect pedestrians. Since the law came into effect, all police forces in the country have been enforcing right-turn pauses, and local governments have been promoting the law, but even today, South Korea still suffers from right-turn accidents involving large vehicles, and the cause has been found to be the driver's limited field of vision.

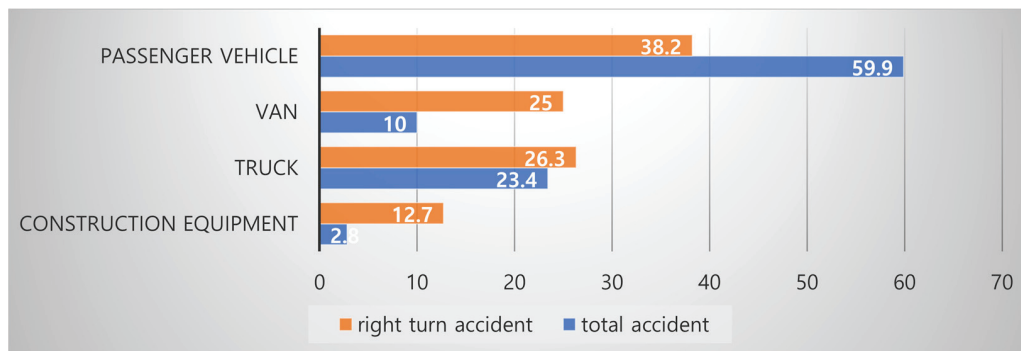
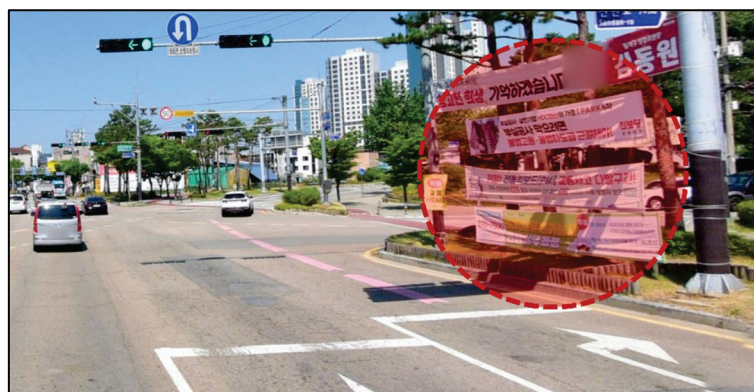


Figure 1. Comparing the right-turn accident rate with the overall accident rate 2018~2020.

On the other hand, today's autonomous vehicle technology has come a long way from the past [1–3]. It has been variously suggested that high-precision sensors and recognition systems can replace human object recognition intelligence [4–6], but it is still difficult to solve this problem technologically if the vehicle's field of view is insufficient. For example, Figure 2 below shows a real-world road in South Korea that obstructs the viewing angle of a vehicle. As shown in Figure 2a, it is very common in South Korea for advertisements to be hung between street trees, obstructing the viewing angle when turning right, and as shown in Figure 2b, vehicles parked on the side of the road for long periods of time limit the viewing angle.



(a)



(b)

Figure 2. Examples of road features that obstruct the driver's view. (a) Example 1 of Intersection in Cheongju-si, Republic of Korea. (b) Example 2 of Intersection in Cheongju-si, Republic of Korea.

To solve this problem of insufficient perception information, many researchers have investigated various strategies. Cooperative perception is a method in which the sensor information of multiple agents is shared and complemented by each other to improve the cognitive performance of a single agent [7–9]. Agents can be not only vehicles but also mobile robots and urban infrastructure systems, suggesting that sensors and systems designed for each environment can compensate for the limited field of view of a robot or vehicle. In particular, Refs. [10–12] propose various sensor fusion methods and 3D-point-cloud-based generation methods for collaborative perception among connected autonomous vehicles. These papers mainly propose solutions to the data occlusion phenomenon by fusing the features of point cloud data between different frames. However, these methods need further technical implementation and safety verification to be applied safely in the real world, and they cannot reliably prevent right-turn accidents when the vehicle is in a dynamic state. In [13,14], a cooperative recognition system is proposed using the infrastructure in urban areas. The implementation of the recognition system by attaching additional sensors to the infrastructure is one of the key components of the cooperative recognition system. This approach overcomes the limitations of existing recognition functions performed by individual vehicles or devices alone and enables more accurate and reliable recognition by cooperating with the infrastructure. However, most of the infrastructure facilities proposed in the literature are designed to target only a specific area, which limits their ability to cover the entire area within an intersection.

There are also studies related to right-turning pedestrian accidents in South Korea, such as [15]. In [15], the authors present criteria that can be legally reviewed to ensure that autonomous vehicles can safely make right turns. This study redesigned the right-turning process based on several case studies and presented an algorithm in the form of a flowchart. In [16], an algorithm is proposed to detect pedestrians by installing a LiDAR sensor in the middle of an intersection. This paper proposes a 128-channel LiDAR sensor for pedestrian detection, but 128-channel LiDAR is generally classified as a high-cost sensor, which is very uneconomical in terms of equipment. Therefore, this paper proposes a more practical right-turn accident prevention system by compensating for these shortcomings and verifies it in a virtual environment.

The primary contributions of this paper are as follows:

- Optimization of a right-turning pedestrian detection system: The use of 64-channel LiDAR is sufficient to satisfy the requirements of the proposed system and is reasonable in terms of system efficiency and cost. These results show that the system can maximize the efficiency of the sensor configuration while maintaining high-performance recognition capability.
- Cost effectiveness: The study shows that pedestrian detection systems in intersections can complement the perceptual capabilities of existing autonomous vehicles and reduce the cost of additional sensors on the vehicle.
- Right-turn scenario configuration and dedicated dataset: As there are not enough datasets for right-turn scenarios compared to the existing studies, we constructed a dedicated dataset based on various right-turn scenarios in the simulator separately.
- Sensitivity to weather conditions: Existing solutions often rely on a combination of multiple sensors to handle different weather conditions. This approach, while effective, can lead to increased system complexity and cost, highlighting the need for a more streamlined and cost-effective solution. Therefore, we selected only LiDAR sensors that are not sensitive to weather changes, as opposed to other sensors that are sensitive to weather changes.

2. System Architecture

The overall system proposed in this study is shown in Figure 3. A LiDAR sensor is placed near the middle of the intersection to observe pedestrians on the crosswalk. A bus is chosen as the experimental vehicle for this purpose because, unlike a regular passenger car, a tall vehicle has a limited field of view. It is assumed that this vehicle is capable of

autonomous driving, so we install a LiDAR sensor on top of the bus to obtain vehicle-centric perception data at the same time. In order to solve the problem presented in this study, it is necessary to recognize pedestrian information from sensors at the intersection and transmit pedestrian information to the bus before an accident occurs. Therefore, we propose that a control tower is required to apply this system in the real world. However, in this experiment, we replace the control tower with the ROS platform server in a virtual simulator environment.

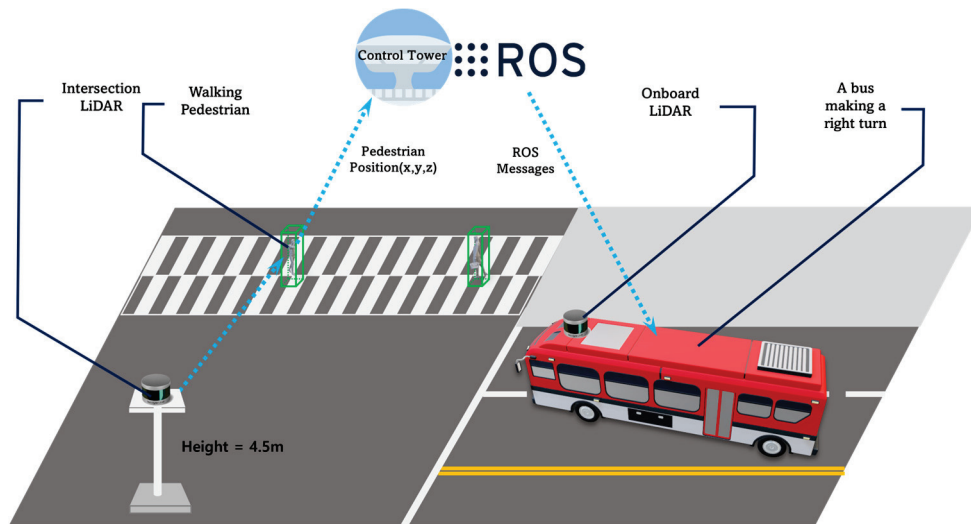


Figure 3. Proposed system in real world.

The pedestrian detection algorithm used in this paper is shown in Figure 4. First, we chose Complex-YOLO as the pedestrian detection deep learning model because unlike other deep learning algorithms, it is appropriate to use a one-stage detection model with fewer constraints on the inference speed [17]. Despite the primary classification of pedestrian classes from the deep learning model, further work needs to be performed, and the reasons are as follows. Unlike vehicles and structures, pedestrians generate data from LiDAR that are regularly hard to identify (Figure 5), which can sometimes reduce the accuracy of Complex-YOLO. Therefore, filtering and clustering of regions of interest designated as dangerous areas are performed to determine the presence or absence of objects. Afterwards, the existing results are combined to increase the stability of pedestrian detection. To compare the performance of pedestrian detection using this approach, we used PV-RCNN as the pedestrian detection algorithm for onboard LiDAR [18]. It is important to note that PV-RCNN outperforms Complex-YOLO in terms of accuracy, although it is weaker in real-time inference, so it is used in this experiment in terms of accuracy comparison with Complex-YOLO.

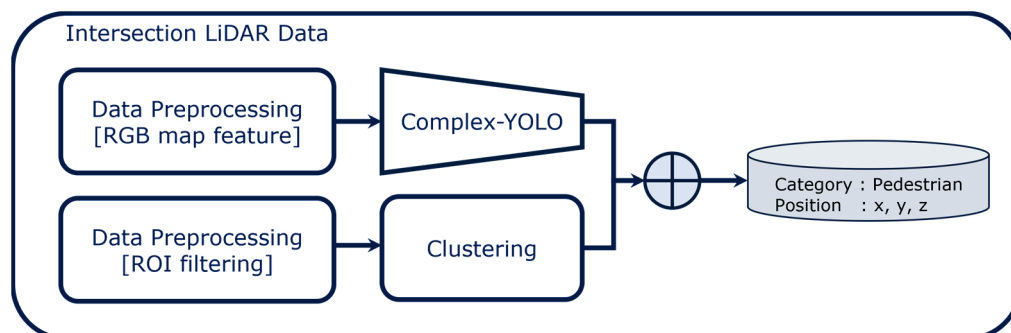


Figure 4. Intersection LiDAR process.

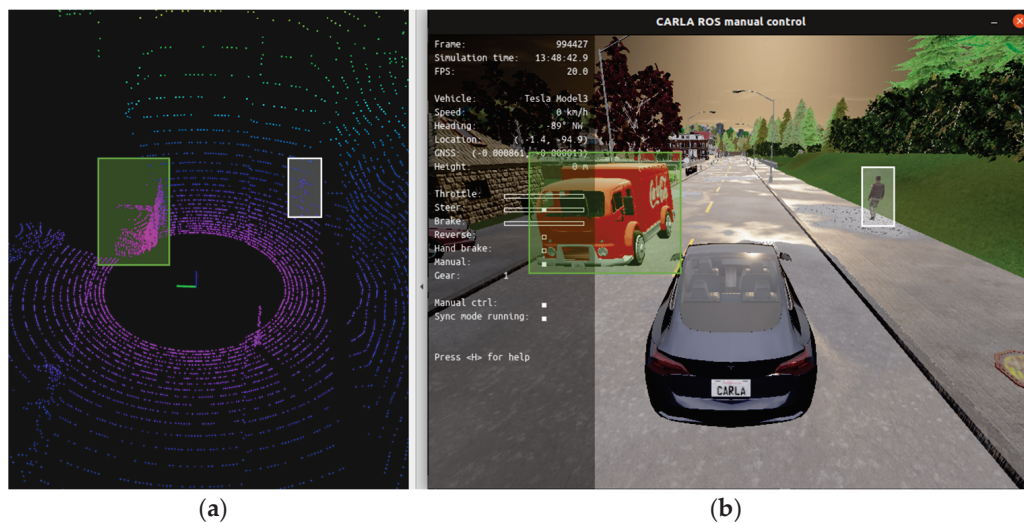


Figure 5. Comparison between vehicle (green box) and pedestrian data (white box). (a) Screenshot of LiDAR sensor frame data in ROS-rviz tool. (b) Screenshot of frame of CARLA simulator.

3. Materials

3.1. Simulator Selection

We used a simulation environment for the purpose of this study. Today, there is a wide variety of simulator software for autonomous driving and road traffic simulation. However, we chose the CARLA simulator for the following reasons [19,20].

- Easy to access

The CARLA simulator is free and open software. Because it is open source, the simulator is continuously used by many users around the world and is well maintained to prevent any functional errors or bugs. We found the CARLA simulator to be a good choice for this study, given its cost and available features.

- Integration with the ROS platform

The CARLA simulator is a simulator that ensures compatibility with multiple robot platforms. Particularly, it is very convenient to integrate with the Robot Operation System (ROS), and many users have conducted research on integrating ROS and CARLA [21–23]. ROS is a robot operating system and an open-source framework for robot software development [24]. It has the advantage of offering various tools and libraries needed to develop robot applications, and it is very well connected with the CARLA simulator. In this study, we chose ROS because we needed to simultaneously create and control multiple agents on a map to collect data. At the same time, we investigated several simulators aimed at autonomous vehicle research, and based on [25], we compared the ROS platform with CARLA and other simulators and determined that the CARLA simulator was the most suitable simulator for this experiment. Figure 6 below shows the actual interworking of the ROS and CARLA simulator, and it can be seen that the data of the LiDAR installed on the vehicle are output normally by the ROS-rviz tool.

3.2. Simulator Setting

The CARLA simulator supports agent assets that can be controlled by the user by default, and the properties contained in the assets are managed by a library of blueprints. In addition, all properties that can be controlled in maps also have blueprints, and information about the various features can be found in [26]. We used these to set up our experimental environment as follows.

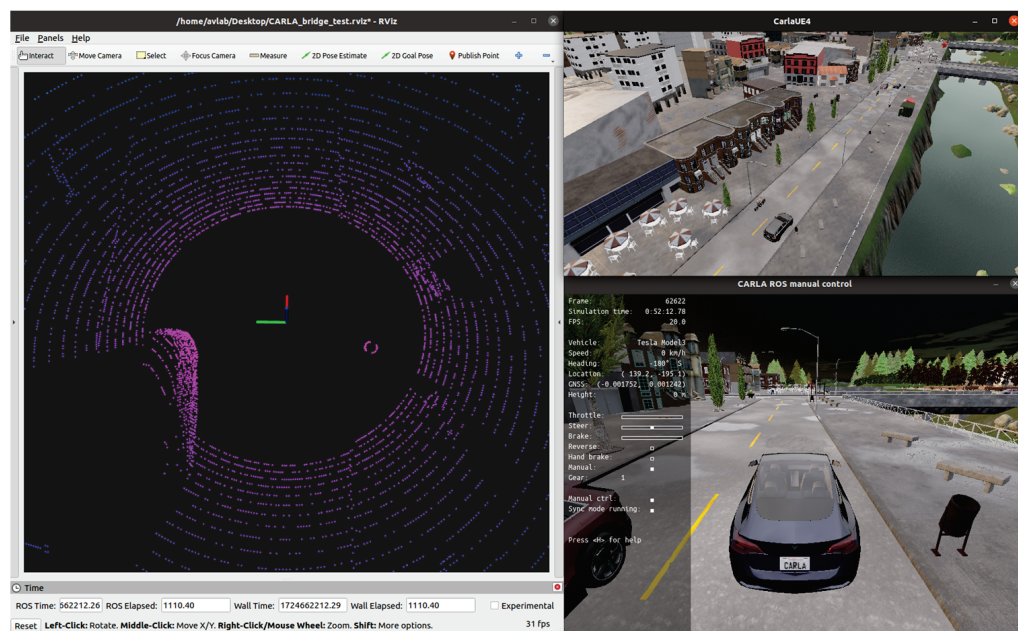


Figure 6. Screenshots of CARLA simulator with ROS platform.

① Experiment Configuration

The CARLA simulator is a program based on the Unreal graphic engine. To run this simulator, a high-end PC environment is usually required. Therefore, to reduce the load on the PC, we configured the simulation environment to be divided into two PCs as shown in Figure 7 above.

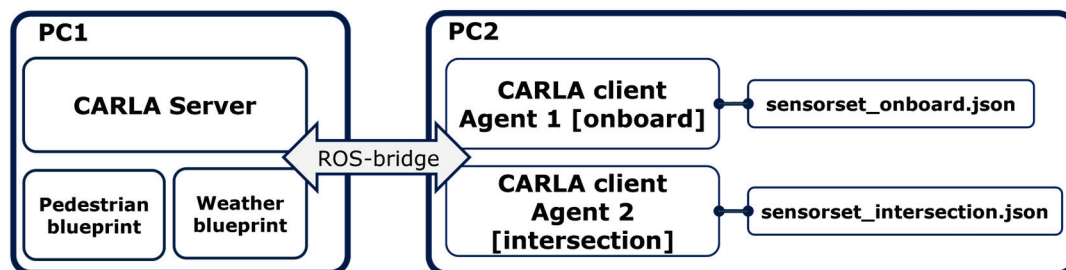


Figure 7. ROS and CARLA integration architecture.

The role of each PC is as follows. First, we set up the CARLA simulator server to run on PC1, which is equipped with a high-end GPU. We also set up PC1 to create and control pedestrian blueprints and weather blueprints to design scenarios over the maps loaded on the server. On the other hand, we set up a network environment for the client to run on a separate PC2, and we associated an onboard agent with the sensorset json file on the target vehicle and an intersection agent with the sensorset json file in the center of the intersection (Tables 1 and 2).

In order to integrate CARLA with ROS, one must use a separately distributed package, and all data generated on CARLA can be accessed through the ROS interface [27]. We experimented by connecting each client to the CARLA server through the package, and when connecting to the server, one must specify the IP address of the host server and run the launch file.

Table 1. Attributes of onboard agent sensorset json file.

Sensor List	Type	ID
Camera	sensor.camera.rgb	rgb_view
LiDAR	sensor.LiDAR.ray_cast	LiDAR
GNSS	sensor.other.gnss	gnss
Objects	sensor.pseudo.objects	objects
Odom	sensor.pseudo.tf	tf
Tf	sensor.pseudo.odom	odometry
Speedometer	sensor.pseudo.speedometer	speedometer
Control	sensor.pseudo.control	control

Table 2. Attributes of intersection agent sensorset json file.

Sensor List	Type	ID
Camera	sensor.camera.rgb	rgb_view
LiDAR	sensor.LiDAR.ray_cast	LiDAR
GNSS	sensor.other.gnss	gnss
Objects	sensor.pseudo.objects	objects
Tf	sensor.pseudo.odom	odometry

② Map

For this study, we chose the largest intersection in Town 10 as the experimental area to simulate accidents that occur within an urban area (Figure 8).

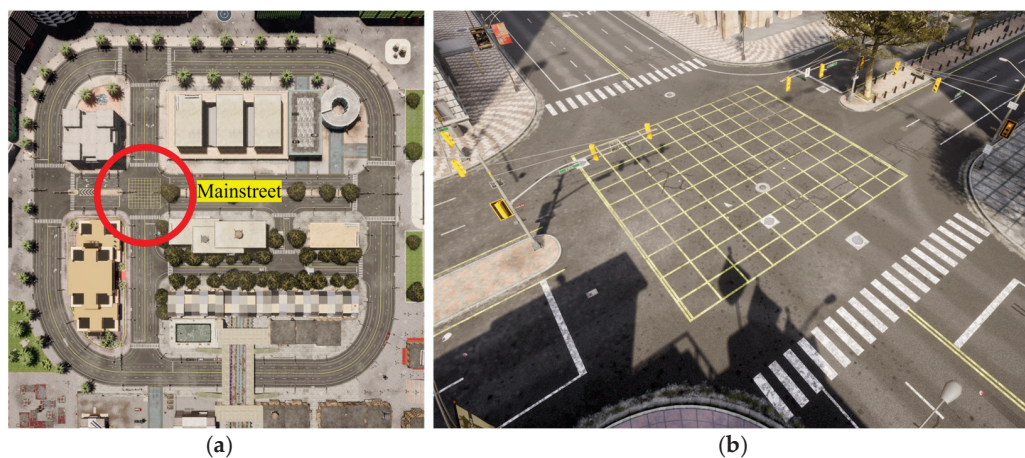


Figure 8. Used map in our experiment. (a) Location of intersection named Mainstreet in Town 10. (b) Screenshot of Mainstreet.

③ Onboard Sensor

For this study, we utilized a Mitsubishi-Fusorosa model bus vehicle asset (Figure 9) and specified a 32-channel LiDAR sensor to be attached to it. The data showed the following limitations of the onboard LiDAR sensor. First, the vehicle's height is higher than that of a normal vehicle, which inevitably leads to blind spots, as shown in Figure 10. Second, the 32-channel LiDAR has a lower resolution compared to other high-channel LiDARs, so the data sparsity is strongly affected by distance (Figure 11). As a result, we can see that the same problems with LiDAR that we encounter in the real world can also be applied in the simulator.



Figure 9. Onboard agent named Mitsubishi–fusorosa.

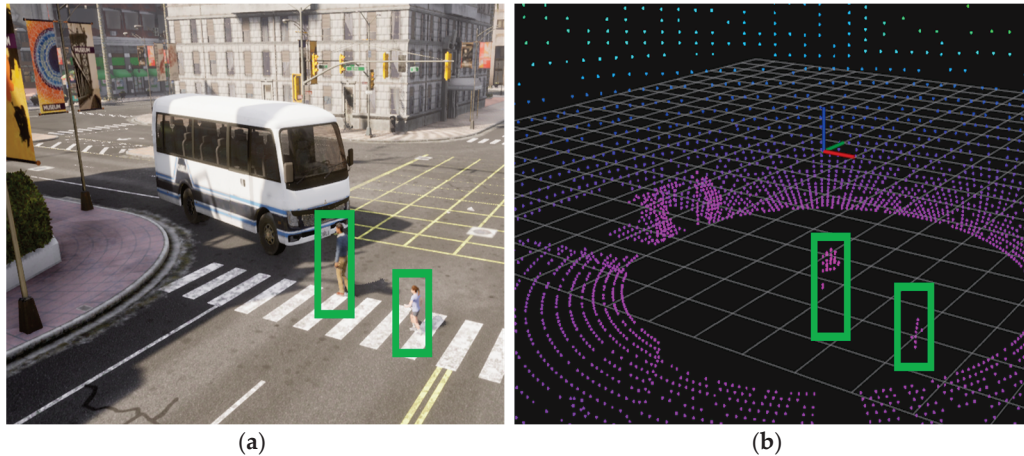


Figure 10. Example of blind spot situation. (a) Simulator screen. (b) ROS–rviz screen.

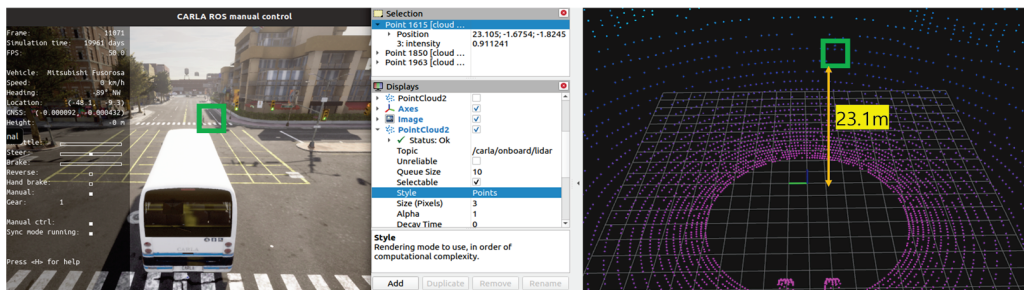


Figure 11. An example of LiDAR data sparsity, where the data points are significantly sparse at a distance of 23.1 m from the person's location (green box).

④ Intersection Sensor

The perception sensors that can be utilized within the CARLA simulator are camera, LiDAR, and radar sensors, and the output of each sensor can be seen as ROS message data. We installed a 64-channel LiDAR sensor at the intersection as a sensor for pedestrian detection and did not consider installing other sensors other than LiDAR for the following reasons. First, CARLA can handle extreme weather conditions, such as heavy fog or rain. For example, as shown in Figure 12a, we can see that the camera data do not produce a good image of the pedestrian in the fog, even though there are two pedestrians on the road, and the radar data also cannot output pedestrian data in the fog (Figure 12b). However, even in the fog, the LiDAR sensor can capture the person on the crosswalk unlike other sensors, and the ROS message data are obtained properly (Figure 12c). Second, unlike cameras and radar sensors, LiDAR sensors have a 360-degree field of view. With a 360-degree field of view, LiDAR can observe objects in all directions, allowing one to see information about every object on the road. Therefore, in addition to the proposed experimental area in this paper, the rest of Mainstreet and the pedestrian crossing area can be observed simultaneously,

which suggests that the LiDAR sensor is a very universal sensor compared to other sensors. Therefore, in this paper, LiDAR is selected as the main sensor for pedestrian identification for these reasons.

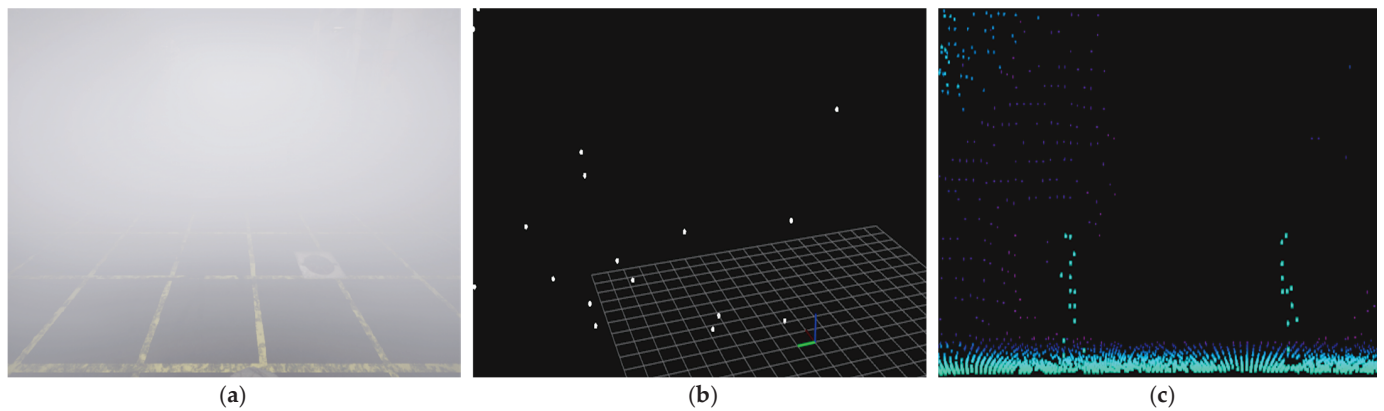


Figure 12. Sensor data display in dense fog condition. (a) Camera. (b) Radar. (c) LiDAR.

However, instead of the approach proposed in [16], we used a 64-channel LiDAR, which is lower than 128 channels. Table 3 below compares the specifications of 64-channel LiDAR and 128-channel LiDAR, and Figure 13 captures one frame of 128-channel LiDAR and one frame of 64-channel LiDAR. From the screen, we can see that the shape of the pedestrian on the crosswalk is displayed correctly.

Table 3. Comparison between 64-channel LiDAR and 128-channel LiDAR.

LiDAR Channel	Range (m)	Points per Second	Upper FoV (deg)	Lower FoV (deg)	Rotation Frequency (hz)
64	80	2,621,440	22.5	−22.5	100
128	80	5,242,880	22.5	−22.5	100

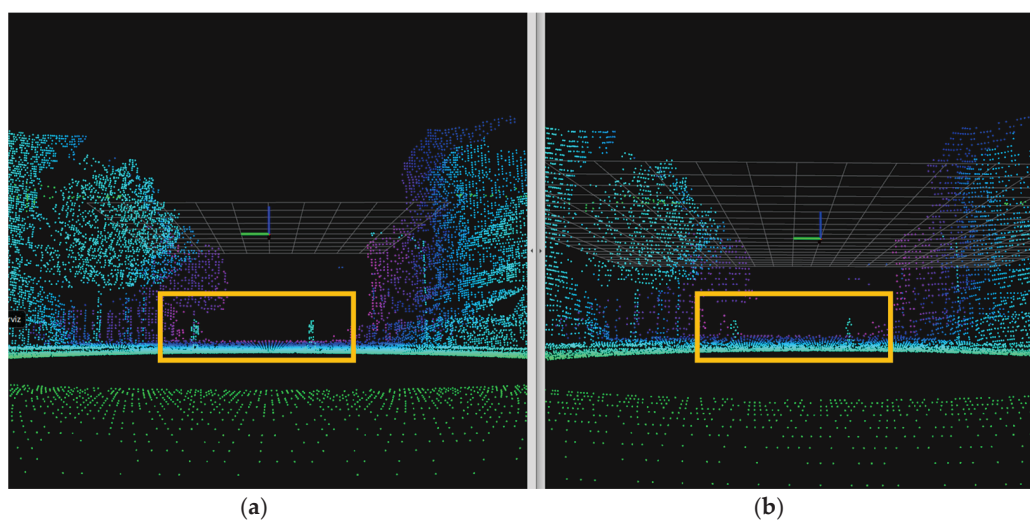


Figure 13. Screenshots of pedestrian point cloud in ROS-rviz tool. (a) One hundred and twenty-eight channels. (b) Sixty-four channels.

⑤ Weather Condition

CARLA also supports blueprints for weather, so one can create any weather situation except for snow conditions. Table 4 below shows representative parameters for each weather type, and we created sunny day, clear night, fog day, fog night, rain day, and

rain night, respectively, and used them in our experiments, and the results can be seen in Figure 14 below.

Table 4. Parameters for adjusting weather conditions.

	Cloudiness	Sun Altitude Angle	Precipitation	Fog Density	Fog Fallout	Precipitation Deposits
Sunny day	0.0	70.0	0.0	-	-	-
Clear night	0.0	-70.0	0.0	-	-	-
Fog day	60.0	70.0	0.0	35.0	7.0	-
Fog night	60.0	-70.0	0.0	25.0	7.0	-
Rain day	85.0	70.0	80.0	10.0	-	100.0
Rain night	85.0	-70.0	80.0	10.0	-	100.0

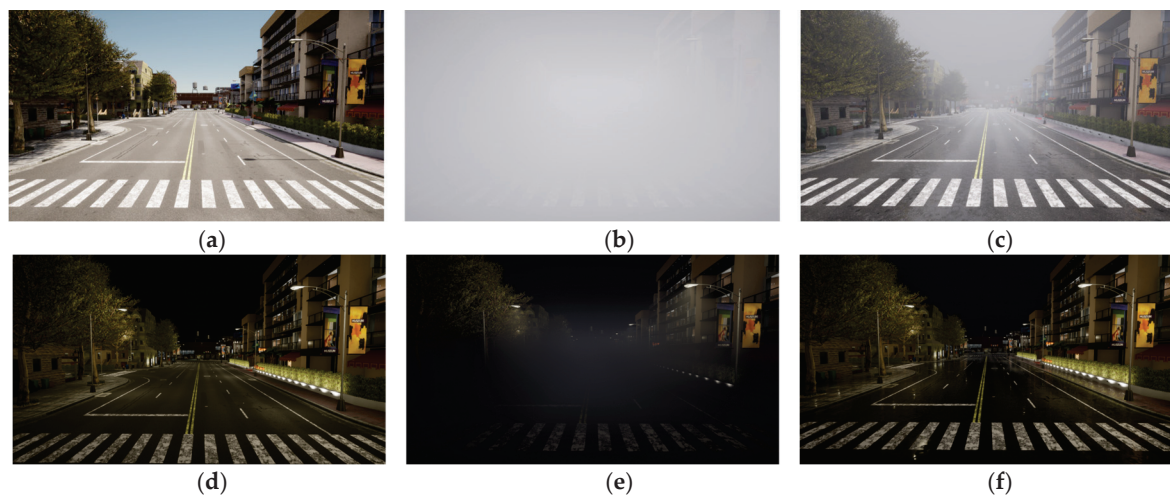


Figure 14. Screenshots of a various of weather conditions. (a) Sunny day. (b) Fog day. (c) Rain day. (d) Clear night. (e) Fog night. (f) Rain night.

4. Experiment

4.1. Dataset

Since many existing datasets do not fit the purpose of this study, we designed a dedicated dataset for this experiment and prepared the dataset in the following way.

① Pedestrian Setting

There are three types of pedestrian blueprints in the CARLA simulator: normal adult, overweight adult, and children (Figure 15), and CARLA supports each type of pedestrian with a different blueprint ID number, so one can create or control a pedestrian of that type at any time. This can be seen in Table 5 below. As shown in Table 5, each blueprint model has a different gender, race, and clothing color, but we found that there are no quantitative data (weight, height) in CARLA to categorize these pedestrian models, so we divided them into three categories: normal adult, overweight adult, and child pedestrians. We used each of these three pedestrian types in our experiments for the following reasons. Each type of pedestrian has a different number of points that make up the LiDAR data, which results in a different shape of the LiDAR data.

② Scenario Configuration

In this study, a right-turning accident scenario was designed to collect data. The target area is the Mainstreet area within Town 10, and various situations were created using pedestrian type, pedestrian speed, and number of pedestrians as detailed variables. The speed of the target vehicle was manually controlled at 15–25 km/h as shown in Figure 16 below, and 18 scenarios were designed by applying various weather conditions during

driving (Table 6). Through this scenario design, we were able to generate a dataset that more closely resembles and accurately reflects real-world right-turn accident situations.



Figure 15. Three types of pedestrians in CARLA simulator. (a) Normal adult. (b) Overweight adult. (c) Child.

Table 5. Blueprint ID lists for different pedestrian types.

Type	Blueprint ID
Normal Adult	0001/0005/0006/0007/0008/0004/0003/0002/0015 0019/0016/0017/0026/0018/0021/0020/0023/0022 0024/0025/0027/0029/0028/0041/0040/0033/0031
Overweight Adult	0034/0038/0035/0036/0037/0039/0042/0043/0044 0047/0046
Child	0009/0010/0011/0012/0013/0014/0048/0049



Figure 16. Screenshot of a part of the scenario. (a) Manual control of bus. (b) Scenario plan diagram.

Table 6. Scenario cases for dataset.

	Weather	Type of Pedestrian	Direction of Pedestrian	Speed of Pedestrian	Vehicle Speed
#1	Sunny day	Adults: 2 (normal)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#2	Sunny day	Adults: 2 (normal, overweight)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#3	Sunny day	Adults: 1, Children: 1	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#4	Clear night	Adults: 2 (normal)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#5	Clear night	Adults: 2 (normal, overweight)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#6	Clear night	Adults: 1, Children: 1	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#7	Fog day	Adults: 2 (normal)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#8	Fog day	Adults: 2 (normal, overweight)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#9	Fog day	Adults: 1, Children: 1	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)

Table 6. Cont.

	Weather	Type of Pedestrian	Direction of Pedestrian	Speed of Pedestrian	Vehicle Speed
#10	Fog night	Adults: 2 (normal)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#11	Fog night	Adults: 2 (normal, overweight)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#12	Fog night	Adults: 1, Children: 1	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#13	Rain day	Adults: 2 (normal)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#14	Rain day	Adults: 2 (normal, overweight)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#15	Rain day	Adults: 1, Children: 1	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#16	Rain night	Adults: 2 (normal)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#17	Rain night	Adults: 2 (normal, overweight)	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)
#18	Rain night	Adults: 1, Children: 1	Ped1: 0°/Ped2: 180°	Ped1: 1.0 (m/s)/Ped2: 1.5 (m/s)	15–25 (km/h)

③ Data Time Synchronization

For our proposed method to work correctly, the onboard agent and the intersection agent must be simulated at the same time and within the same period, which can be adjusted through a parameter named *passive* in CARLA. This parameter is specified as a bool type, and we were able to synchronize the time of the ROS Topic data through this parameter. In Figure 17 below, one can see how the time synchronization is achieved through the true/false of the *passive* parameter, and in this way we collected about 40 Gb of ROS bag files.

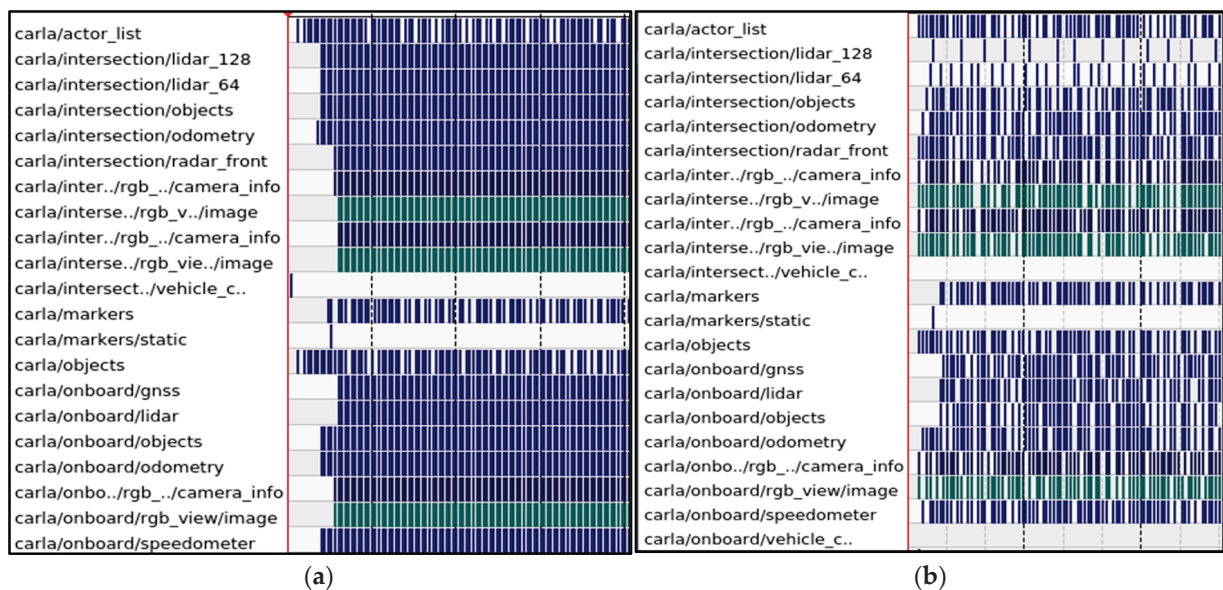


Figure 17. Comparison of synchronization status. (a) Synchronous ROS messages. (b) Asynchronous ROS messages.

④ Data Extraction

To compare the pedestrian detection performance between the two agents, we extracted LiDAR bin files for onboard and intersection data from the ROS bag files and label txt files containing pedestrian information. The ROS-ApproximateTimeSynchronizer package was utilized for extraction, and the label files stored label data in the order of *x*, *y*, *z*, *dx*, *dy*, *dz*, heading, and class type for 3D LiDAR detection training. As a result, the number of extracted data for each scenario is shown in Table 7 below.

Table 7. Number of datasets.

	Sunny Day	Clear Night	Fog Day	Fog Night	Rain Day	Rain Night	Total
Onboard	5299	4066	5143	4876	5420	5555	30,359
Intersection	5299	4066	5143	4876	5420	5555	30,359
							60,718

4.2. Training Details

We trained the PV-RCNN algorithm on the onboard LiDAR data and the Complex-YOLO algorithm on the intersection LiDAR data from the extracted data. The GPU specification of the PC used as a training environment is NVIDIA GEFORCE-RTX-3090ti, and the parameter properties of each algorithm set for training are shown in Table 8 below. We utilized 70% of the total dataset as training data, and the training data were randomly mixed with scenario data of pedestrian type and weather type.

Table 8. Training parameters.

	Class List	Anchors	Filtering [m]	Feature Type	Feature Size
Complex-YOLO [Intersection]	Pedestrian	[1.08, 1.19]	Min/Max x: 0, 40 Min/Max y: 0, 40 Min/Max z: $-4.5, 0$	BEV	[512,1024,3]
PV-RCNN [Onboard]	Pedestrian	[0.96, 0.88, 2.13]	Min/Max x: ± 75.2 Min/Max y: ± 75.2 Min/Max z: ± 4.0	Voxel	[0.1,0.1,0.15]

4.3. Clustering Details

We used Complex-YOLO for pedestrian detection and clustering at the same time. Since our experiment targets pedestrians on crosswalks, we first performed filtering by specifying a region of interest. By filtering the region of interest, the obstacles on the crosswalk are more visible. Then we applied the DBSCAN clustering method to cluster the objects on the crosswalk. The DBSCAN method is a density-based clustering algorithm that is robust to noise and performs well in clustering objects in the target area. One can see the sequential clustering process in Figure 18 below.

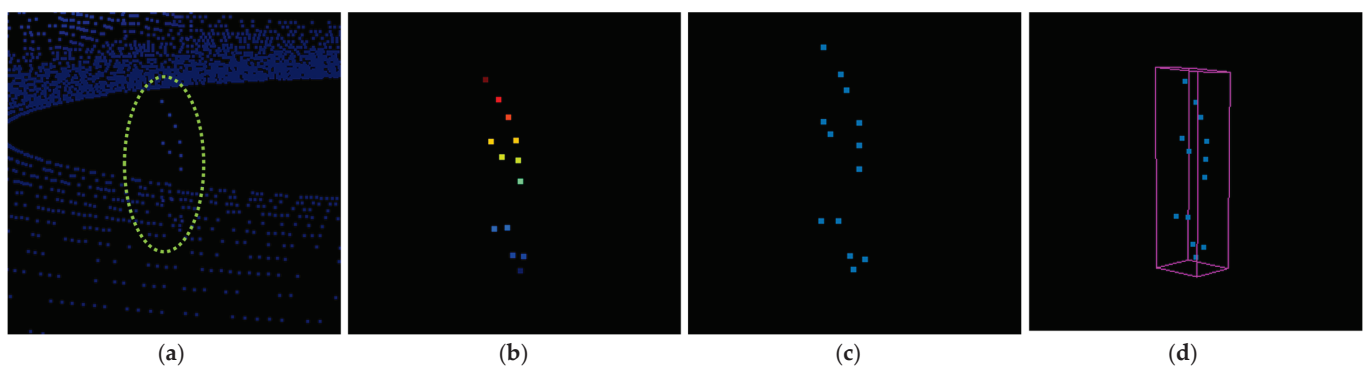


Figure 18. Clustering process. (a) Raw data (pedestrian in green circle). (b) Filtered data by region of interest (ROI). (c) Clustered data. (d) Bounding box of object (magenta color).

5. Experimental Result

We evaluated the performance of the algorithm proposed in this paper with about 30% of the data from our own dataset. At this time, we prepared evaluation datasets for each type of pedestrian according to the designed scenarios (Table 9) so that they can be evaluated in various environments, and the number of datasets prepared for each scenario can be found in Table 10 below.

Table 9. Classification of pedestrian for evaluation.

Attributes of Cases	
Case 1 (#1)	Normal adults: 2
Case 2 (#2)	Normal adults: 1, Overweight adults: 1
Case 3 (#3)	Normal adults: 1, Children: 1

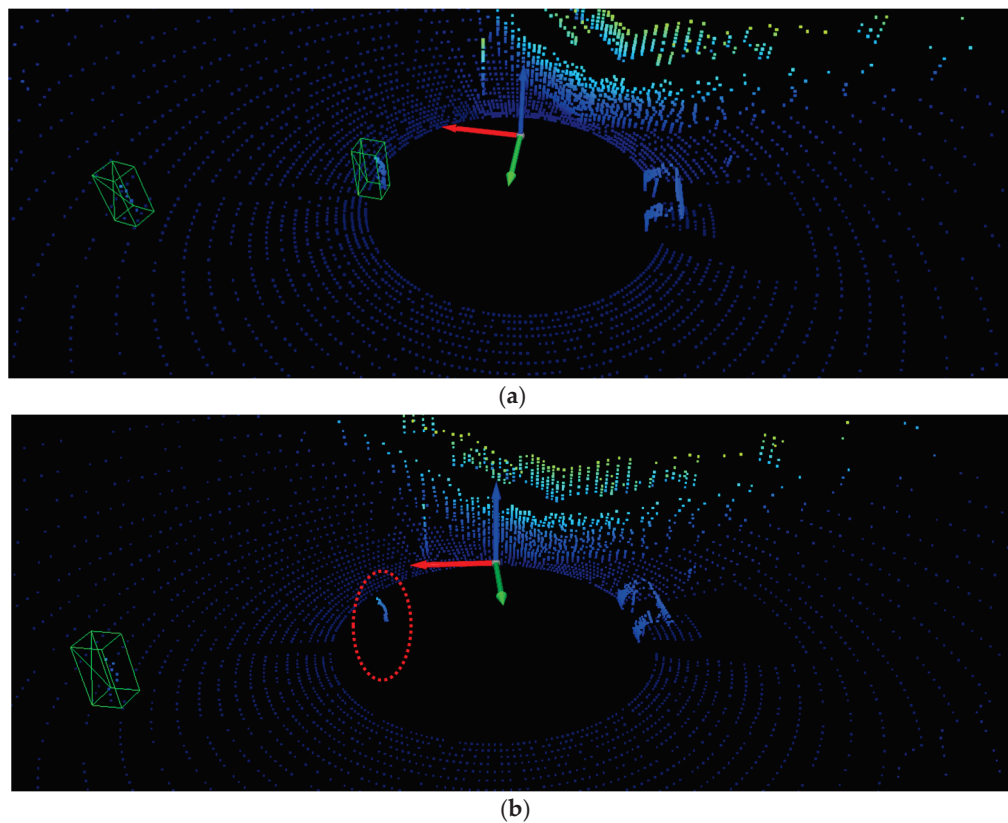
Table 10. Evaluation dataset.

Weather Type	Num.	Total
Sunny Day	#1: 609/#2: 499/#3: 483	1591
Clear Night	#1: 390/#2: 389/#3: 442	1221
Fog Day	#1: 494/#2: 519/#3: 531	1544
Fog Night	#1: 456/#2: 437/#3: 571	1464
Rain Day	#1: 566/#2: 555/#3: 507	1628
Rain Night	#1: 561/#2: 585/#3: 523	1669
Total		9117

5.1. Onboard Evaluation

5.1.1. Onboard Qualitative Evaluation

The PV-RCNN qualitative evaluation of onboard data is shown below. As shown in Figure 19, it can be seen that pedestrians located within the blind spot of the bus are not detected properly. In addition, pedestrians located outside of a certain range are also poorly detected. From these results, we can conclude that large vehicles need to perform safe recognition functions for autonomous driving, and the larger the volume, the wider the blind spot tends to be. This shows not only the limitations of deep learning but also the need for additional sensors to compensate for blind spots, but we can conclude that installing additional sensors may not be economically reasonable.

**Figure 19.** Cont.

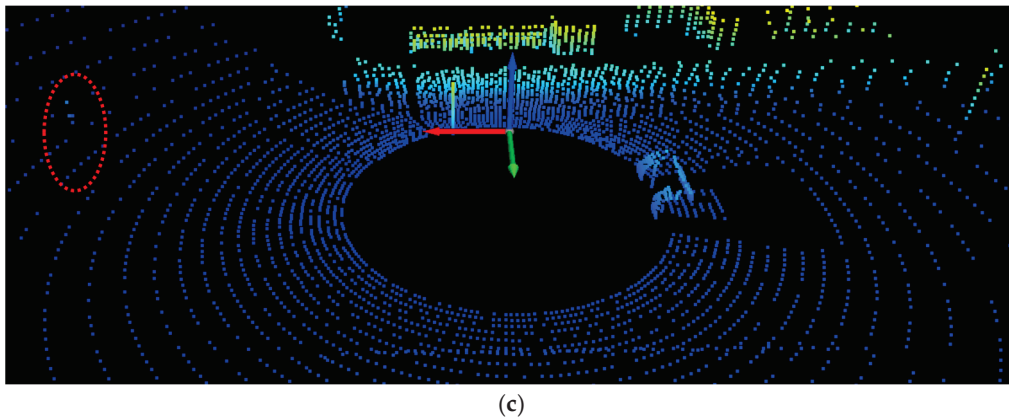


Figure 19. PV-RCNN result images. (a) True positive. (b) Undetected pedestrian due to blind spot. (c) Undetected pedestrian due to data sparsity by range limit.

5.1.2. Onboard Quantitative Evaluation

The PV-RCNN quantitative evaluation of onboard data is shown below. As can be seen from Table 11, the results show low accuracy due to the failure to detect pedestrians within the blind spot and pedestrians beyond a certain distance. In particular, the LiDAR data that constituted pedestrians beyond a certain distance were too few to infer the model. (Figure 20). Therefore, it can be concluded that the 32-channel LiDAR in the simulator is not reliable for vehicle safety, and the lack of perception data in autonomous vehicles necessarily raises the need for external sensor involvement.

Table 11. Quantitative evaluation of onboard LiDAR process.

	Sunny Day			Clear Night			Fog Day			Fog Night			Rain Day			Rain Night		
	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3
PV-RCNN	0.53	0.60	0.53	0.52	0.44	0.35	0.36	0.43	0.39	0.51	0.51	0.45	0.46	0.61	0.37	0.43	0.52	0.34

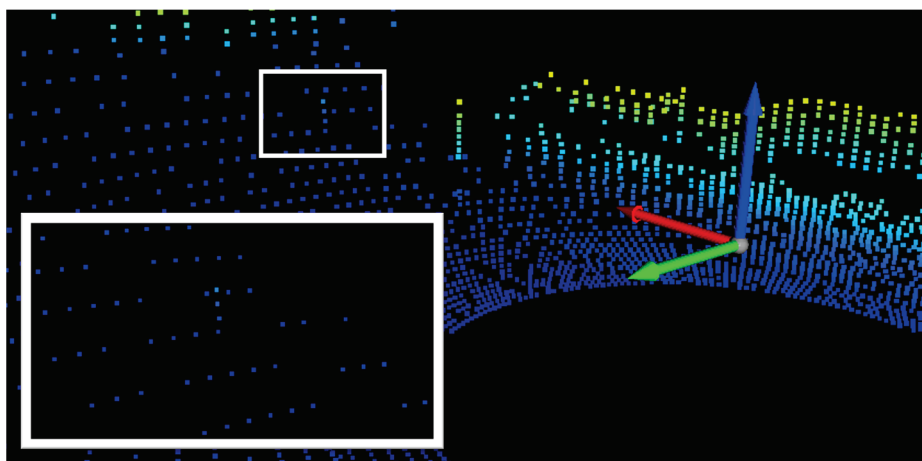


Figure 20. Pedestrian data captured by a 32-channel LiDAR (onboard).

5.2. Intersection Evaluation

5.2.1. Intersection Qualitative Evaluation

The qualitative results of Complex-YOLO evaluated on our dataset were as follows. We found that sometimes two pedestrians were not detected even though they were on the crosswalk. The reason for this is that the number of LiDAR data corresponding to pedestrians is less than 128-channel LiDAR data, so BEV features are not fully reflected in

the training. In particular, we found that child pedestrians, as shown in Figure 21, have significantly fewer points than adult pedestrians, so the general deep learning method sometimes fails to detect them. Figure 22 shows the examples of correctly detected and incorrect results when compared to the ground truth in each case (Table 9).



Figure 21. Pedestrian data captured by a 64-channel LiDAR (intersection).

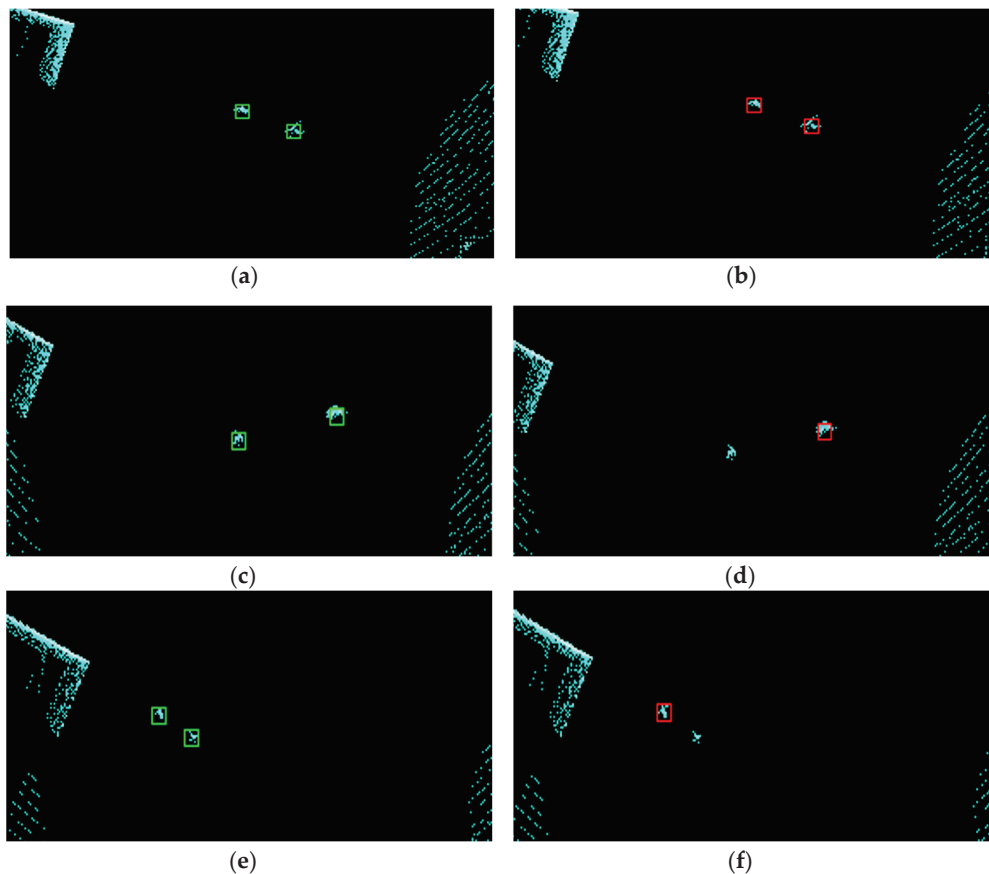


Figure 22. Complex-YOLO result images. (a) Ground Truth of case 1. (b) Complex-YOLO output of case 1. (c) Ground Truth of case 2. (d) Complex-YOLO output of case 2. (e) Ground Truth of case 3. (f) Complex-YOLO output of case 3.

Figure 23 below is an example of the clustering results. As one can see in the result figures, after performing the clustering operation, we reconstructed the boxes in a 2D bird eye view (BEV) view, and we can clearly see that even objects that were not detected by Complex-YOLO were correctly detected.

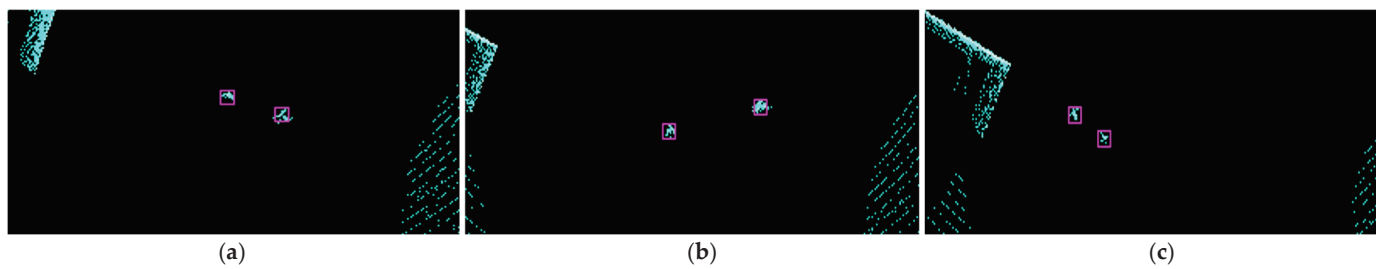


Figure 23. Clustering result images. (a) Clustering output of case 1. (b) Clustering output of case 2. (c) Clustering output of case 3.

Figure 24 below shows the final output of the fusion of Complex-YOLO and clustering results. The fusion of the bounding box from Complex-YOLO and the bounding box from clustering complements the results of Complex-YOLO. As a result, we can note that the current location of the pedestrian can be determined based on the intersection LiDAR.

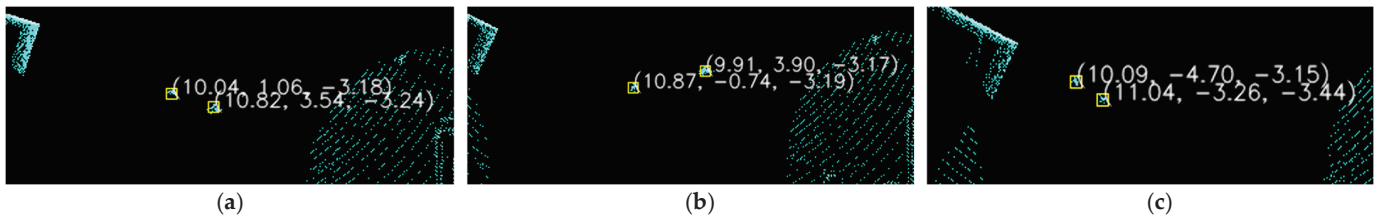


Figure 24. Output of bounding boxes' fusion. (a) Output of case 1. (b) Output of case 2. (c) Output of case 3.

5.2.2. Intersection Quantitative Evaluation

The following is a quantitative evaluation of the intersection LiDAR process. Table 12 shows the quantitative results of Complex-YOLO and our proposed model for each scenario. We can see that most of the results of Complex-YOLO detect pedestrians at a certain accuracy level, but when we fused the clustering results, we can see that the accuracy results are mostly above 0.9. This shows that our model is better at detecting pedestrians when fused with the clustering process, suggesting that LiDAR is better than other sensors at detecting pedestrians in a simulated environment. Furthermore, the performance is not significantly different from the previously proposed 128-channel LiDAR experiment, suggesting that the 64-channel LiDAR in our system is sufficient and can be replaced (Table 13).

Table 12. Quantitative evaluation of intersection LiDAR process (64 channels).

	Sunny Day			Clear Night			Fog Day			Fog Night			Rain Day			Rain Night		
	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3
Complex-YOLO	0.81	0.68	0.90	0.88	0.86	0.86	0.85	0.92	0.90	0.80	0.83	0.70	0.66	0.79	0.92	0.72	0.71	0.81
Ours	0.98	0.91	0.88	0.98	0.95	0.94	0.93	0.98	0.97	0.97	0.98	0.94	0.93	0.94	0.96	0.97	0.95	0.91

Table 13. Quantitative evaluation of intersection LiDAR process (128 channels).

	Sunny Day			Clear Night			Fog Day			Fog Night			Rain Day			Rain Night		
	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3
Complex-YOLO	0.73	0.85	0.81	0.90	0.78	0.83	0.78	0.82	0.80	0.88	0.79	0.66	0.86	0.54	0.66	0.76	0.86	0.56
Ours	0.96	0.98	0.98	0.93	0.85	0.94	0.98	0.99	0.88	0.98	0.98	0.75	0.98	0.97	0.88	0.98	0.95	0.98

6. Conclusions and Discussion

Through this experiment, we found that the main cause of right-turning pedestrian accidents is the limited field of view, which is a problem that can also occur in large-scale autonomous vehicles. Therefore, we proposed a solution for cooperative recognition with vehicles through simulation of pedestrian detection experiments using LiDAR installed at intersections and confirmed that pedestrian detection performance using 64-channel LiDAR is excellent. In addition, while the original system only observed pedestrians in right-turn scenarios, all objects in the road infrastructure (cars, pets) have the potential to cause traffic accidents, so we plan to study a wider range of object recognition in the future. However, this experiment was only verified in a virtual simulation, and there are limitations to implementing it in the real world, such as the following.

- ① Sensitivity to weather: The LiDAR sensor used in this experiment is considered to be less sensitive to noise in different weather conditions because it produces idealized data in virtual environment. However, in the real world, LiDAR sensors are very sensitive to extreme external environments, making data collection difficult [28]. Therefore, in future research, we will install LiDAR in an urban environment in a real testbed (Figure 25) and collect and analyze LiDAR data directly as the weather changes.
- ② The need for a flawless wireless communication environment: For the system to work in the real world, a process is required to transmit pedestrian data from the sensors to the vehicle without loss. In this study, the data transmission was performed by replacing the ROS server, but in the real world, we plan to design a separate communicable hardware to further design the data transmission and reception process and verify the safety. In addition, the role of sensor-mounted equipment is very important in this system, and many studies have been conducted in this regard [29–31]. Based on this, we plan to implement this system by designing a device that satisfies the Korean road traffic law.
- ③ The need for edge computing for intersection LiDAR process: In order for the proposed system to be applied in the real world, a low-power embedded board that is capable of performing the deep learning process should be used. It is meaningful to measure the performance of this system by using it inside an embedded board, and we aim to develop a port of the proposed system to embedded boards in the future.
- ④ Limited system performance: The proposed method can only detect pedestrians on the road, and only the type of pedestrian in the virtual simulator. In real life, the objects on the road consist of not only pedestrians but also cars, animals, and bicycles, which are potentially enough to cause an accident in the right-turn scenario. Therefore, in the future, we would like to improve the performance of the algorithm to detect these objects as well.



Figure 25. C-track test bed. (a) Aerial view of C-track test bed. (b) Urban area in C-track test bed.

In addition, quantitative targets are required to ensure that the system is safe and reliable, which are discussed below for each section.

- ① Accident risk reduction rate: When this system is provided to the road environment, the accident rate must be reduced by more than 90% compared to the existing one to prove its safety, and accident risk reduction will also occur.
- ② Detection accuracy and response time: In order to integrate LiDAR sensors into this system, an edge computing board capable of deep learning computation is required. The pedestrian detection accuracy performed within this board will need to meet 95%, and the average reaction time will need to be within 0.5 s.
- ③ Communication reliability and latency: To prove the reliability of this system, it must be a wireless communication system, with an average latency of 100 ms or less and a data transmission success rate of 99% or more.
- ④ Stability of data acquisition in each environment: Unlike the simulator environment, LiDAR data will vary greatly in various weather environments in real life. Therefore, in order to ensure data reliability when using LiDAR sensors in this system, the success rate of data acquisition in each condition must be presented.

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Article

Scenario-Based Analysis of Electrification Effects on Value Creation and Employment Structures for the Automotive Industry in the Federal State of Baden-Wuerttemberg, Germany

Benjamin Frieske ^{1,*}, Samuel Hasselwander ¹, Özcan Deniz ¹, Sylvia Stieler ² and Simon Schumich ²

¹ Institute of Vehicle Concepts, German Aerospace Center (DLR), Pfaffenwaldring 38-40, 70569 Stuttgart, Germany

² IMU Institute GmbH, Hasenbergstraße 49, 70176 Stuttgart, Germany

* Correspondence: benjamin.frieske@dlr.de

Abstract: The transformation path to electric mobility will have fundamental impacts on the existing value chain and employment structures in the automotive industry. The purpose of this paper is to derive and examine these effects based on two different electric mobility market scenarios for the European (EU27) passenger car as well as truck market 2040 with special focus on the highly export-oriented industrial automotive cluster in Baden-Wuerttemberg. To achieve this, both a moderate and a progressive market scenario were simulated using the scientifically validated DLR VECTOR21 vehicle technology scenario model, based on two different parameter sets derived from actual and possible framework conditions on the European car and truck markets. Based on a detailed analysis of the industrial branch, value creation, and employee structure in Baden-Wuerttemberg and its automotive cluster, the effects resulting from the transformation to electric mobility will be displayed. With detailed Fade-In and Fade-Out analysis, the shifts from internal combustion engine components to electrified components will be derived and illustrated for each employee segment in the automotive cluster in Baden-Wuerttemberg, which leads to completely new and original results at this level of detail. Furthermore, the detailed display of the automotive cluster in this study allows for regionalized statements on employment effects, considering, for the first time, not only the car but also the truck segment. The analysis shows that battery electric vehicles will achieve a share of 34% or 57% for new registrations on the German car market in 2030, depending on the scenario framework conditions. The resulting employment effects for the entire automotive cluster in Baden-Wuerttemberg reach −37,000 (−8%) or −66,000 (−14%) by 2030 with further negative development until 2040 (−155,000, −30%) for the respective scenarios. Employment segments, in particular powertrain-dependent production employees, are at risk, with a potential decline of up to −60%. R&D employees could also be significantly affected with a reduction in workforce of about −50%.

Keywords: market development; EV forecast; value creation; employment effects; BEV

1. Introduction

Technological change is leading to a transformation of the automotive industry. Driven by the trends of electrification, digitalization, and automation, additional economic opportunities will emerge throughout markets worldwide. Electric mobility in particular will alter the existing automotive industry structures, with classic components such as the internal combustion engine (ICE) ultimately losing importance, while at the same time new, electrified components become more relevant [1].

As one of the most important automotive industry locations in the world, Germany, and especially the region of Baden-Wuerttemberg, will be affected in terms of shifts in value creation and employment structures [2]. To sustain its role as a leading cluster of industrial innovation, it is essential for Baden-Wuerttemberg to adapt to and shape this

process of transformation and structural change in order to precociously take advantage of evolving economic opportunities and, at the same time, mitigate risks for losing value creation shares and employment figures.

The aim of this paper is to derive and analyze the effects resulting from the electrification of the European passenger car and truck market on value creation and employment structures for the region of Baden-Wuerttemberg and its automotive cluster. Results serve as a basis for the further discussion of policy recommendations and measures for the Ministry of Economic Affairs, Labour and Tourism as well as the Ministry of Transport in Baden-Wuerttemberg.

This study builds on the results and implications of previous studies by the authors such as the “Structural Study BWe mobil 2019” [1] and “Viable Supply Chains and New Value Creation Structures in the Automotive Industry” [2] as well as other current reference studies [3–10], extending them in terms of topicality, scientific quality, breadth, and depth.

Available literature on the analysis of value creation and employment effects for Germany use different premises and methods. As such, they cannot be directly compared to each other. A key difference lies first and foremost in the definition of the industrial sector under consideration: While some studies consider the automotive industry in terms of economic statistics [8], others cover general employment effects for the automotive industry as a whole [9], partially including or excluding other sectors, industries, and services related to automotive value creation [11]. In turn, other publications analyze the effects on specific employment segments or focus on powertrain-dependent employment only [3,4,7]. Scientific results on employment effects in the commercial vehicle industry are completely missing. Moreover, most of the current literature excludes the regional specifics of the automotive industry in the interaction of vehicle manufacturers and suppliers in their analysis [3,4,7–9].

In addition, current studies lack a scientifically consistent derivation of scenarios for the market ramp-up of alternative drivetrain technologies and actual current framework conditions in Germany and Europe. A scientifically validated basis for simulating the future market demand for new and conventional vehicle components (passenger cars and trucks) is missing, and therefore value creation and employment effects cannot be calculated adequately.

This study addresses these problems and, for the first time, provides results on value creation and employment effects based on:

- scientifically verified scenario simulations on the market ramp-up of alternative drivetrain technologies for current framework conditions in the automotive environment for the European passenger car and truck market;
- detailed analyses of the employment structures and segments of a complete automotive cluster and other sectors with upstream services for value creation in the automotive sector;
- regional characteristics and specifics of the automotive industry in Baden-Wuerttemberg;
- Fade-In and Fade-Out analyses of conventional and new components for passenger cars and trucks specifically tailored to the regional specifics and structures in Baden-Wuerttemberg.

Table 1 summarizes the methodological setup of different studies on value creation and employment effects:

Table 1. Comparison of methodological setup of studies on regionalized value creation and employment effects (BW = Baden-Wuerttemberg; GER = Germany; EU = European Union; BAY = Bayern).

Study	Differentiation by									
	Definition of Automotive Branch	Incorporation of Automotive Related Sectors	Employment Segments	Regional Specifics in Value Creation Structures	Regional Specifics in Employment Structures	Passenger Car Segment	Commercial Vehicle Segment	Scientifically Validated Market Scenarios	Component-Based Fade-In and Fade-Out Analysis	Geographical Region Considered
	by Economic Statistics	by Industry Activity	by Other Empirical Basis	Fuel Supply	Charging Infrastructure	Vehicle Trade				
ELAB 2 [4]	-	-	x	-	-	-	x	-	x	-
Mobiles Baden-Württemberg [5]	x	x	-	x	-	-	x	-	-	BW
Strukturanalyse BW [6]	x			x	x	x	x	-	x	BW
Beschäftigung 2030 [7]			x	-	-	-	x	-	x	-
Autojobs u. Strom [8]	x			x	x	x	x	-	x	GER
Employment trends [9]	x		x				x	-	-	EU
Transformation in Bayern [10]	x	-	-	x	-	-	x	-	x	BAY
Strukturstudie 2019 [1]	x	x		x	x	x	x	x	x	BW
Strukturstudie 2023 [12]	x	x		x	x	x	x	x	x	BW

2. Methodology

The aim of this analysis is to derive and quantify the effects of electrification on value creation and employment for the region of Baden-Wuerttemberg and its automotive cluster in detail. The focus of the scenario-based investigation lies on the development of the EU27 passenger car and truck markets under different framework conditions, as well as the development of their technologies and components until 2040. The methodology to achieve this goal is:

- Analysis of the industrial, value chain, and employment specifics of the automotive sector in Baden-Wuerttemberg through literature research and expert interviews;
- Analysis of existing European electrification scenarios and critical parameters for market success of electrified vehicles through literature research and expert interviews;
- Simulation of each two European passenger car and truck market scenarios with the scientifically validated DLR VECTOR21 vehicle technology scenario model, based on each a moderate and progressive set of framework conditions and critical parameters;
- Investigation of the resulting market shares for different powertrain configurations in Europe, including production cost and sales development until 2040;
- Derivation of “Fade-Out” and “Fade-In” effects for ICE-related/electrified technologies and components;
- Impact analysis on employee groups for each individual automotive cluster level and value-added segment in Baden-Wuerttemberg.

3. DLR VECTOR21 Electric Mobility European Passenger Car and Truck Market Scenarios Until 2040

To determine the impact of electrification on value creation and employment, the development of market volumes for vehicle components (e.g., internal combustion engines, transmissions, fuel and exhaust systems, electric machines, power electronics, fuel cell systems, and battery systems) is needed. In order to quantify these volumes of new, modified, and discontinued drivetrain components, new vehicle market scenarios for the market penetration of electrified vehicles—both for passenger cars and trucks—were developed, simulated, and analyzed. The vehicle scenario model VECTOR21 (www.vector21.de (accessed on 18 October 2024)), developed and scientifically verified at DLR, is used for this purpose [12]. The model enables the simulation of the purchasing behavior of customers when buying a new car, taking complex framework conditions into account. On the one hand, the simulation generates customer profiles with different characteristics (e.g., annual mileage, vehicle size) and specific vehicle requirements. This makes it possible to simulate individual utility values, depending on the type of customer, and, for example, to realize purchases for environmentally friendly vehicles with, if necessary, comparatively higher costs. These are understood as total ownership costs and consist of the acquisition costs and the operating costs (TCO, Total Cost of Ownership).

On the other hand, vehicles with different powertrain concepts, technologies, and fuel types are generated annually in the model and offered to customers. Technological and cost developments of the vehicles and a large number of components are taken into account (e.g., battery system, electric motor, power electronics). The purchase decision of more than 900 customer types each year until 2040 is simulated in a modeled environment that is based on political framework conditions (e.g., fuel taxation, CO₂ fleet limit, development of energy costs, expansion of charging, and refueling infrastructure).

The customer is assumed to be buying the one vehicle that meets his requirements best, has the necessary infrastructure available, and is most favorable in terms of overall cost. The vehicles generated in the VECTOR21 scenario model differ according to vehicle segment and powertrain concept, so that each vehicle is defined by a specific energy consumption as well as specific costs of the installed components. For the calculation of the vehicle and component costs, cost curves and DLR cost models are used. The model outline for the simulation of the passenger car market is shown in Figure 1:

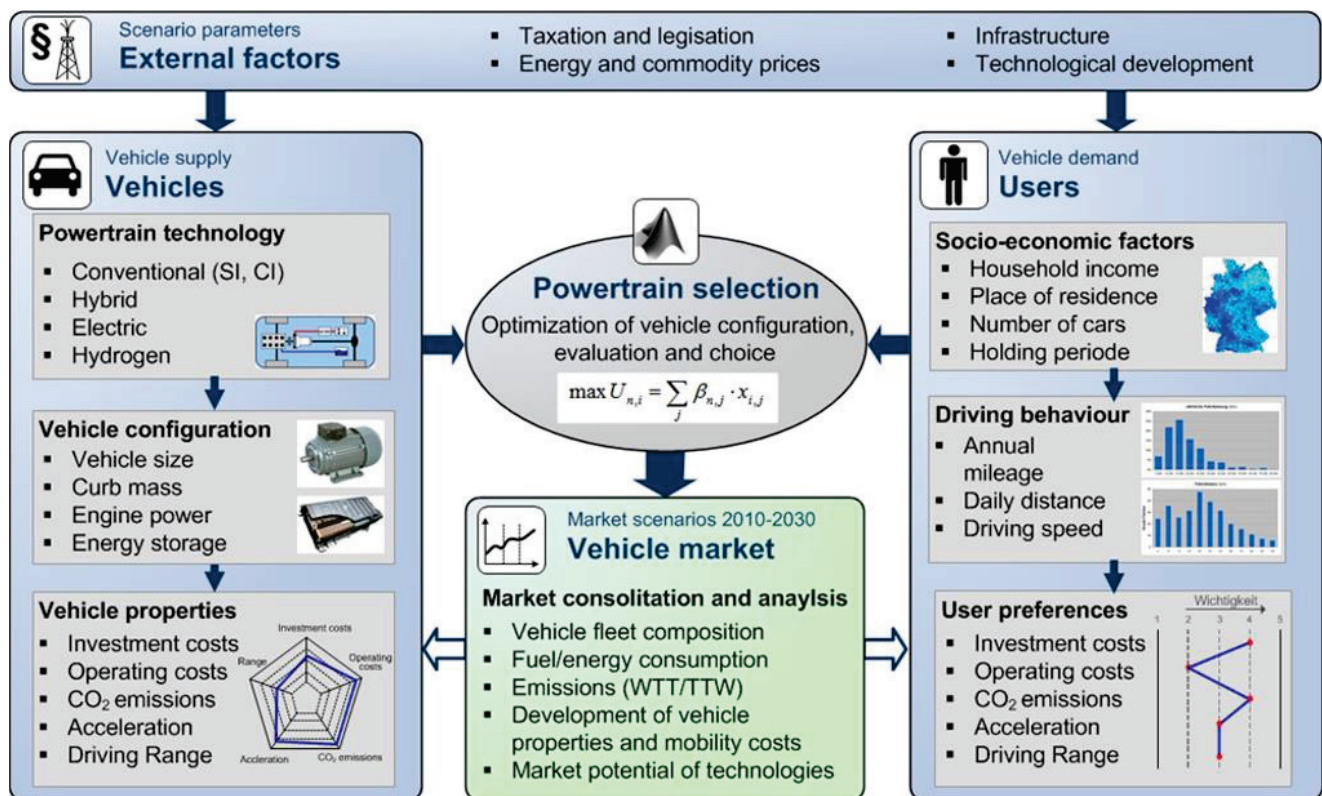


Figure 1. Structure of the DLR VECTOR21 Vehicle Technology Scenario Model [12].

Based on preliminary investigations and scenario definitions described in “Structural Study BWe mobil 2019” [1], selected critical scenario parameters, influencing factors and variables, their design, and the underlying assumptions are as follows:

The most important lever for the market launch and ramp-up of low-emission and zero-emission powertrain technologies in the European passenger car and truck market are CO₂ emission standards, regulated in Regulation EU 2019/631 (for passenger cars and light commercial vehicles) and EU 2019/1242 (for trucks). The CO₂ fleet target aims at restricting the average CO₂ emissions of all vehicles registered in the EU within a one-year timeframe. In the “business-as-usual” scenario, the CO₂ reduction rates for passenger cars are assumed to be 15% in 2025 and 37.5% in 2030 compared to 2021. The regulation for light commercial vehicles deviates from the passenger car reduction quotas in 2030 and is set to 31% in 2030. A reduction rate of 30% in 2030 applies to heavy commercial vehicles. In the “Progressive” scenario, the reduction rates are inclined to the goals of the “Fit-for-55” package and reach 55% for passenger cars and 50% for light commercial vehicles in 2030. Similarly, a 50% CO₂ reduction rate in 2030 is derived for the heavy commercial vehicle segment.

For passenger cars and light commercial vehicles, a ban on new registrations of combustion vehicles powered by fossil fuels from 2035 is assumed in both the “business-as-usual” and “progressive” scenarios, following the agreement reached by the EU member states and the European Parliament on 27 October 2022. The possible use of synthetic fuels in cars and trucks powered by internal combustion engines is not considered in this study. For heavy commercial vehicles, the ban on combustion engine vehicles in the “business-as-usual” scenario in 2040 is based on an independent commitment by European commercial vehicle manufacturers to stop selling vehicles powered by fossil fuels. In the “Progressive” scenario, a ban on new registrations of combustion vehicles powered by fossil fuels in 2035 is also assumed for heavy duty commercial vehicles.

The CO₂ price in road traffic in Germany is set in accordance with the regulatory framework and reaches EUR 30 in 2022 and EUR 45 by 2025. From 2026 onwards, the price is to be determined by the market within a price corridor of EUR 55–65. This is followed

by a moderate increase to EUR 65 in 2030 in the “business-as-usual” scenario and a linear increase to EUR 100 per ton of CO₂ by 2050. In the “progressive” scenario, the price in 2030 reaches EUR 100 per ton, then increases linearly to EUR 300 by 2050. The same CO₂ price applies to both the car and truck sectors. The decision on the new European Emissions Trading System II (ETS), which sets a Europe-wide CO₂ price of EUR 45 for the transport sector from 2027 on, was made after the framework assumptions were finalized and is therefore not included in the VECTOR21 EU model.

Monetary purchase incentives such as “environmental bonuses” or tax exemptions on electrified vehicles and other economic support measures are implemented in the car and truck sector on a country-specific basis. The following is an example of how the parameters are structured in Germany: Based on the funding guideline for the environmental bonus for passenger cars, BEVs and FCEVs with a net list price of up to EUR 40,000 will receive EUR 6750 in 2023 and vehicles between EUR 40,000 and EUR 65,000 will receive EUR 4500 (sum of federal and manufacturer share). From 1 January 2024, the subsidy will be further reduced to EUR 4500 and then only apply to zero-emission vehicles with a net list price of up to EUR 45,000. PHEVs, which were still subsidized by up to EUR 6750 in 2022, will no longer be eligible for monetary incentives from 2023 onwards. For light and heavy-duty vehicles, 80% of additional investment costs with plug-in hybrid, battery, and fuel cell powertrains as well as the refueling and charging infrastructure required for operation are subsidized. Within the scenarios, the funding program has been extended until the end of 2026. In addition, plug-in hybrids, battery, and fuel cell electric trucks will initially be completely exempt from the truck toll for an indefinite period. However, a double burden due to additional charges via both the CO₂ price and a CO₂ toll should be prevented, which is why no CO₂ differentiation was made in the assumed truck toll rates for both scenarios. In addition, battery electric vehicles are exempt from vehicle tax until the end of 2030.

Technology costs for battery packs and fuel cells have a strong influence on market development as they significantly contribute to the purchase price of all electrified vehicles. The cost of a lithium-ion battery pack in 2022 amounts to around EUR 143/kWh. For heavy duty applications (N2 and N3 class), a cost premium for the traction battery of a factor of 1.2 is assumed in order to cover additional costs for the more complex battery integration in the commercial vehicle sector. Based on the current costs, a cost degression of the battery system was developed, varying according to moderate and progressive developments. For the “business-as-usual” scenario, the assumed moderate technological developments result in prices below EUR 100/kWh at pack level in 2030. Due to economies of scale and learning curve effects, they then further decrease and reach EUR 62/kWh in 2050. In the “progressive” scenario, on the other hand, higher research expenditures and investments in more efficient production technologies are assumed, so that the cost threshold of EUR 100/kWh is already undercut in 2025. Battery costs of EUR 81/kWh are reached in 2030 and EUR 62/kWh in 2040.

Currently, the costs for a fuel cell system amount to around EUR 297 per kW for small quantities (up to 1000 units/year). In the BAU scenario, moderate technological developments and the increase in annual production volumes lead to decreasing fuel cell costs of EUR 76/kW in 2030. In the PROG scenario, a significantly higher level of investment in more efficient production technologies is assumed, so that costs of less than EUR 58/kW are already achieved by 2030. The study assumes minimum costs of EUR 53/kW, which is reached in both scenarios in 2050.

The availability of charging infrastructure is another decisive criterion for customers when purchasing electric vehicles. If there is insufficient availability, a significant market penetration of electrified passenger cars (especially BEVs) will not be achieved; it also represents a major obstacle for the market ramp-up of electrified trucks in the commercial vehicle sector. In the VECTOR21 scenarios, the influences of charging infrastructure on the vehicle market ramp-up are modeled as follows: The charging infrastructure is considered in the car market simulation by comparing the user demand of the simulation agents with a defined infrastructure availability per living situation. Agents with high

infrastructure availability, for example, own private parking spaces that can be equipped with a wallbox relatively easily. Agents with low infrastructure availability, on the other hand, represent the situation of so-called “lantern parkers”, i.e., they are completely dependent on the expansion of public charging infrastructure. The timing of the expansion of the charging infrastructure is differentiated according to clusters: In the progressive scenario, the charging infrastructure will be sufficiently expanded up to 2030 to meet the needs based on the “Charging Infrastructure Master Plan II”. In the “business-as-usual” scenario, the expansion takes place analogously, but with a time delay for customers with low infrastructure availability.

According to the master plan, the development of public charging networks for electric trucks is to be initiated from 2023 onwards. In particular, locations with particularly high charging capacities (e.g., via megawatt charging systems) relevant for long-distance transport are to be established. Furthermore, the expansion of the hydrogen infrastructure will be subsidized by the state and efforts by OEMs such as Daimler Truck in cooperation with partners from the energy sector aim to further expand the H₂ infrastructure with the market launch of hydrogen trucks (planned for the second half of the 2020s). Therefore, in both scenarios, a moderate expansion of this infrastructure is assumed.

In addition to insufficient infrastructure availability, the integration of electric charging into daily operations also poses a challenge for commercial vehicles. In the truck market modeling with VECTOR21, it is assumed that, in addition to the development of public charging networks, it will also be possible to fully recharge electric trucks overnight, e.g., at the company’s own depot. The purchase decision algorithm within the model compares the agents’ average daily route with the electric vehicle range in order to rule out possible usage restrictions due to longer charging times. In addition, the investment and operating costs for electric vehicle supply equipment (e.g., a private charging station) are included in the total cost of ownership calculations.

Energy prices for both fuel and electricity vary regardless of the scenario category. Fuel prices in general depend on complex macroeconomic effects, which are not considered in this study. Both scenarios are therefore based on the same assumptions with regard to the development of energy prices (oil, petrol, diesel, CNG, electricity, hydrogen) and the availability of petrol/diesel and CNG infrastructure.

There is a close correlation between the oil price and the filling station price for petrol and diesel. Therefore, the development of future petrol and diesel prices in the model can be mapped using a linear regression analysis as a function of the oil price. The resulting price functions enable the calculation of petrol and diesel prices up to 2050. Due to the high proportion of biogas in CNG in Germany and Europe, it is assumed that the CNG price will remain constant in real terms and will also not be influenced by the CO₂ price in the future. However, the reduction in the energy tax on CNG in Germany will be gradually withdrawn by the end of 2026. A constant price trend is also assumed for LNG price. The average household electricity price in Germany in 2020 was EUR 0.33/kWh (incl. VAT). In the car market modeling, a higher electricity price is assumed for public charging, with a premium of approx. 23%. The hydrogen price in 2020 amounted to EUR 9.50/kg. It is assumed that cheaper hydrogen can be offered with the expansion of production capacities in the future. For the truck market modeling, VAT is omitted for all energy prices.

As a result, and derived from an in-depth analysis of the existing market as well as technology and regulatory framework conditions for each European car market, two different sets of critical parameters were defined and used as input data for market development simulation with the DLR VECTOR21 model (see Table 2). The assumptions for charging station availability and CO₂ limits differ in each scenario, since they have been identified as critical for the market success of electrified vehicles on the European car market. Energy prices and availability of gasoline, diesel, CNG (Compressed Natural Gas), and H₂ stations, however, were used equally for both scenarios.

Table 2. Overview of framework parameters for creating the DLR VECTOR21 scenarios [12].

			2020	2030	2040	Source
Energy price development (for both scenarios)	Oil price	€/bbl	36.1	67.8	72.6	[13]
	Gasoline price	€/L	1.22	1.50	1.51	Own calculation
	Diesel price	€/L	1.11	1.39	1.44	Own calculation
	CNG price	€/kg	1.10	1.33	1.26	[14]
	LNG price	€/kg	0.83	1.00	0.95	[15]
	Electricity price	€/kWh	0.33	0.33	0.33	[16]
	H ₂ price	€/kg	9.5	6.8	5.5	[17,18]
Availability of infrastructure (for both scenarios)	Fuel stations	%	100	100	100	Model assumption
	CNG stations	%	7	7	7	Model assumption
	H ₂ stations	%	1	4	9	Model assumption
Specifics for “business-as-usual” scenario	Charging stations	%	20	70	100	Model assumption
	CO ₂ limit	g/km	119	72	0	[19]
Specifics for “progressive” scenario	Charging stations	%	20	100	100	Model assumption
	CO ₂ limit	g/km	119	52	0	[20]

Based on these parameters, two scenarios for both the European passenger car and truck market were simulated for every single country within the European Union until 2040. Battery Electric Vehicles (BEV) reach a market share of between 34% (“business-as-usual” scenario, BAU) and 57% (“progressive” scenario, PROG) in the German new car market in 2030, with BEV trucks reaching a share of between 31% and 50%, as can be seen in Figure 2. For the whole of Europe (EU27), these market shares differ only slightly: the BEV passenger car market share reaches 45% in the “business-as-usual” scenario and 62% in the “progressive” scenario. All other light-duty vehicles sold at this time already have electrified components installed, e.g., start-stop systems, electrified auxiliary units, or 48-V systems. For BEV trucks, market shares of between 24% and 50% will be reached in Europe in 2030, depending on the scenario.

In the BAU scenario for passenger cars in Germany, it can be seen that new registrations of BEV will increase continuously until 2035, primarily due to CO₂ limits and the associated penalties for combustion engine vehicles. The environmental bonus, in general, has a direct and significant impact on the share of new registrations of battery electric vehicles. As such, BEV market shares of up to 30% can be achieved in the small- and medium-sized vehicle sector in 2025. In the same year, the share of new registrations for vehicles with a combustion engine powertrain (G-Gasoline/Petrol; D-Diesel) is 52%, for hybrid vehicles (HEV) 15%, and for plug-in hybrids (PHEV) 4%. After the defined end of direct monetary purchase incentives in 2026, there will be a temporary shift in demand away from BEVs and towards PHEVs in the medium-sized vehicle sector as well as to gasoline powered vehicles in the small-sized vehicles sector. The small vehicle sector will then be dominated by petrol vehicles again due to the significantly lower purchase costs. A comparable effect will also be seen after the elimination of purchase premiums for plug-in hybrid models in 2023, with market shares temporarily shifting in favor of battery electric and fully hybrid vehicles. Buyers with a low range requirement and already sufficient infrastructure availability are more likely to opt for a BEV at this point, while agents with a high range requirement or still too little infrastructure availability tend to purchase HEVs.

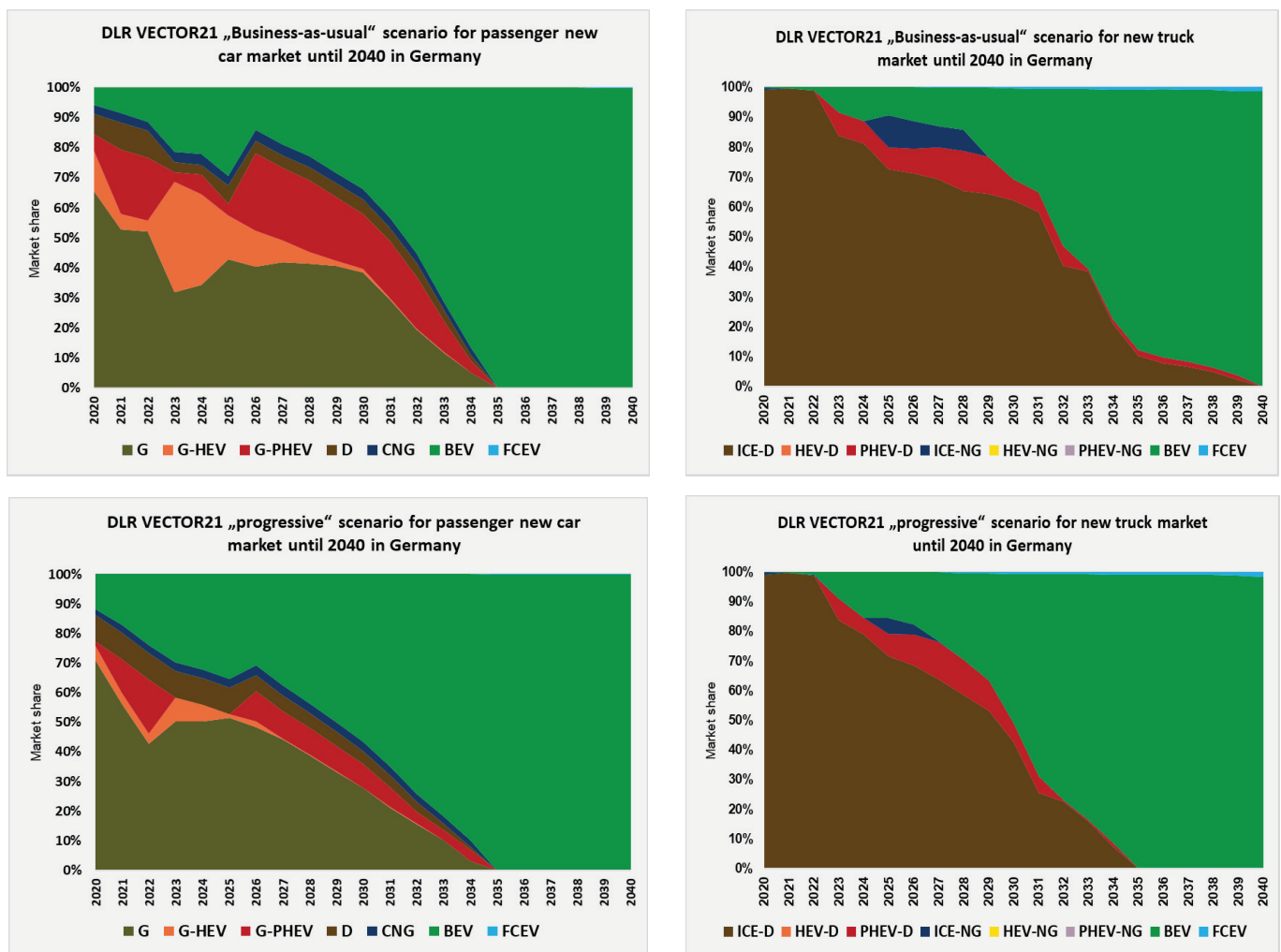


Figure 2. DLR VECTOR21 Electric Mobility European Passenger Car and Truck Market Scenarios, 2020–2040 [12].

In 2030, the market potential for plug-in hybrid vehicles will increase to 18%. Battery electric vehicles will then account for 34%, combustion engine vehicles for 46%, and hybrid vehicles will only have a market share of 1%. In the medium term, diesel and CNG vehicles with biogas will remain attractive for customers with high annual mileage and range requirements due to their favorable operating costs but will be replaced by PHEVs and BEVs as CO₂ limits become even stricter.

With CO₂ limits further decreasing until 2035, BEVs will be the dominant powertrain option across all segments in the long term. As the possible use of synthetic fuels in passenger cars powered by internal combustion engines was not taken into account in this study, the market share of BEVs will be up to 100% once the 0 g CO₂/km fleet limit is reached in 2035. Fuel cell vehicles in the large vehicle segment represent a further option for customers with high range requirements after 2035 due to a sharp drop in fuel cell costs [12].

In the PROG scenario, due to lower battery costs, a quicker expansion of charging infrastructure availability, and a stricter CO₂ limit in 2030, the share of new BEV registrations in all vehicle segments is higher than in the BAU scenario, while the influence of direct monetary incentives on the purchase decision is lower. Even with a very optimistic assumption of the development of battery costs, small petrol vehicles continue to be cheaper than BEVs in this scenario, which is why there is a slight decline in the share of new BEV registrations from 35% in 2025 to 30% in 2026. In the mid-range vehicle segment, BEVs are

economically competitive at the assumed battery and electricity prices. The CO₂ limits are mainly met through high shares of battery electric cars, so that the market shares of HEVs and PHEVs are significantly lower in favor of gasoline-only vehicles compared to the BAU scenario. In 2025, the share of new registrations for BEVs is 35%, for HEVs 1%, and for vehicles with a purely combustion engine powertrain as high as 63%. It is assumed that by 2030, all combustion engine vehicles will have mild hybridization and corresponding improvements in fuel consumption and CO₂ emissions.

Higher potential for PHEVs and diesel vehicles lies primarily in the large vehicle sector with high range requirements, where fuel cell vehicles will also have a small share of new registrations from 2035. In the long term, however, BEVs will be the dominant powertrain option. Despite the high BEV share of 57% of new registrations in 2030, the German government's interim target of 15 million battery electric vehicles in Germany is not expected to be reached until after 2030, even in the progressive scenario.

Figure 3 illustrates exemplary cost developments (net) for mid-range vehicles with different powertrains (ICE, PHEV, BEV) in the “progressive” scenario for 2020 and 2030. The development of the differential costs between ICE and BEV is particularly interesting: while the acquisition costs of a conventional vehicle with a internal combustion engine are still around EUR 8500 higher than those of a BEV in 2020, these additional costs will be reduced to around EUR 700 (excl. VAT and purchase premiums) by 2030 under the progressive framework assumptions made. This is primarily due to decreasing battery costs, but also to increasing costs for combustion engine efficiency technologies, which are necessary for ICEs to comply with statutory emission limits while at the same time leading to a reduction in fuel consumption.

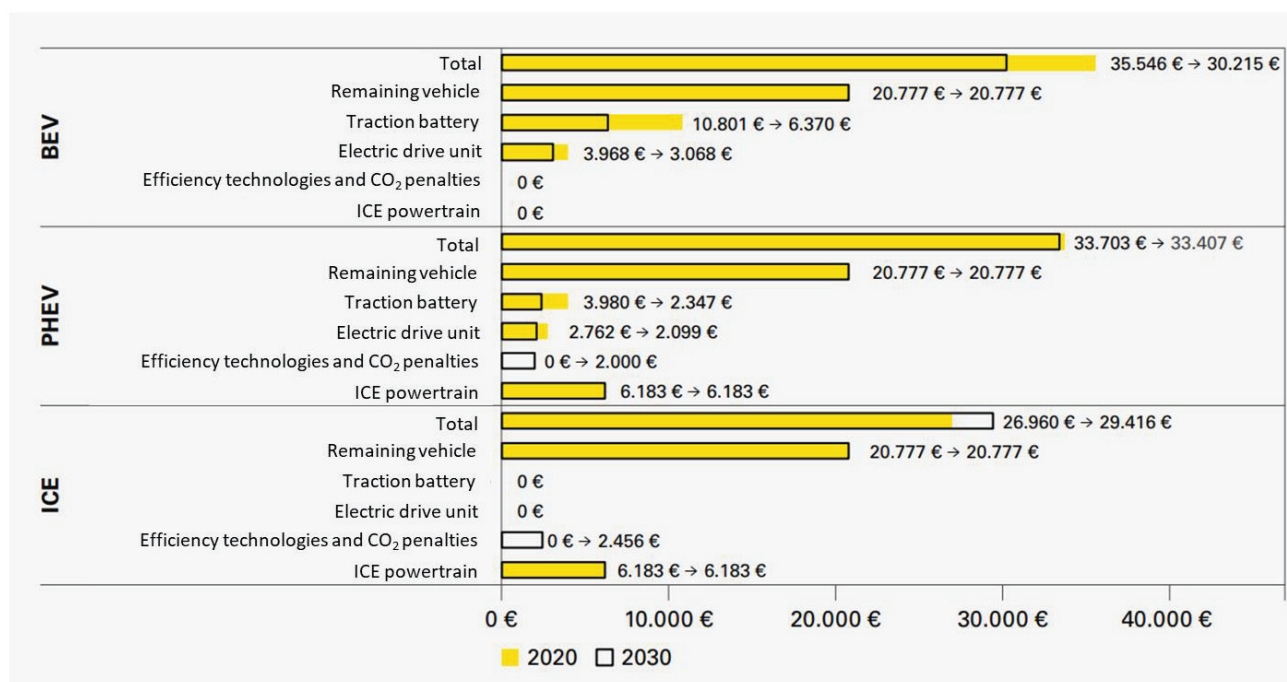


Figure 3. Exemplary cost development (incl. margins, excl. VAT and purchase premiums) of ICE, PHEV, and BEV mid-range passenger cars up to 2030 [12].

It is assumed that the ICE powertrains will undergo mild hybridization and that a CO₂ reduction potential of 10% can be achieved by 2030 [21]. However, as these increases in efficiency will not be sufficient to fulfil the specific CO₂ limit for combustion engine vehicles in 2030, CO₂ penalty payments of EUR 95 per g/km of excess emissions incurred by the manufacturer will be passed on directly to the customers in terms of vehicle price [20]. In combination with lower operating costs, battery electric vehicles then represent the more attractive vehicle option for many buyers.

Based on the assumptions made, battery costs will decrease by around 40% in the period under review up to 2030. This is mainly due to economies of scale resulting from progressive development through higher production volumes, but also because of technological improvements in the battery system and further developments in cell chemistry. In addition to the battery systems, there will also be further cost reductions in power electronics and the electric motor (summarized as electric drive unit in the following figure), albeit with a much smaller absolute impact on the purchase price.

4. Value Creation and Employment Effects for the Automotive Industry in Baden-Wuerttemberg, Germany

Baden-Wuerttemberg is one of the world's leading centers of automotive production and innovation, with a fully developed automotive cluster comprising the entire value chain of manufacturing, ancillary services, and suppliers from the mechanical and plant engineering sectors. The three Baden-Wuerttemberg-based original equipment manufacturers (OEMs) are classed as belonging to the premium sector and numerous suppliers specialize in the development and production of power trains.

The automotive industry is one of the key industrial sectors in Baden-Wuerttemberg and Germany as a whole. In 2022, the core industry "Manufacture of motor vehicles and motor vehicle parts" accounted for sales of EUR 135 billion in Baden-Wuerttemberg (Germany 2021: EUR 413 billion), generated by around 225,000 employees—just under 5% of all employees subject to social security contributions in Baden-Wuerttemberg (Germany: approx. 900,000 employees). At about EUR 13 billion, the industry's high contribution to research and development is a major factor in the region's economic prosperity, accounting for 53% of R&D expenditure in Baden-Wuerttemberg and 47% of the industry's R&D expenditure in Germany as a whole [22,23]. The fact that electrical engineering and mechanical engineering follow far behind, with EUR 2.9 billion and EUR 2.5 billion R&D spending, respectively, further highlights the importance of the automotive industry. In total, the economy in Baden-Wuerttemberg accounts for 83% of R&D activities, a significantly higher proportion than in Germany (69%) or the EU-27 average (66%).

However, after decades of growth with short economic downturns, the industry is currently facing an unprecedented transformation [24]. Driven by the political pressure to minimize climate change, all new vehicles in the European Union must have net zero-emission drives by 2035, and, by 2050 at the latest, net production emissions should be completely eliminated. At the same time, events such as the COVID-19 pandemic, supply chain disruptions, and the war in Ukraine, challenges in energy supply and increasing trade disputes in recent years have made the economic conditions in the automotive industry increasingly volatile.

The transition to electric mobility will impact very differently on different groups of employees. As a basis for the impact analysis, the employment structure in Baden-Wuerttemberg's automobile branch has thus been analyzed in detail, and the various groups of employees have been categorized at different levels of the cluster and value segments, as shown in Figure 4.

The core of value creation includes companies that are directly involved in the production of motor vehicles. These are the vehicle manufacturers such as Mercedes-Benz Group AG, Daimler Truck AG, Porsche AG, and Audi AG, as well as suppliers of the Tier 1 to Tier 2 value-added stages (e.g., Robert Bosch GmbH, ZF Friedrichshafen AG, the Mann + Hummel Group, Elringklinger AG, and the Eberspächer Group). Other manufacturing sectors, such as the glass industry, metal processing, and the rubber and plastics industry, whose products are directly related to vehicle parts and components, are also assigned to the cluster core in proportionate terms. The cluster also includes parts of the mechanical engineering industry (e.g., piston production), automotive development service providers, as well as plant service providers working directly at automotive locations (e.g., security services, logistics providers at automotive locations) and temporary employment agencies. In total, 315,500 employees can be assigned to this cluster.

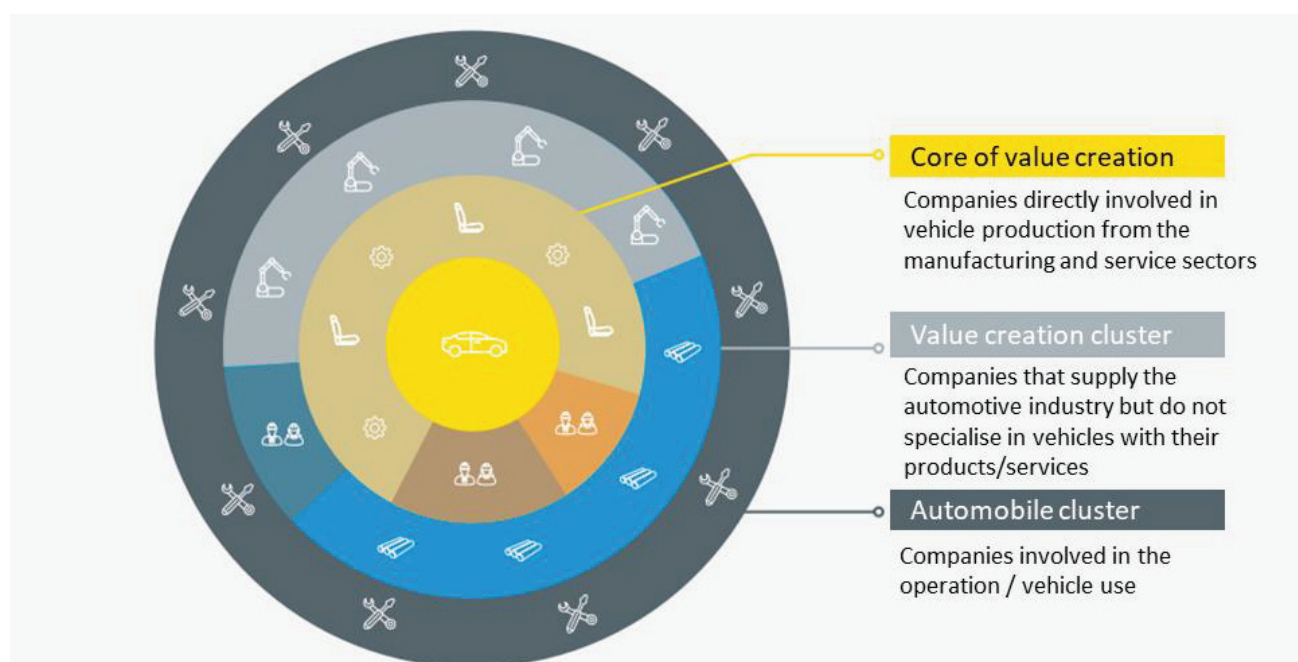


Figure 4. Value creation structure of Baden-Wuerttemberg's automobile cluster [1].

The extended value creation cluster comprises companies that supply the automotive industry but whose products are not specialized in motor vehicles. This includes the mechanical engineering industry (in particular part of the machine tool industry), which acts as a supplier to the automotive industry, as well as other material suppliers at Tier 3 to Tier 4 level (screws, technical textiles, etc.) and services such as legal advice, advertising agencies, and wholesalers. This cluster covers 381,600 employees in Baden-Wuerttemberg.

About 91,300 employees in the vehicle trade segment complement the automobile cluster in Baden-Wuerttemberg, as well as about 6000 employees in the field of fuel supply, including petrol stations and refineries.

In total, a workforce of about 480,100 can be attributed to the automobile cluster in Baden-Wuerttemberg as a whole. Employees in these value segments can be further broken down into different functional areas, as shown in Figure 4.

Based on the outcome of the DLR VECTOR21 scenarios, the effects on employees of the Baden-Wuerttemberg automotive industry were estimated. In a multi-stage process, so called Fade-Out effects, due to the decline of market shares for internal combustion engine components, and Fade-In effects, due to the increasing production volume of new components for electrified drivetrains, were determined. The detailed display of the automotive cluster in this study allows for regionalized statements on possible employment effects [12].

The Fade-Out analysis (see Figure 5) determines the drivetrain-dependent employees of the automobile industry in Baden-Wuerttemberg. To do so, the total number of employees in the industry is used as starting point to add the employment effects of market growth until 2030 (step 1), then all employees in the utility, truck, and commercial vehicle sectors are identified (step 2), and those working on non-drivetrain products are subtracted (step 3). In the final step, an assessment of how the powertrain mix of the DLR VECTOR21 scenarios affects the number of employees dependent on the powertrain in steps 1 to 3 is carried out.

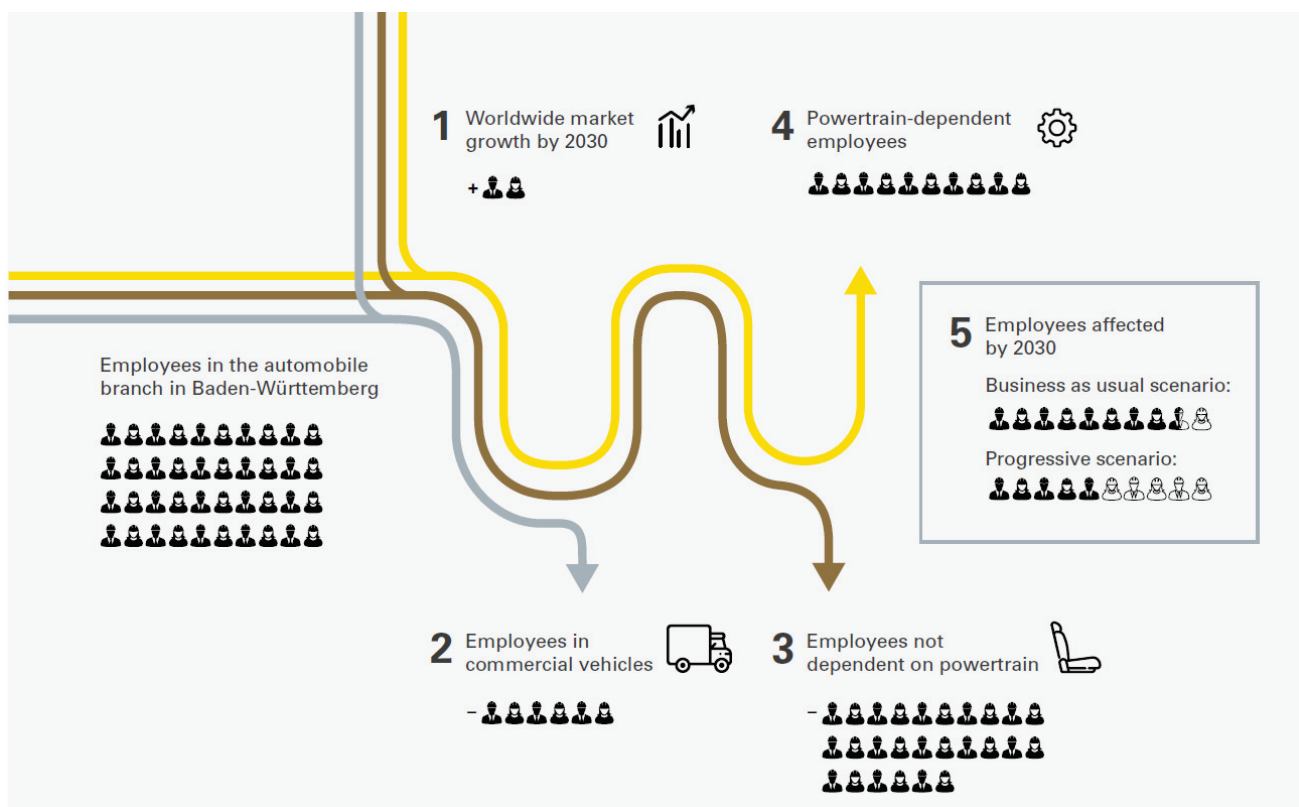


Figure 5. Procedure used to identify the number of employees affected by electric mobility in 2030 (Fade-Out) [Reprinted with permission from Ref. [1]. 2019, e-mobil BW GmbH].

The Fade-In analysis (see Figure 6) takes the scenario-based production volumes of the electric powertrain core components as a baseline. Step 1 displays the number of components needed in the European market in 2030. In step 2, the proportion of new electric mobility components that could realistically be manufactured for the European market in Baden-Wuerttemberg is determined. On this basis, the respective labor productivity (in employees per component) can be used to determine the number of employees required for production (step 3). This results in the sum of positive employment effects posed by new electric mobility components.

The effects of the discontinuation of the internal combustion engine (Fade-Out) and the market ramp-up of components for electric mobility (Fade-In) have a significant impact on the entire automotive cluster in Baden-Wuerttemberg:

- In the “business-as-usual” scenario, a reduction in employment of around 8% or 36,700 employees will occur by 2030;
- In the “progressive” scenario, a reduction of 14% or 66,000 employees can be identified. By 2040, the effect will be much stronger (over –30%, –154,500 employees).

In addition, it is already assumed that Baden-Wuerttemberg production sites will be consistently converted and expanded to new technologies and that companies will achieve similar market shares for the new components as today for components for the internal combustion engine powertrain. An exemplary analysis of the planned expansion of production capacities for batteries shows that the locations for battery production in Germany, with a volume of more than 545.5 GWh, account for around 20% of the total capacity planned in Europe. However, Baden-Wuerttemberg’s share is only around 2% and therefore significantly lower than the federal state’s previous turnover and employment shares in the European automotive industry. With the expected competition from Chinese manufacturers for electric vehicles and high price pressure, considerable risks emerge, especially for Baden-Wuerttemberg’s suppliers. Only if these conditions are met can the

calculated Fade-In effects be fully realized and the impact on the entire cluster be considered manageable. This requires joint efforts from companies, politics, and society.

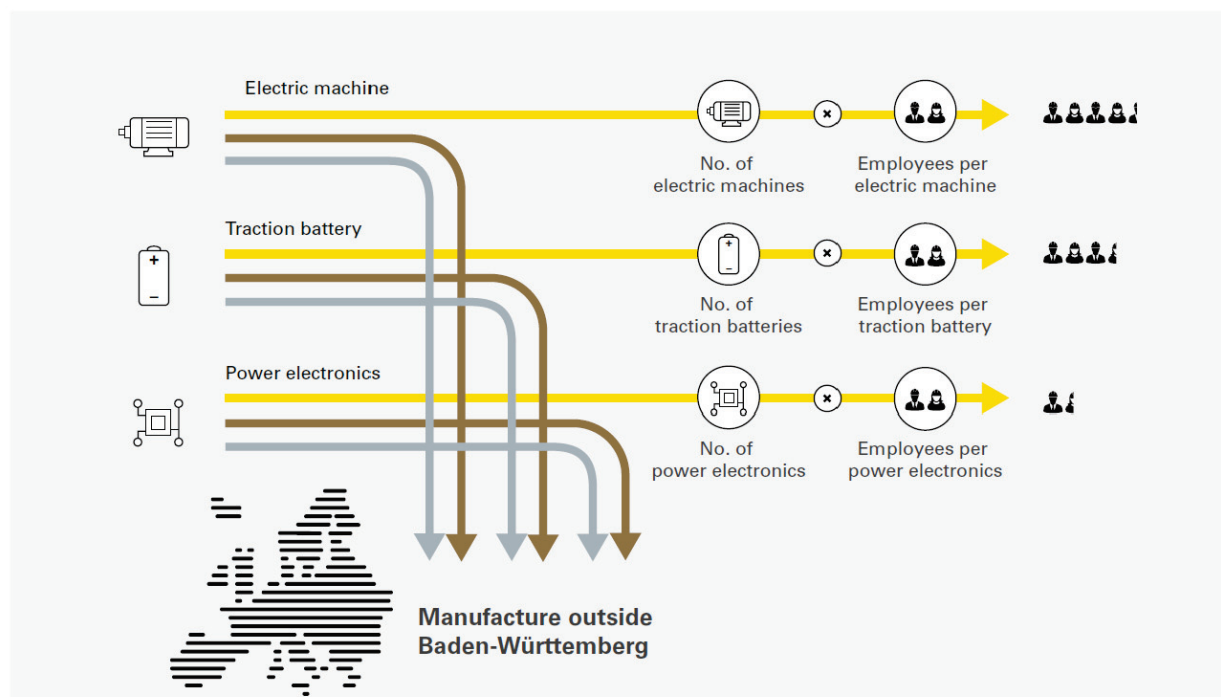


Figure 6. Procedure used to identify the number of employees affected by electric mobility in 2030 (Fade-In) [Reprinted with permission from Ref. [1]. 2019, e-mobil BW GmbH].

In the context of demographic change, a decline of around 29,500 people of working age is expected for the Baden-Wuerttemberg automotive cluster by 2030. The retirement of large age cohorts in the coming years is seen as an option for organizing a decline in employment in the automotive industry in a “socially acceptable” manner, i.e., without redundancies. By 2040, the number of employable people in the cluster would decrease by 39,400 to around 413,800 compared to today. Here, the Fade-Out effect of electric mobility is considerably larger than the effect of demographic change (decline in the model to approx. 330,000 people).

However, a detailed analysis of individual cluster segments highlights that they are affected, to varying degrees, by the decline in employment. This also leads to regional differences in the extent to which individual locations are affected. Production sites for components and parts as well as research and development are affected to a much greater extent by the decline in employment; even in the “business-as-usual” scenario, half of the labor volume will be lost by 2030. Expected rationalization effects and relocations will lead to even greater employment losses, particularly at powertrain production sites. This jeopardizes key segments of Baden-Wuerttemberg’s innovation cluster. The results of the impact analysis are shown in Table 3.

The transition to electric mobility primarily affects the powertrain-dependent production locations in the cluster core. The model shows the Fade-Out and Fade-In effects separately for this cluster segment. In both scenarios, 26% ICE market shares are simulated for 2030 in the “business-as-usual” scenario, 47% in the “progressive” scenario, and 100% in 2040 for both scenarios. This has a direct impact on employees in this cluster segment. In addition, regular productivity increases have led to employment losses for years, and production shares in the European production networks are being relocated to “low-cost countries” in Eastern Europe.

Table 3. Potential impacts of electric mobility on the Automobile Cluster in Baden-Wuerttemberg, Germany [12].

Cluster Segment		2022	2030 Scenario BAU	2030 Scenario PROG	2040 Scenario BAU and PROG
OEM	Components	21,200	17,400	13,000	3900
	R&D	19,300	17,500	15,800	11,200
	Assembly	42,500	39,400	39,400	35,500
	Administration	13,500	12,600	12,600	11,300
Manufacturer of bodies, superstructures, trailers		6100	5700	5700	5100
Automotive supplier	Components and parts	91,500	99,800	91,600	68,300
	R&D	30,500	27,600	24,900	17,700
Other sectors of the manufacturing industry	Components and parts	37,700	38,300	36,200	28,900
	R&D	16,100	12,600	11,700	8900
Development service provider		16,100	14,600	13,200	9300
Temporary workers	General	8600	8000	8000	7200
	Powertrain dependent	10,900	4600	3800	2200
In-house services		1500	1400	1400	1300
Total cluster core		315,000	299,500	277,300	210,800
Other manufacturing industry	Components and parts	22,100	20,500	20,500	18,400
Mechanical engineering as a supplier		29,300	26,500	23,900	17,000
Non-product-specific services for OEMs and suppliers		14,700	13,700	13,700	12,300
Total value creation cluster		381,600	360,200	335,400	258,500
Vehicle trade		91,300	71,000	64,000	55,000
Fuel supply		6000	4900	4500	1900
Charging infrastructure and power supply		1200	7300	10,200	10,200
Total Baden-Wuerttemberg automotive cluster		480,100	443,400	414,100	325,600

With a decline of 6%, the “business-as-usual” scenario shows a development that seems to be manageable over a time frame until 2030. Here, lower employment losses due to the discontinuation of the ICE can partly be offset by an increase in employment due to production of electrified vehicles. In contrast, the “progressive” scenario will result in significant employment losses due to electric mobility in 2030 and even more so in 2040. The decline in market share for combustion engine components means that the work volume of around 92,000 employees currently assigned to this powertrain in the passenger car sector will be lost, which is around 19% of the entire cluster. This shows the imminent pressure to initiate measures for maintaining employment in Baden-Wuerttemberg.

If the positive Fade-In employment effects for the production of electric mobility components fail to materialize, this segment in the cluster core will shrink to around one third of its current size. However, this segment is central to both employment and the innovative strength of the cluster. If additional relocation and rationalization effects are included in the analysis for this cluster segment, the high employment risk and the correspondingly lower compensatory effect of Fade-In effects become clear:

1. For powertrain-dependent employees in the “business-as-usual” scenario, around 23,500 of the total workforce (−33%) will be affected by the discontinuation of components and parts for the internal combustion engine (Fade-Out). If the expected productivity increases and relocations to low-cost countries are implemented for pro-

duction sites, a further 18,900 employees (27% in 2022) could be affected. This means that up to 60% of powertrain-dependent employees in the cluster core are at risk in the “business-as-usual” scenario and up to 81% in the “progressive” scenario. Even if all Fade-In effects for electric mobility in Baden-Wuerttemberg will be realized with great effort, a loss in employment of 29,300 (scenario “business-as-usual”) or 42,700 (scenario “progressive”) remains in the cluster core, which alone causes a decline in employment of 6% or 9% in the entire cluster. This means that even in the BAU scenario, great efforts are required from all industry stakeholders in order to master the transformation at as many production sites as possible. In the PROG scenario, the jobs of four-fifths of employees will change or even disappear as a result of the transformation if only Fade-Out effects are considered. The faster the ramp-up of electric mobility takes place, the greater the challenges will be to maintain all cluster segments in Baden-Wuerttemberg;

2. The number of employees in research and development areas in the cluster core among OEMs, automotive suppliers, and suppliers from other sectors of the manufacturing industry will drastically change. Initially, and depending on the scenario, between 9700 and 34,900 (2040) jobs will be lost. A look at the employment effect in 2040 is alarming, as it highlights the perspective of R&D employees in the transition to electric mobility: of the approx. 66,000 R&D employees, more than 50% are affected by the Fade-Out of ICE components, around half of whom work for automotive suppliers. In addition, around 40% of employees work for development service providers and a further 4400 developers in the mechanical and plant engineering sector, which equips the automotive industry in the value creation cluster and is also classified as powertrain-dependent in the model. As equipment suppliers, they are only indirectly dependent on the automotive industry, but with its strong specialization in the powertrain, Baden-Wuerttemberg’s mechanical engineering sector (especially machine tool manufacturing) must also adapt to new products. At the same time, Chinese mechanical engineering is also creating new competition in the fields of electric mobility (e.g., cell production, recycling);
3. In research and development, the model classifies 32,700 R&D employees as powertrain-dependent, the majority of whom are still focused on ICE technologies. In the scenarios, 12,000 and 18,000 employees, respectively, will be affected by the loss of work volume by 2030, with Fade-In effects of electric mobility compensating for around half of the decline. In practice, this means that this compensation can only take place through employee training and qualification. This already affects several thousand employees, and with the perspective of a full Fade-Out of ICE powertrains, over 30,000 employees will have to be trained in new technologies in the next 10 to 15 years.

5. Discussion

The transition to electric mobility should enable the transport sector to meet its climate targets. However, the calculations in this analysis show that the associated loss of employment in Baden-Wuerttemberg’s automotive cluster as a result of the transformation could lead to economic and social upheaval.

The results of other studies on employment effects cannot be directly compared with each other due to different assumptions and methods. A key difference lies in the respective industry reference: while some studies refer to the automotive industry in the definition of economic statistics, others only assume powertrain-dependent employment or emphasize general employment in the entire automotive cluster, including other sectors from industry and services. In addition, the forecasts are based on assumptions about the market ramp-up of electric mobility that are not directly comparable. Studies conducted in a timeframe before the year 2020 are difficult to apply to the current situation; at the same time, very few studies and publications on the employment effects in the industry from 2021 onwards exist. Early studies tended to expect an increase in employment resulting from higher proportions of hybrid vehicles with higher employment effects than, for example, vehicles

with gasoline combustion engines (G-ICE) or BEVs [3,11]. The 2018 study “ELAB 2.0: Electrification of the powertrain—Effects on employment in Germany”, on the other hand, assumes a decline in employment of between -11% and -35% of powertrain-dependent employees by 2030, depending on the expected share of BEVs, without taking productivity increases into account. Considering productivity increases, the decline in employment is even stronger (-37% to -53%) [4].

Three other studies refer specifically to effects in the region of Baden-Wuerttemberg: the project “Mobile Baden-Wuerttemberg: Paths of Transformation to Sustainable Mobility” predicts a possible decline in employment of between 50,000 and 160,000 jobs by 2030, depending on the scenario with different numbers of new vehicle registrations and different market shares of electrified vehicles [5]. In the study “Structural Analysis and Perspectives of Baden-Württemberg as a Business Location in National and International Comparison”, the following conclusion was drawn: 23% of employees in Baden-Wuerttemberg’s automotive production are involved in the manufacture of products that are potentially negatively affected by a transition to electric mobility. The proportion of employees who manufacture products potentially positively affected by electric mobility is significantly lower and amounts to 3% of the total workforce in the automotive production sector. This means that up to 61,000 employees could be negatively affected by electric mobility, while up to 8700 employees could potentially benefit from new work potentials [6]. The “Structural Study BWe mobil 2019: Transformation through Electric Mobility and Prospects for Digitalization” [1] displays a moderate loss of employment of 7% in the automotive cluster as a whole by 2030, depending on the scenario, although the effects will be considerably higher for powertrain-dependent production locations (up to 56%), thus threatening the whole cluster’s core value creation.

In contrast, more studies in recent years have assumed a decline in employment. Current key findings are as follows:

For Volkswagen, the study “Employment 2030: Effects of Electric Mobility and Digitalization on the Quality and Quantity of Employment at Volkswagen” concludes a decline of 12% in vehicle production and job retention or moderate job losses in internal services, as well as an increase in employment (up to 7%) due to the expansion of IT areas. The authors attribute only a minor effect on employment to electric mobility, with the optimization of work processes having a greater impact. More challenging than the quantitative employment effects are the shifts in activities, which trigger a high need for qualifications [7].

For Germany, the study “Autojobs unter Strom” predicts a growth of 25,000 employees by 2030 and thus a one percent increase in employment. Increases from growing market volumes and a shift in product portfolios will be offset by employment losses from productivity increases, electric mobility, and the relocation of jobs. Autonomous and connected driving could create a further 20,000 jobs nationwide, 14,000 of which would be with OEMs and 6000 with suppliers [8].

The study “Electric Vehicle Transition Impact Assessment Report 2020–2040” predicts a loss of jobs in the powertrain-dependent supplier industry in Germany of around 14% by 2030, followed by a significant decline in employment of 60% by 2040, when around 84% of employees will be responsible for the production of electric vehicles [9].

The study “Transformation of the Vehicle and Supplier Industry in the State of Bavaria” allocates around 196,000 employees to business areas at imminent risk and 179,000 employees to areas of opportunity out of around 450,000 employees in the Bavarian automotive cluster [10].

As shown in this paper for Baden-Wuerttemberg, the “Structural Study BW 2023” suggests possible employment risks of 14% by 2030 in the entire Baden-Württemberg automotive cluster, with the powertrain-dependent supplier industry and component plants particularly affected, up to 40%, thus jeopardizing the entire cluster. By 2040, the transformation to electric mobility could lead to a reduction of employment in the cluster to around 2/3 of its current size. The study assumes that the German automotive industry, as well as its manufacturers and suppliers, will gain similar market shares in Europe for

new powertrain components (battery system, electric motors, power electronics, etc.) as for conventional components (e.g., combustion engine, exhaust system, fuel system, etc.) [12].

These transformation effects will be overlaid and reinforced by the relocation of production and employment abroad, ongoing rationalization effects, particularly at production sites, as well as expected rationalization effects in office/R&D activities and the decline in the potential workforce due to demographic change. For the employment prospects at German supplier locations, it is therefore crucial to determine whether production numbers will increase to volumes reached in 2018/2019 and whether R&D and production capacities for new components of the electrified powertrain will actually be built up to a sufficient extent in Germany. The creation of competitive framework conditions for production sites by policymakers is an essential prerequisite for this.

6. Conclusions

The production locations in Baden-Wuerttemberg specializing in powertrain components in particular are experiencing difficulties as a result of the technological change in the automotive industry, leading to a risk of losing value creation and employment shares in competition with other world regions. As shown in this paper, positive and negative employment effects in the automotive cluster will occur and at least partially balance each other out when considering the industry as a whole. However, it is foreseeable that positive effects from the potential production of new powertrain components will not be achieved by every single company and at every production site in Baden-Wuerttemberg, resulting in potentially large differences in the impact of the transformation at local level.

The preservation of value creation and employment in Baden-Wuerttemberg's automotive industry is decided anew for each individual location by weighing up business management criteria and (business) political influence. This applies to the federal state as a whole, but also to individual districts where the automotive industry is particularly important.

In addition, maintaining employment is associated with a significant change in activities and the development of new qualifications. In practice, this requires considerable effort if it is to succeed.

The successful transformation of the automotive cluster in Baden-Wuerttemberg will depend on whether an accompanying guiding principle for social and economic change can be developed to prevent a potential loss in prosperity, in which all stakeholders (companies, politics, civil society, research) can participate. Baden-Wuerttemberg can and must redefine itself as a successful industrial location and raise its profile as a new location for sustainable industry and business.

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Article

Model Predictive Control with Powertrain Delay Consideration for Longitudinal Speed Tracking of Autonomous Electric Vehicles

Junhee Lee ¹ and Kichun Jo ^{2,*}

¹ Department of Smart Vehicle Engineering, Konkuk University, Seoul 05029, Republic of Korea; jun998@konkuk.ac.kr

² Department of Automotive Engineering, Hanyang University, Seoul 04763, Republic of Korea

* Correspondence: kichunjo@hanyang.ac.kr

Abstract: Accurate longitudinal control is crucial in autonomous driving, but inherent delays and lag in electric vehicle powertrains hinder precise control. This paper presents a two-stage design for a longitudinal speed controller to enhance speed tracking performance in autonomous electric vehicles. The first stage involves designing a Model Predictive Control (MPC) system that accounts for powertrain signal delay and response lag using a First Order Plus Dead Time (FOPDT) model integrated with the vehicle's longitudinal dynamics. The second stage employs lookup tables for the drive motor and brake system to convert control signals into actual vehicle inputs, ensuring precise throttle/brake pedal values for the desired driving torque. The proposed controller was validated using the CarMaker simulator and real vehicle tests with a Hyundai IONIQ5. In real vehicle tests, the proposed controller achieved a mean speed error of 0.54 km/h, outperforming conventional PID and standard MPC methods that do not account for powertrain delays. It also eliminated acceleration and deceleration overshoots and demonstrated real-time performance with an average computation time of 1.32 ms.

Keywords: autonomous driving; longitudinal control; model predictive control; delay compensation

1. Introduction

As autonomous driving technology advances, the increasing importance of accurate speed tracking in real driving scenarios such as adaptive cruise control and lane merging has led to a growing demand for improvements in longitudinal control systems. Furthermore, with the advent of Electric Vehicles (EVs) and the shift from internal combustion engines to motor-driven powertrains in recently produced vehicles, significant research and development has focused on longitudinal control methods suited to these new characteristics [1–3]. As shown in Figure 1, the longitudinal control systems covered in this paper output throttle or brake pedal commands to track a given speed profile created by the high-level planning system. A key requirement for these control systems is to reduce speed tracking errors without resorting to aggressive brake or throttle operations.

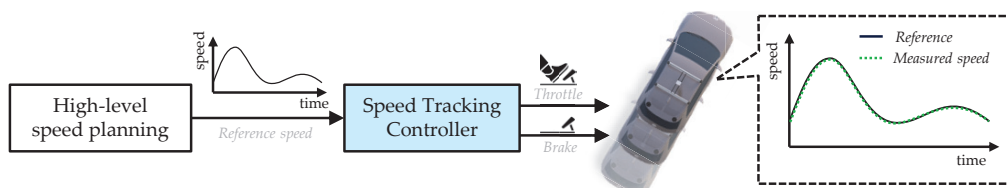


Figure 1. Longitudinal speed tracking control flow. Speed tracking controller determines appropriate throttle and brake values to follow the reference speed from high-level speed planning.

Traditionally, Proportional-Integral-Derivative (PID) control has been widely utilized for longitudinal speed tracking due to its simplicity and ease of implementation without

relying on a system model [4–6]. However, PID control does not account for system dynamics and external disturbances, which can lead to significant overshoot or persistent oscillations when subjected to noise or delays [7,8]. To address these limitations, advanced control techniques such as Sliding Mode Control (SMC) [9–11], Linear Quadratic Regulator (LQR) [12,13], and Model Predictive Control (MPC) [14–16] that directly consider vehicle dynamics have been developed. SMC, for instance, drives the system states toward a predefined sliding surface, ensuring rapid convergence to the desired state based on the designed dynamics. However, these methods are not inherently designed to minimize a given cost function or performance metric and thereby lack the ability to consider multiple objectives such as tracking performance and steering stability in the determination of control actions. In contrast, techniques like LQR and MPC solve optimization problems based on a multivariable objective function, enabling the derivation of optimal control actions that balance tracking accuracy and stability. Notably, MPC has emerged as one of the most widely studied model-based approaches in the field of autonomous driving control [17]. MPC allows for the establishment of goals considering a variety of variables, the definition of constraints on system inputs and states during the initial design phase, and the facilitation of real-time control through a receding horizon technique that continuously updates the prediction horizon [18].

Given the nature of MPC, which predicts and controls the vehicle's state based on a model, using a model that accurately represents the longitudinal characteristics of actual vehicles can significantly improve tracking performance. Existing MPC studies [14,19,20] have focused primarily on improving vehicle dynamics models. However, to fully replicate the longitudinal behavior of real vehicles, it is crucial to consider factors such as powertrain delays in addition to dynamics. These additional factors are vital because control signals take time to be executed in the actual vehicle and actuator lag further delays the response, regardless of the vehicle model. This delay means that the calculated longitudinal commands will not be executed instantly, leading to a model mismatch and deteriorated performance. As a result, control oscillation and instability can occur.

In longitudinal driving, any vehicle will experience delays in response to control inputs. As shown in Figure 2, the overall signal delay observed in our experimental electric vehicle was approximately 0.2 s. Additionally, the powertrain gradually responds after a certain period when a step wheel torque input is applied. Therefore, powertrain delays can be decomposed into pure delay and actuation lag. Pure delay arises from CAN communication and computation processes between the control module and the drive/brake motor system, and driveline freeplay, where gaps in mechanical components cause delays in torque transmission, can also contribute to pure delay. Furthermore, actuation lag occurs because the drive motor or brake actuator requires time to respond to the vehicle, and this lag is influenced by the hardware capability of the actuator and the design of the low-level control system. Moreover, mechanical filtering in the driveline, caused by the elasticity of components such as drive shafts and tires, can exacerbate this lag.

To address these challenges, this paper presents a novel MPC approach for longitudinal control in autonomous electric vehicles that explicitly incorporates powertrain delays into the control model using a First Order Plus Dead Time (FOPDT) model [21]. Unlike existing MPC methods that primarily focus on improving vehicle dynamics models without accounting for actuator delays, our approach models both the pure time delay and actuation lag inherent in electric vehicle powertrains. This integration allows the controller to anticipate and compensate for delays, significantly enhancing speed tracking accuracy and control stability.

Additionally, we develop detailed torque maps for both the motor and brake systems, capturing the non-linear torque characteristics of the electric vehicle's powertrain. By integrating these torque maps into the control framework, the controller can accurately translate the desired drive force into appropriate throttle and brake inputs, further improving control precision.

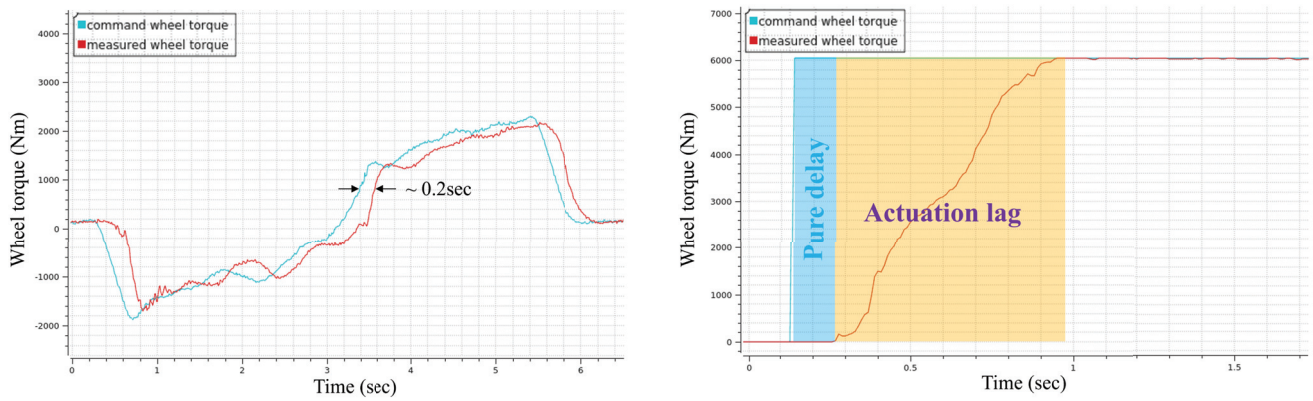


Figure 2. Response of drive motor in the experimental EV. When comparing the measured driving wheel torque with the commanded driving wheel torque, it can be observed that there is an approximate delay of 0.2 s, which consists of a pure time delay and an actuation lag.

The key contributions of this work are as follows:

1. By incorporating a FOPDT model into the MPC, the controller effectively handles the inherent delays in electric vehicle powertrains, which has been largely overlooked in previous studies.
2. The creation of detailed torque maps for the motor and brake systems, enabling precise control over throttle and brake inputs in response to the target wheel torque.
3. A comprehensive evaluation of the proposed controller through both simulation and real-world experiments, demonstrating significant improvements in speed tracking accuracy and control smoothness compared to conventional MPC and PID controllers.

The remainder of this paper is organized as follows. Section 2 introduces the proposed system architecture for longitudinal speed tracking control. Section 3 delves into the MPC considering powertrain delays, while Section 4 discusses the torque map for the throttle and brake pedals. Section 5 presents the experimental results and analysis from both simulations and real vehicles. Finally, Section 6 concludes the paper.

2. Overall System Architecture

As illustrated in Figure 3, the proposed longitudinal control system for Autonomous Electric Vehicles (AEVs) tracks the reference speed profile planned by the higher-level module and outputs the throttle and brake pedal values for the vehicle. This control system is composed of two key modules: (1) a longitudinal MPC module considering powertrain delays and (2) a wheel torque table module for drive/brake torque and throttle/brake pedal values.

The MPC module first receives a reference speed profile, v_{ref} , composed of target speeds over a fixed horizon as input, and outputs the target drive force, F . The currently measured longitudinal speed of the vehicle is used as the initial state of the MPC. The MPC solves an optimization problem using a model that considers powertrain delays, aiming to minimize the difference between the given reference speed profile and the predicted vehicle longitudinal speed.

The wheel torque table module then receives the F output from the MPC module and converts it to the wheel torque T_{wheel} . Based on the T_{wheel} input, the current vehicle speed, and the throttle torque table during acceleration, or the brake torque table during deceleration, it determines the throttle and brake values. These throttle and brake values are then communicated to the AEV.

This wheel torque table module is designed by acquiring driving data from the vehicle CAN, which consists of pedal positions, motor torque, acceleration, and speed, and then interpolating and smoothing the data to accurately reflect the torque characteristics of the drive motor and brakes.

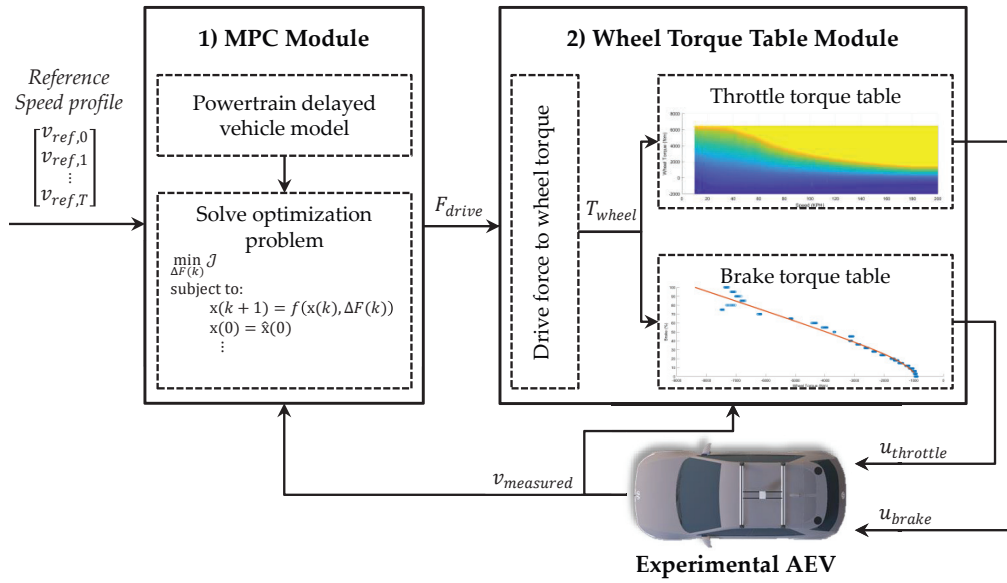


Figure 3. Overall longitudinal control system architecture. The proposed system consists of two main modules: (1) a longitudinal MPC module that accounts for powertrain delays and (2) a wheel torque table module for converting drive force to throttle and brake pedal values.

3. MPC Module

3.1. Baseline Vehicle Model

The longitudinal model used in the proposed MPC system is primarily based on the vehicle's dynamic model, incorporating factors such as aerodynamic drag, rolling resistance, and gravitational forces [22] as the following equation:

$$m\dot{v} = F - mg \sin \theta - fmg \cos \theta - 0.5\rho A_c C_d v^2, \quad (1)$$

where $\dot{v}$ is the vehicle's longitudinal acceleration; m is the vehicle's mass; F is the drive force; θ represents the vehicle's pitch (substituting for the ground slope); f is the rolling resistance coefficient; and ρ , A_c , C_d , v represent air density, frontal area of the vehicle, drag coefficient, and longitudinal velocity, respectively. The primary objective of this model is to accurately capture the vehicle's longitudinal acceleration behavior under varying conditions of force and resistance. To achieve this, the model focuses exclusively on the longitudinal dynamics of the vehicle, which involves a single degree of freedom related to the longitudinal velocity. This approach ensures that the model effectively represents the vehicle's acceleration response under the influence of longitudinal forces, without incorporating additional complexities such as lateral dynamics, suspension components, driveline, or tire models.

Based on Equation (1), a discrete-time model can be established as follows:

$$x_{k+1} = \left[v_k + \frac{F_k - mg \sin \theta - fmg \cos \theta - 0.5\rho A_c C_d v_k^2}{F_k + \Delta F_k dt} dt \right], \quad (2)$$

where the change in drive force, ΔF , is the input, u , and the speed, v , and drive force, F , are the states, x . The model update interval is represented by dt , and x_{k+1} denotes the model state at time step $k + 1$.

3.2. Powertrain Delayed Vehicle Model

To account for the delay in the vehicle's powertrain within the MPC model itself, a FOPDT model was integrated with the existing baseline model. This integration approximates the signal delay as dead time and the actuator lag as a first-order system. Although the time delay and lag for the drive motor and brake system can vary, and different time

delays and lag parameters may be applied depending on acceleration or deceleration situations, we assume that the delay and lag elements applied to each system are identical. The FOPDT model can be expressed in the differential equation form of a continuous-time model as follows:

$$\tau \frac{dy(t)}{dt} + y(t) = u(t - D). \quad (3)$$

In the FOPDT model, $u(t)$ represents the system's input and $y(t)$ represents the system's output at time t . The dead time, D , represents pure signal delay, and the first-order system with time constant τ corresponds to the actuator's lag response.

To integrate the FOPDT model into the discrete-time baseline vehicle model, a state augmentation technique was utilized. To implement the dead-time and first-order system, the state was augmented from $x = [v, F]$ to $x = [v, F_{lag}, F_{N_d-1}, F_{N_d-2}, \dots, F_0, F]$. The state F_{lag} was added to represent the first-order system, while F_0 to F_{N_d-1} were added to account for the dead time. After state augmentation, the longitudinal vehicle model considering powertrain delays is as follows:

$$x_{k+1} = \begin{bmatrix} v_{k+1} \\ F_{lag,k+1} \\ F_{N_d-1,k+1} \\ \vdots \\ F_{0,k+1} \\ F_{k+1} \end{bmatrix} = \begin{bmatrix} v_k + \frac{F_{lag,k} - mg \sin \theta - f mg \cos \theta - 0.5 \rho A C_d v_k^2}{m} dt \\ F_{lag,k} + \left(\frac{-F_{lag,k} + F_{N_d,k}}{\tau} \right) dt \\ F_{N_d-2,k} \\ \vdots \\ F_k \\ F_k + \Delta F_k dt \end{bmatrix} \quad (4)$$

In this augmented model, the states added for dead time simply update with the drive force values from the previous steps, ensuring that the control values affect the actual baseline model after a delay of $N_d \cdot dt$ time. Furthermore, the state F_{lag} , added for the first-order system, ensures that the control values are gradually applied to the baseline model according to the time constant τ .

Finally, to transform this model into a Quadratic Programming (QP) form and solve it as a linear MPC problem, the model was linearized using a Taylor first-order expansion around the operating point $\hat{x}$ based on the reference speed profile and the driving force from previous solved states. This can be expressed mathematically as follows:

$$\begin{aligned} x_{k+1} &\approx \hat{x}_{k+1} + \left. \frac{\partial f(x, u)}{\partial x} \right|_{x=\hat{x}, u=\hat{u}} (x_k - \hat{x}_k) + \left. \frac{\partial f(x, u)}{\partial u} \right|_{x=\hat{x}, u=\hat{u}} (u_k - \hat{u}_k) \\ &= Ax(k) + Bu(k) + d \\ \text{where} \\ A &= \left(I + dt \left. \frac{\partial f}{\partial x} \right|_{\hat{x}, \hat{u}} \right) \\ B &= dt \left. \frac{\partial f}{\partial u} \right|_{\hat{x}, \hat{u}} \\ d &= \left(f(\hat{x}, \hat{u}) - \left. \frac{\partial f}{\partial x} \right|_{\hat{x}, \hat{u}} \hat{x} - \left. \frac{\partial f}{\partial u} \right|_{\hat{x}, \hat{u}} \hat{u} \right) dt \end{aligned} \quad (5)$$

Applying the powertrain delayed vehicle model to the above equation can be expressed as follows:

$$x_{k+1} = Ax_k + Bu_k + d, \quad (6)$$

$$A = \begin{bmatrix} 1 - dt \frac{\rho A C_d \bar{v}}{m} & \frac{dt}{m} & 0 & 0 \\ 0 & 1 - \frac{dt}{\tau} & \frac{dt}{\tau} & 0 \\ 0 & 0 & 1 & 0 \\ & & \ddots & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ dt \end{bmatrix}, C = \begin{bmatrix} -dt \left(-\frac{\rho A C_d \bar{v}^2}{2m} + g \sin \theta + f g \cos \theta \right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

3.3. MPC Problem Formulation

The longitudinal MPC controller aims to minimize the error between the reference speed and the amount of change in drive force, solving a multivariable optimization problem as follows:

$$\begin{aligned} \min_{u=\Delta F_0:\Delta F_T} & \left[Q \sum_{t=0}^{T-1} (x_{k,\text{ref}} - x_t)^2 + R \sum_{k=0}^T (u_k)^2 \right] \\ \text{s.t.} & \\ & x_{k+1} = Ax_k + Bu_k + d, \\ & F_{\min} < F < F_{\max} \end{aligned} \quad (7)$$

where Q is a diagonal weight matrix for state error and R is a weight for the change in driving force, used to find the optimal driving force that minimizes the objective function. The MPC model utilizes the linearized delayed powertrain vehicle model, with constraints on the driving force to prevent excessively large acceleration or deceleration. The resulting quadratic problem was addressed using the gradient-based, interior-point solver HPIPM [23], which uses the BLASFEO [24] linear algebra software framework. The HPIPM solver was chosen for its efficiency in handling structured QP problems typical in MPC applications, particularly due to its ability to exploit problem sparsity for faster computation, and as an open-source tool, it offers flexibility and accessibility.

4. Wheel Torque Table Module

The output of the MPC module is the driving force, F , while the actual control input of the AEV is the values of the throttle and brake pedal values. Therefore, the wheel torque table module is designed to effectively convert F into throttle and brake pedal values. As illustrated in Figure 4, the F is multiplied by the wheel radius, r_{wheel} , to convert it into the driving wheel torque, T_{wheel} , in the initial stage of the module.

$$T_{\text{wheel}} = F \cdot r_{\text{wheel}} \quad (8)$$

This torque is then used as the input for the wheel torque tables for throttle and brake.

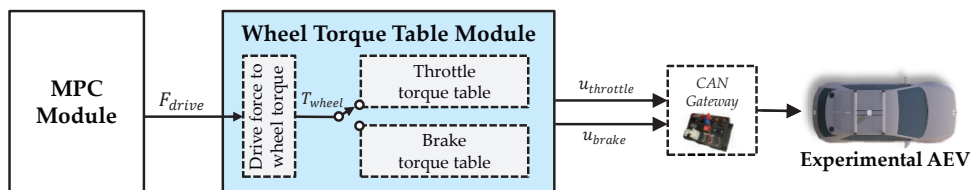


Figure 4. Process of control commands moving from the MPC module to the AEV. The driving force, F_{drive} , output by the MPC module, passes through the wheel torque table module to be converted into the vehicle's inputs u_{throttle} and u_{brake} .

In the wheel torque table module, the amount of brake or throttle pedal input is determined based on the target wheel torque input, T_{wheel} . Therefore, modeling is required

for the drive motor used during acceleration and the brake system used during deceleration. To prevent simultaneous throttle and brake inputs, we use the regenerative braking torque value when both the throttle and brake pedals are at zero as a neutral value. If T_{wheel} exceeds this neutral value, the throttle torque table is used; if it is below, the brake torque table is employed to determine the control inputs.

4.1. For the Throttle Pedal

In conventional internal combustion engine vehicles, converting torque values to throttle pedal position required torque tables for each gear, taking into account engine RPM and the current gear ratio [4,25]. However, electric vehicle powertrains mostly operate with a single gear without a transmission, eliminating the need for gear shifting and thereby requiring only one torque table for the drive motor. Given that motor torque decreases as motor RPM increases, achieving a specific torque requires different throttle positions depending on the speed of the vehicle. Therefore, in this study, motor torque data relative to vehicle speed and throttle position were collected from both on-road natural driving and experimental driving on the proving ground.

As shown in the data acquired section of Figure 5, the orange data obtained from the proving ground tests with constant throttle inputs and the blue data distribution obtained from normal on-road driving are presented. The necessary vehicle speed, throttle position, and motor torque data for the table generation were collected through the vehicle CAN. Then, as illustrated in the wheel torque table of Figure 5, these data were interpolated into continuous values using the cubic spline approximation method [26] to create a lookup table. Through this process, when the current speed and target wheel torque values are input, the appropriate amount of throttle pedal is determined.

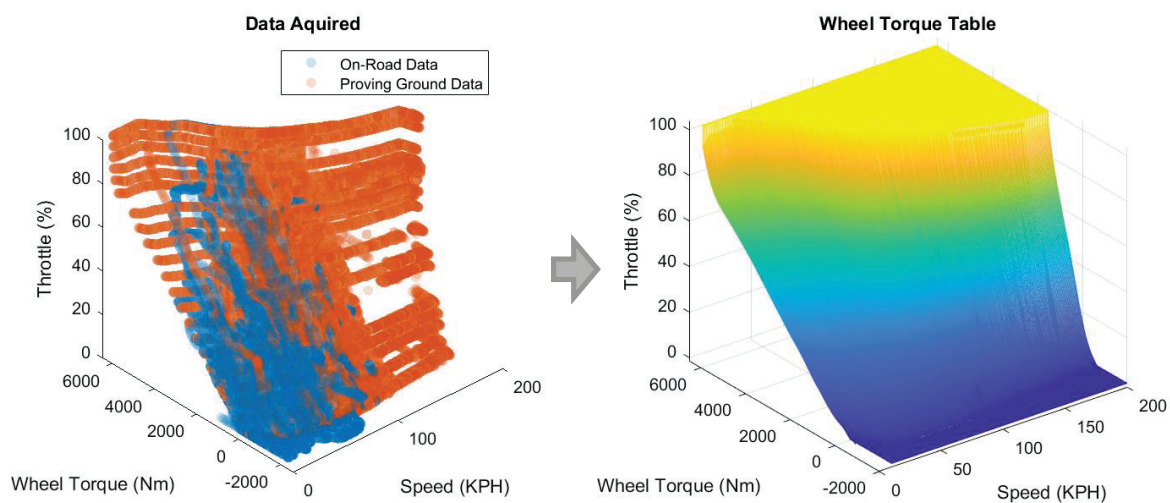


Figure 5. Acquired drive wheel torque data from on-road driving and proving ground tests, and generated drive motor torque table for the throttle. The drive wheel torque data were obtained by converting the drive motor torque from the vehicle CAN, and these data were interpolated and smoothed to create a lookup table.

4.2. For the Brake Pedal

The vehicle's brake system is designed based on hydraulic brakes, which typically provide braking force proportional to the brake pedal input. Therefore, when determining the required brake pedal input for a target drive wheel torque, speed information is not necessary, unlike in the case of the throttle pedal, and the modeling can be conducted based on the relationship between the brake pedal input and the drive wheel torque. However, unlike the motor torque used for the throttle pedal, the torque values during braking are not provided by the vehicle's CAN bus. Thus, to convert the longitudinal acceleration data obtained from the CAN into wheel torque, we inversely applied Equations (1) and

(8) inversely to convert the longitudinal acceleration value obtained from the CAN into wheel torque. Subsequently, as illustrated in Figure 6, this relationship was modeled using a cubic polynomial, such that when a target wheel torque below the neutral value is input, the appropriate brake pedal input is determined.

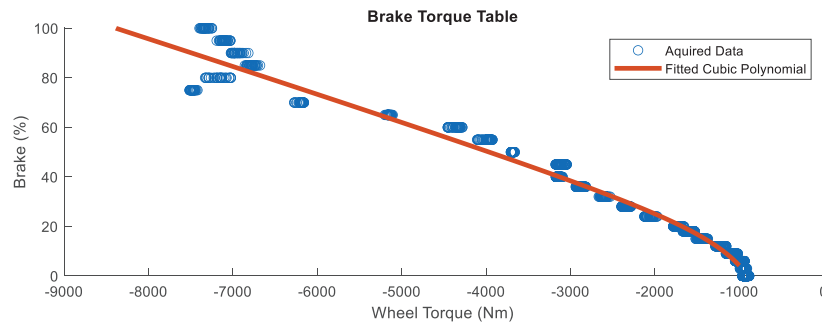


Figure 6. Generated brake torque table. Data were collected by increasing the brake input by 10% increments from an initial speed of 100 km/h. From 70% brake input onwards, similar brake torque was observed due to the intervention of the Anti-lock Braking System (ABS).

5. Experiment

The speed tracking performance of the proposed MPC, which considers powertrain delay, is analyzed against a conventional MPC that does not consider delay and a classical PID control approach. The main parameters of the proposed MPC are shown in Table 1. A wheel torque table module is used uniformly across all controllers to ensure consistency in the evaluation. All these control algorithms were implemented in C++ on the Ubuntu ROS1 Noetic middleware and were run on an Intel i9-13900TE CPU (Intel, Santa Clara, CA, USA) with 64 GB of RAM.

Table 1. Main parameters of proposed MPC.

Parameter	Symbol	Value	Units
Model update interval time	dt	0.02	s
Number of prediction steps	T	100	-
Delayed steps	N_d	5	-
Time constant	τ	0.15	s
Weight matrix for states	Q	$\text{diag}(300, 0, \dots, 0)$	-
Weight matrix for input	R	0.0001	-
Max driving force	F_{max}	10,819.0	N
Min driving force	F_{min}	-14,485.0	N

5.1. Comparative Controllers

(1) Conventional MPC: This MPC without a delay consideration approach utilizes the proposed MPC framework but omits the FOPDT model, simplifying the system model to include only vehicle speed and drive force as a state X without considering dead time and lag, i.e., $X = [v; F]$. The inputs remain the same, $u = [\Delta F]$, as in the powertrain delay considered MPC. The discrete linearized model for this controller is defined as follows:

$$x_{k+1} = Ax_k + Bu_k + d, \quad A = \begin{bmatrix} 1 - dt \frac{\rho AC_d \bar{v}}{m} & \frac{dt}{m} \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ dt \end{bmatrix}, \quad d = \begin{bmatrix} -dt \left(-\frac{\rho AC_d \bar{v}^2}{2m} + g \sin \theta + f g \cos \theta \right) \\ 0 \end{bmatrix} \quad (9)$$

and all parameters are the same as in the delay considered MPC.

(2) PID: The PID controller is a widely used control technique across various industries due to its simplicity and effectiveness in a range of applications. The method operates on the principle of feedback control, where the control action is based on the difference

between the current speed and the reference speed from the speed profile. The speed profile, part of the vehicle's reference trajectory, provides target speeds assigned to the closest trajectory points relative to the vehicle. Through careful tuning of the P, I, and D gains, the PID controller calculates the appropriate target wheel torque, T_{wheel} , to accurately follow the target speed.

5.2. Simulation Validation

To evaluate the performance of the proposed MPC considering powertrain delay, we first compared the proposed MPC with powertrain delay, a conventional MPC, and a PID controller in the IPG Automotive CarMaker vehicle simulator. The simulation used a Hyundai IONIQ5 electric vehicle provided by CarMaker, and a wheel torque map module was specifically designed for the simulated vehicle using data acquired from the simulator. The vehicle parameters used in this paper were based on the IONIQ5 data from CarMaker, as shown in Table 2. The powertrain delay in the simulator was modeled as 0.1 s using a queue buffer, while the lag was modeled as 0.15 s using a first-order system, both applied just before the throttle and brake inputs. The performance of the proposed MPC with delay consideration was compared against an MPC without delay consideration and a PID controller, and validation was performed under two scenarios: (1) a step speed profile from 30 km/h to 50 km/h and (2) a trapezoidal speed profile with acceleration and deceleration ranging from -4 m/s^2 to 4 m/s^2 .

Table 2. Vehicle parameters for validation and experimental AEV.

Parameter	Symbol	Value	Units
Vehicle mass	m	2300.0	kg
Rolling resistance coefficient	f	0.015	-
Mass density of air	ρ	1.21	kg/m^3
Frontal area of the vehicle	A	2.88	m^2
Aerodynamic drag coefficient	C_d	0.35	-
Wheel radius	r_{wheel}	0.32	m

First, the driving results for the step speed profile are shown in Figure 7. In the subfigure for target wheel torque and commanded throttle, the MPC-based methods began accelerating earlier than the PID controller, owing to their ability to predict future states through the prediction horizon. As a result, the PID controller showed the slowest response to the step speed profile and, therefore, exhibited the lowest speed tracking accuracy. The conventional MPC, which did not account for powertrain delay, demonstrated slower convergence compared to the proposed MPC and responded later to the step speed profile. As shown in Table 3, the proposed MPC exhibited the highest speed tracking accuracy among the three controllers, with a maximum speed error of 11.48 km/h and an average speed error of 0.68 km/h.

Second, when examining the tracking performance for the trapezoidal speed profile shown in Figure 8, similar to the step speed profile scenario, it can be observed that the proposed MPC, conventional MPC, and PID controller responded quickly to the acceleration and deceleration speed profiles in that order. Also, the proposed MPC had the smallest control overshoot and thus required the smallest amount of control input. Through this, the proposed MPC's longitudinal acceleration converged to a stable value without oscillation during both acceleration and deceleration phases. As shown in Table 4, the maximum absolute speed error was largest for the PID controller (8.93 km/h), followed by the conventional MPC (2.19 km/h), and smallest for the proposed MPC (0.77 km/h). This result indicates that the proposed longitudinal controller quickly responds to the given speed profile in the presence of powertrain delays and exhibits excellent speed tracking performance.

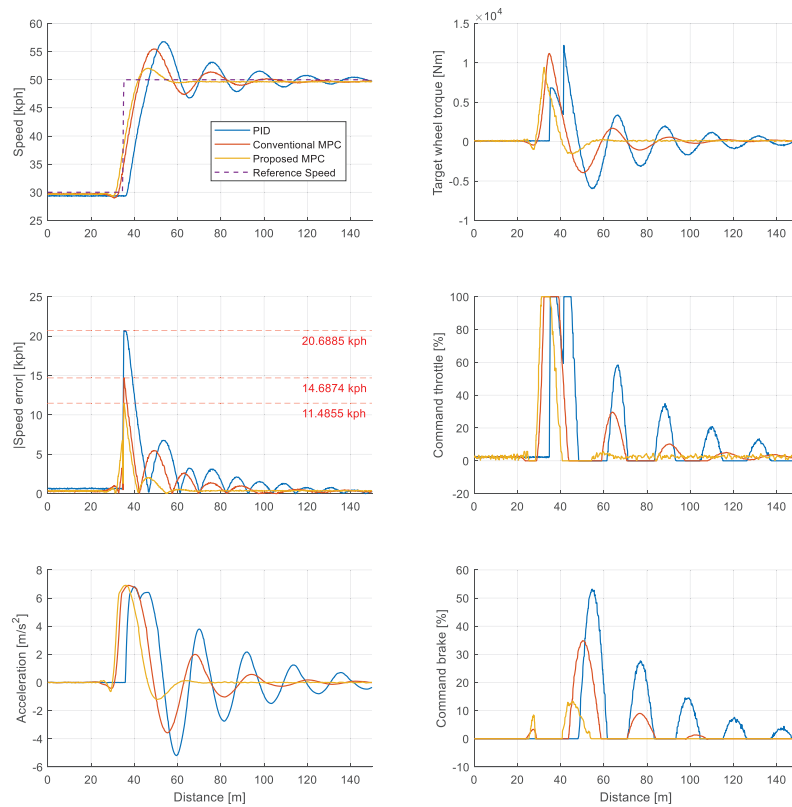


Figure 7. Simulation result of step speed profile in CarMaker simulator. This scenario involves tracking a reference speed that increases from 30 km/h to 50 km/h.

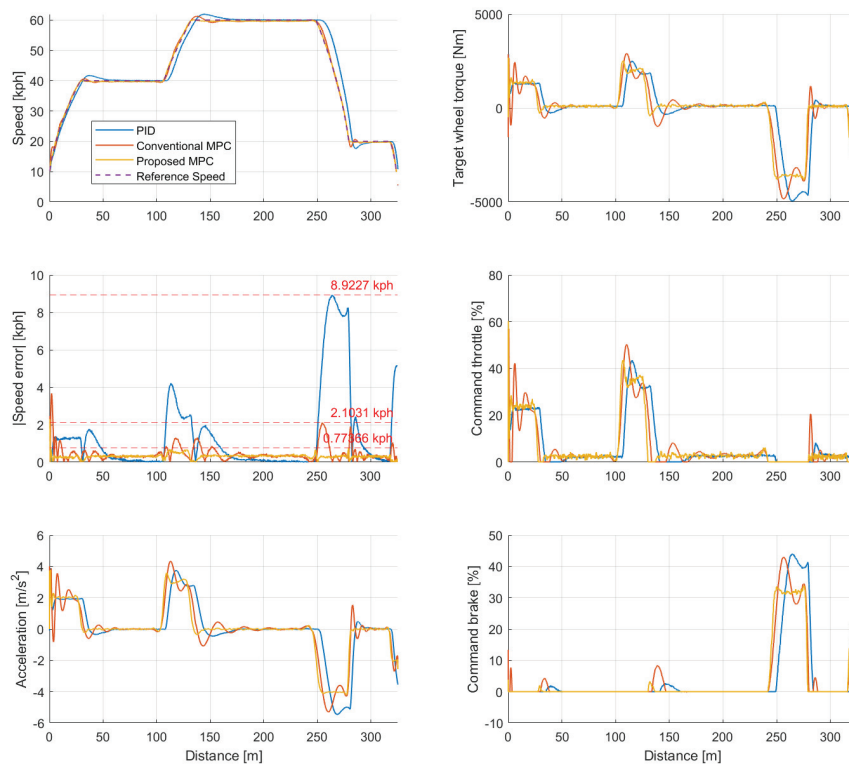


Figure 8. Simulation result of the trapezoidal speed profile in the CarMaker simulator. This scenario involves tracking a reference speed with acceleration and deceleration ranging from -4 m/s^2 to 4 m/s^2 .

Table 3. Speed tracking performance of step speed profile in the simulation.

	Max Speed Error (km/h)	Mean Speed Error (km/h)
PID	20.69	2.13
Conventional MPC	14.68	1.09
Proposed MPC	11.48	0.68

Table 4. Speed tracking performance of trapezoidal speed profile in the simulation.

	Max Speed Error (km/h)	Mean Speed Error (km/h)	Mean Acceleration Error (m/s ²)
PID	8.93	1.43	0.59
Conventional MPC	2.19	0.47	0.45
Proposed MPC	0.77	0.29	0.18

5.3. Real-World Vehicle Experiment

For the real vehicle experiments, the same speed profile used in the simulator verification was used, with additional acceleration and deceleration phases added towards the end. As shown in Figure 9, these tests were conducted at a highway section of the K-City, the autonomous driving testbed of the Korea Automotive Technology Institute. The experimental vehicle was a Hyundai IONIQ5 AWD model, and the wheel torque map module was also developed based on real vehicle experimental data. Vehicle pose estimation utilized results from a Novatel CPT7 dual antenna RTK-GNSS/INS solution, and vehicle control inputs, including throttle and brake pedal positions, were applied through a CAN/CAN-FD gateway.

**Figure 9.** Experimental AEV Platform, Hyundai IONIQ5, and the test site, K-City highway section.

In the real-vehicle experiments, the same three controllers used in the simulation validation were tested for speed tracking performance, and the experimental results are presented in Figure 10. In the speed error subplot, the PID controller shows high errors during rapid acceleration and deceleration due to its delayed response in following the reference speed. Additionally, while the conventional MPC reduced the speed error with a faster response than the PID controller, thanks to its predictive characteristics, the target wheel torque subplot shows that it converged more slowly than the proposed MPC. As shown in Table 5, the maximum absolute speed error was highest for the PID controller (8.53 km/h), followed by the proposed MPC (1.98 km/h), and the conventional MPC (1.71 km/h). The ranking for mean absolute speed error differed slightly, with the PID controller showing the highest error (2.12 km/h), followed by the conventional MPC (0.88 km/h), and the proposed MPC exhibiting the lowest error (0.54 km/h).

Compared to the simulation, tracking errors increased due to external disturbances and approximations in the actual model. However, the proposed MPC still showed the best performance in terms of mean error. The PID controller exhibited significant overshoots in acceleration and deceleration due to its delayed response. While the conventional MPC demonstrated speed tracking performance similar to the proposed MPC, it showed larger overshoots in the target wheel torque during the acceleration and deceleration phases.

compared to the proposed algorithm. As confirmed in Figure 11 and Table 6, although the computation time increased due to the additional number of states, the proposed MPC sufficiently maintained real-time performance, with an average computation time of 1.32 ms, satisfying the CAN data cycle requirement of 10 ms.

Table 5. Speed tracking performance in the real-vehicle experiment.

	Max Speed Error (km/h)	Mean Speed Error (km/h)	Mean Acceleration Error (m/s^2)
PID	8.53	2.12	0.48
Conventional MPC	1.71	0.88	0.32
Proposed MPC	1.98	0.54	0.22

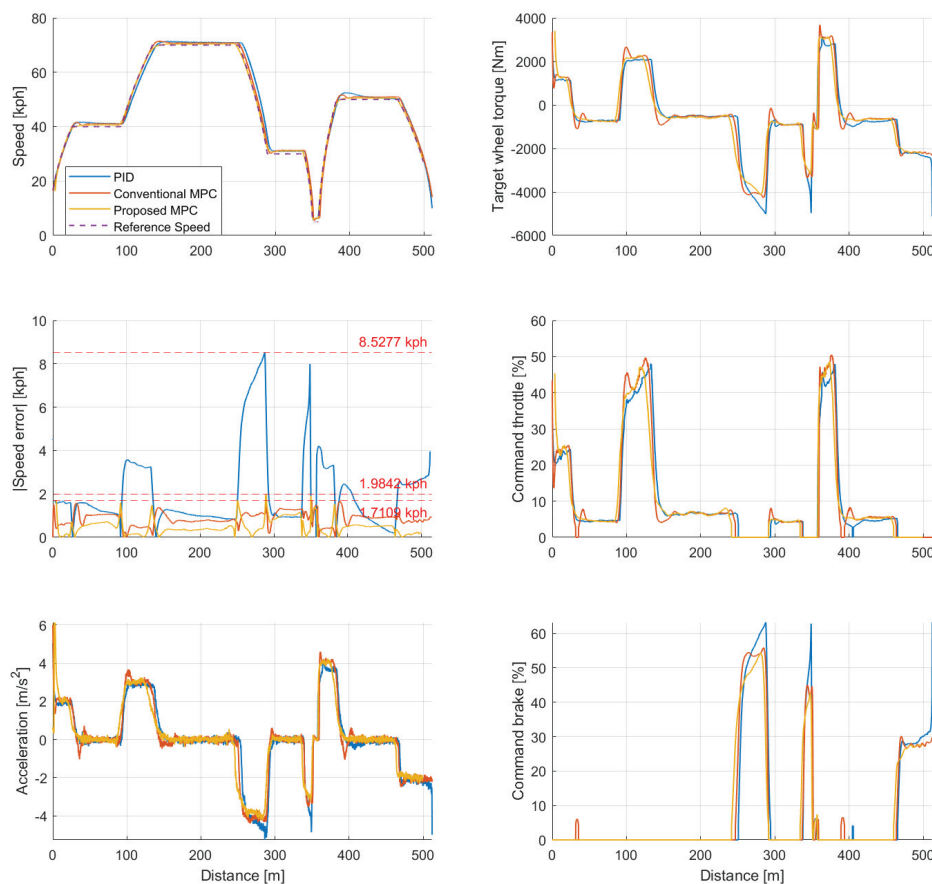


Figure 10. Real-vehicle experiment result of the trapezoidal speed profile in K–City. This scenario involves tracking a reference speed with acceleration and deceleration ranging from -4 m/s^2 to 4 m/s^2 .

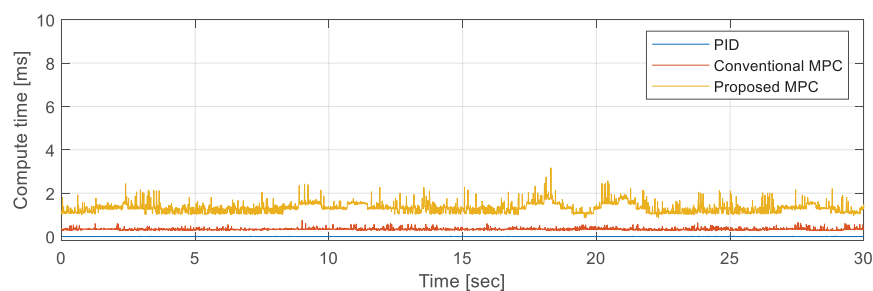


Figure 11. Computational time of each comparative controller.

Table 6. Mean computational time of each comparative controller.

	Mean Computation Time (millisec)
PID	0.02
Conventional MPC	0.74
Proposed MPC	1.32

6. Conclusions

This paper proposes a longitudinal control system that considers powertrain delay to enhance speed tracking performance in autonomous electric vehicles. The longitudinal controller models the actuator lag and signal delays as a FOPDT model, incorporating them into the MPC module. The resulting wheel torque output is converted into the throttle and brake pedal positions using a torque table. The designed controllers were implemented and tested on a Hyundai IONIQ5, demonstrating reduced speed tracking errors and smoother control behaviors. Despite an increase in the number of states, real-time performance is still maintained with a response time of less than 10 ms. The proposed controller has been validated through both simulator and real-vehicle experiments, offering superior speed tracking performance and eliminating acceleration and deceleration overshoots compared to traditional PID and MPC methods, which do not consider powertrain delays. Future work will focus on online estimation of powertrain delays, which is expected to reduce the time and effort required for system calibration and further improve the control system's adaptability and performance.

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Article

Examining Model-Based Fast-Charging and Preconditioning on a Vehicle Level

Kareem Abo Gamra *, Maximilian Zähringer, Aaron Ladner, Christian Allgäuer and Markus Lienkamp

Institute of Automotive Technology, Department of Mobility Systems Engineering, School of Engineering & Design, Technical University of Munich (TUM), 85748 Garching, Germany

* Correspondence: kareem.abo-gamra@tum.de

Abstract: To establish battery electric vehicles as an attractive alternative to internal combustion vehicles, charging times of 15 min or less are increasingly demanded. This is especially challenging for lower battery temperatures, as this exacerbates the risk of accelerated battery degradation due to lithium plating. Therefore, active battery heating is utilized in state-of-the-art electric vehicles. To evaluate the impact of such heating strategies at vehicle level, we deployed an electrochemical battery model coupled with a longitudinal vehicle dynamics model. Using anode potential control to prevent lithium plating, we assess the time-saving potential versus the energy cost of different preconditioning and fast-charging strategies. The results reveal substantial energy saving and charge speed increase potential through optimal charge-stop planning, preconditioning timing, cost-adjusted thermal management thresholds, and considering driving behavior. This emphasizes the need for advanced operation strategies, taking into account both battery-level electrical and thermal restrictions, as well as vehicle integration and route planning.

Keywords: lithium-ion battery; fast-charging; battery management; thermal management; electric vehicle

1. Introduction

Although current-generation electric vehicles offer increasing charging speeds, achieving the often-demanded charging time of 15 min or less to charge from 10% to 80% state-of-charge (SOC) remains challenging due to several technological barriers from materials to the system level [1]. One main limiting factor is lithium plating, which has a higher risk of occurring at lower temperatures, high SOC, and high charging rates [2]. As plating only occurs with negative anode potentials, suitable battery models can be deployed to perform model-based fast-charging, which has been demonstrated to permit faster charging with reduced battery degradation [3–5]. Due to the highly coupled nature of the electrical and thermal effects within lithium-ion batteries, recent studies have, however, shown that fast-charging requires suitable heating and cooling strategies to achieve shorter charge durations while taking battery self-heating and safety limitations into account [6]. In particular, cold ambient conditions lead to a considerable deterioration in electric vehicle fast-charging capabilities [7].

While this has been examined at the cell level in several publications [8–10], applying such fast-charging and preconditioning strategies to the vehicle level poses additional challenges [11], stemming from greater thermal constraints and the required energy consumption and cost considerations [12]. These need to be coupled with infrastructure constraints [13] and vehicle design factors, such as application-specific dimensioning of the thermal management system [14] or the battery system and vehicle electrical architecture [15]. Previous charging and heating strategies are furthermore usually based on complex models and nonlinear optimization methodologies [3,16–18], which could be challenging within vehicle applications due to limited computation resources, necessitating

simplified approaches and generalized operation guidelines. While some previous examinations have integrated models to derive vehicle-level operation strategies to optimize energy consumption, charging time, and travel duration, these are based on simplified-battery-equivalent circuit models that do not offer insight into lithium plating behavior and the resulting fast-charging capability [19–22], or focus mainly on cooling [23].

Optimized thermal management strategies, in particular, have been demonstrated to offer improvement potential, but need to be coupled with a prediction of the battery behavior to be implemented in real-world applications [24]. This could be particularly attractive for commercial use cases, in which the route and driving behavior are usually known in advance [25], although approaches exist that also take route uncertainties into account [26]. While heating may offer benefits regarding charging speeds, high temperatures also pose a risk regarding accelerated aging due to side reactions and safety, which also necessitates an appropriate cooling strategy [27].

To our knowledge, the application of model-based fast-charging to derive vehicle-level operation strategies has not been examined in previous studies. This is particularly interesting, as observed driver behavior often contradicts recommended best practices for lithium-ion battery fast-charging [28,29]. While the highest charging currents can be achieved at lower starting SOC [9], past surveys and field data evaluations have indicated that range anxiety leads a large portion of drivers to fast-charge at SOC higher than 30% [30]. This increase in range anxiety is especially pronounced at low ambient temperatures [30]. As achievable charging rates grow, users increasingly tend towards lower charging-stop SOC [31], which may improve overall charging speed and efficiency. By deploying electrochemical battery models coupled with thermal behavior and integrating them into vehicle examinations, a physics-based derivation of optimal fast-charging and thermal management strategies can be achieved.

1.1. Contributions

In this study, we examine the influence of different operation parameters on achievable fast-charging times and energy consumption to derive strategy recommendations at the vehicle level. These include the vehicle driving behavior, the temperature targets for battery cooling or heating, the timing of preconditioning prior to a charge stop, and the scheduling of charge stops at different SOC. These factors are influenced by many environmental and technical conditions, which have to be taken into account for practical applications, as depicted in Figure 1.

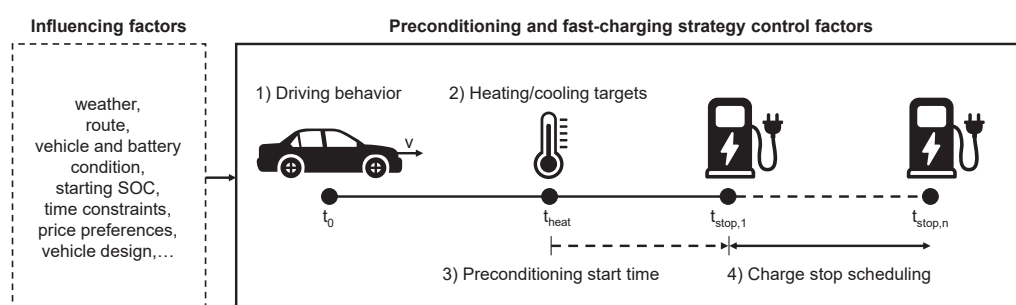


Figure 1. Influencing and control factors for vehicle-level fast-charging and preconditioning strategies using model-based approaches.

Through such multi-scale examinations, physics-informed operation decisions can be made at the vehicle level, facilitating trade-offs between charging time and energy consumption depending on the specific use case and vehicle or ambient conditions.

1.2. Organization of the Article

The remainder of this article is structured as follows: Section 2 presents the utilized methodology consisting of an electrochemical battery model coupled with a longitudinal

vehicle model in MATLAB/Simulink[®], as well as the used vehicle and battery parameters. Section 3 presents the general impact of different thermal conditions, charge-stop SOC_s, heating efficiencies, and driving behavior on the vehicle-level fast-charging capability and energy consumption before analyzing the impact of different operation strategies by the example of a typical long-distance journey. Section 4 concludes with derived operation recommendations for vehicle fast-charging applications and an outlook on limitations and future work.

2. Methodology

To examine the fast-charging behavior under different ambient and battery conditions, as well as preconditioning strategies, a longitudinal vehicle dynamics model is implemented in MATLAB/Simulink[®] (<https://ww2.mathworks.cn/products/simulink.html>, accessed on 14 August 2024). The vehicle under study represents a hypothetical mid-size current-generation electric vehicle with an 800 V battery system with a capacity of 65 kWh. Using the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) driving profile, the model calculates the resulting current profiles, which is input into a commercially available electrochemical battery model by the company Batemo [32]. The battery cell under study is a high-power 18650 cell by TerraE with a nominal capacity of 2.5 Ah. The used vehicle and battery parameters are listed in Table 1. The vehicle longitudinal forces are modeled according to the following equation:

$$F_{\text{total}} = \frac{1}{2} \rho_a c_d A v^2 + c_r m g + m a c_m \quad (1)$$

with the air density ρ_a , the velocity v , the gravitational acceleration g , and the remaining parameters as listed in Table 1. An additional inertia coefficient c_m of 1.3 is used to account for the acceleration of rotational masses within the vehicle. The vehicle is operated at ambient temperatures of -10°C to 30°C . At charging SOC_s of 10% or 30%, the vehicle is stopped and charged using an anode potential control strategy with a maximum charge rate of 4C. The current is hereby controlled using a PID controller to maintain an anode potential reserve of 50 mV, which achieves maximum charging speed while preventing the onset of lithium plating [33]. An example charging profile is shown in Figure 2.

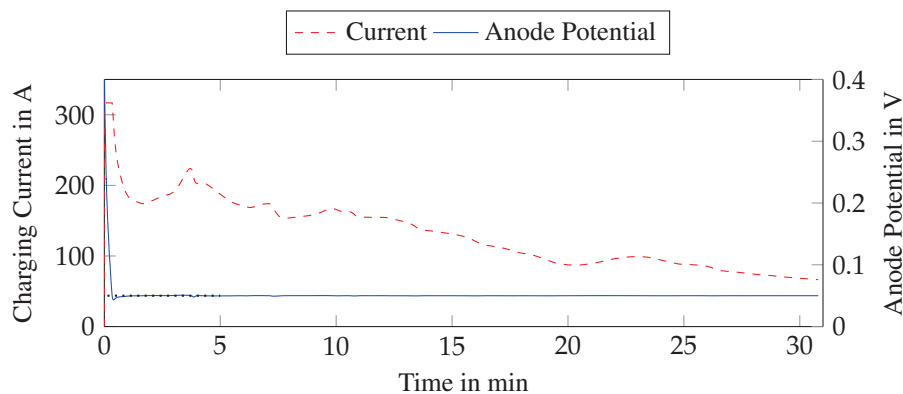


Figure 2. Charging procedure for the battery pack with an initial charging rate of 4C from 0% to 80% SOC at a starting temperature of -10°C using anode potential control.

Additionally, a thermal management system is modeled, which heats the battery to target temperatures of up to 40°C before the charging event with an assumed heating power of 0.5 W per cell and a coefficient of performance (COP) value of 1. This represents a direct translation of electrical power to heating power, such as using a resistive heater while neglecting conductive losses. It should be noted that electric vehicles are equipped with different heating technologies in practice, ranging from drivetrain heat loss usage to dedicated heat pumps, which leads to lower or higher COP values [12,34,35]. Heat losses to

ambient are considered using a heat transfer coefficient of 22 W/K, which was determined experimentally from the Tesla Model 3 in a previous study [36]. The battery is furthermore cooled with a power of 1.5 W per cell with a COP value of 2, which is representative of the commonly used integration of the battery in the refrigerant circuit to maintain a maximum temperature of 60 °C and return the battery to a temperature of 25 °C after the charge is complete. This follows a similar approach as preconditioning strategies observed in state-of-the-art vehicles [9]. These parameters are reference conditions, which are utilized to examine the coupled impact of electrical and thermal behavior during vehicle fast-charging. These form the foundation for further analyses, in which heating thresholds and timings, as well as driving and charge stop behavior, are varied to achieve improved charging times while taking energy cost into account.

Leveraging the demonstrated relationships between ambient and initial conditions, as well as preconditioning strategy and driving behavior, we simulate an example long-distance journey of 400 km with a full battery at different ambient conditions to propose a fast-charging thermal management and vehicle operation strategy that provides a trade-off between charging time and energy consumption. This is achieved by reflecting user preferences through the definition of a maximum energy cost per charge time reduction, allowing preconditioning target temperatures to be selected depending on the importance of charge duration versus cost and preventing battery heating beyond the point of receding benefits. This is expected to additionally reduce other degradation mechanisms that are exacerbated at high temperatures. The resulting operation recommendations could be implemented in electric vehicles in the form of lookup tables, allowing for easy implementation in current hard- and software infrastructures.

Table 1. Parameters of the modeled electric vehicle and battery.

Domain	Property	Value	Unit
Vehicle	Vehicle mass m	1870	kg
	Drag coefficient c_d	0.288	-
	Vehicle cross-section A	2.576	m ²
	Rolling resistance coefficient c_r	0.015	-
Battery pack	Capacity	65	kWh
	Nominal voltage	800	V
	Total cells	7359	-
	Series cells	223	-
	Parallel cells	33	-
	Heat transfer coefficient	22.2 [36]	W/K
Battery thermal management	Heater COP	1	-
	Heating power per cell	0.5	W
	Cooler COP	2	-
	Cooling power per cell	1.5	W
	Cooling maximum threshold	60	°C
Cell	Manufacturer	TerraE	-
	Type	INR18650-25P	-
	Format	18650	-
	Anode material	Graphite	-
	Cathode material	NMC	-
	Rated capacity	2.5	Ah
	Voltage boundaries	2.5–4.2	V
	Nominal voltage	3.6	V
	Maximum charge rate	4	C

3. Results and Discussion

The following section examines the impact of different driving and preconditioning behaviors under various operation conditions regarding resulting charge speed and energy

consumption. Building upon this, an example journey of 400 km is simulated to propose a thermal management strategy that balances charging speed and efficiency.

3.1. Impact of Preconditioning on Charge Speed and Energy Consumption

Figure 3 shows the resulting charging times versus combined preheating and cooling energy consumption for both simulated charge stops at different ambient and preconditioning target temperatures, with heating starting 1 h before the charging event. It becomes apparent that higher target temperatures lead to shorter charging times, allowing for a reduction by up to 60%. This is due to the beneficial impact of higher temperatures regarding reduced anode overpotentials, leading to a later derating of the current. Higher temperatures, however, show diminishing benefits, while the associated energy cost to heat the battery and subsequently cool it grows almost linearly. Furthermore, temperature dependency and preconditioning benefits are more pronounced at higher starting SOC, as the battery has less time to self-heat while charging, which matches the observations from the literature [6].

On the contrary, lower starting SOC allow the battery more time to self-heat during the charge, facilitating faster charging times due to higher anode potentials [6]. This is in line with previous examinations at cell level [9], although the effect is less pronounced, as vehicle battery packs show stronger self-heating behavior due to the increased thermal isolation compared to single cells under laboratory conditions.

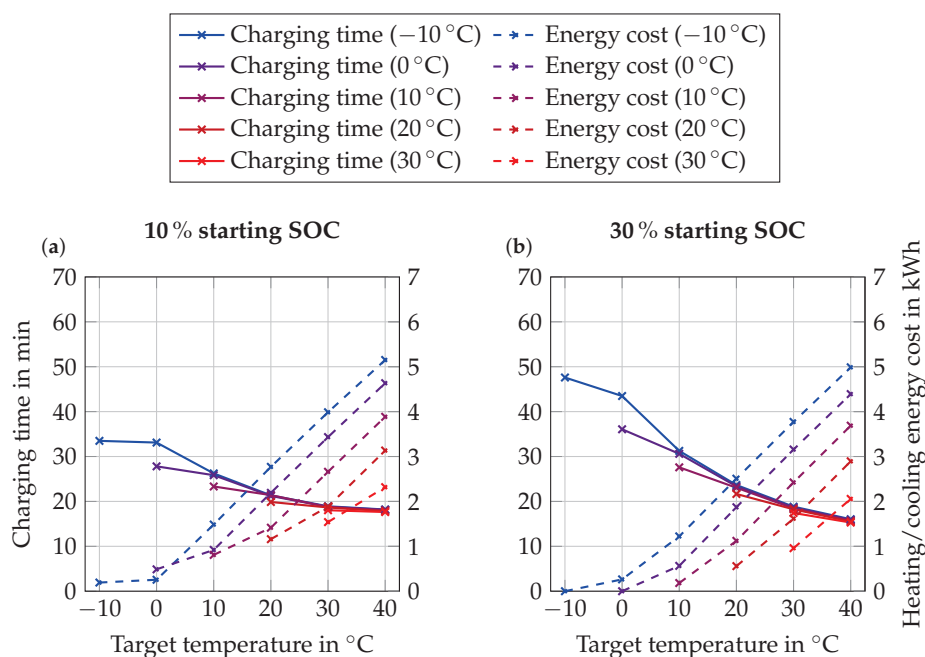


Figure 3. Charging times to 80 % SOC and energy consumption at the vehicle level using anode potential control at (a) 10 % and (b) 30 % charging event starting SOC and ambient temperatures of -10°C to 30°C with preconditioning to target temperatures of 0°C to 40°C 1 h before the charging event.

To evaluate the resulting economic impact, Figure 4 shows the associated energy consumptions for heating and cooling the battery to achieve charging times of 30 min to 18 min from 10% to 80% SOC at ambient temperatures of -10°C and 20°C using heater COP values of 0.5, 1, and 2. This shows exponentially growing thermal management energy costs, leading to an additional consumption of up to 5.5 kWh with the chosen default heater to achieve a charging time of 18 min, which corresponds to more than 10% of the total charged energy. For increasing ambient temperatures, this effect is not only driven by heating costs but also increasing cooling requirements to maintain recommended battery temperatures during and after the fast charge event.

These findings emphasize the need for model-based fast-charging strategies to take vehicle-level integration into account to achieve the optimal trade-off between charge time reduction and energy cost depending on the respective vehicle concept and driving behavior. This is expected to differ depending on the utilized cell, as designs vary strongly depending on the specific trade-off between power and energy requirements [37], especially in regard to temperature rise [38] and heat rejection [39], which has been shown to strongly influence fast-charging performance [40]. Furthermore, this consumption represents hidden costs that are not directly apparent to the vehicle owner, as they are not directly visible in the charging process. This neglects potential differences regarding fast-charging preferences, for example, when the driver explicitly desires longer breaks.

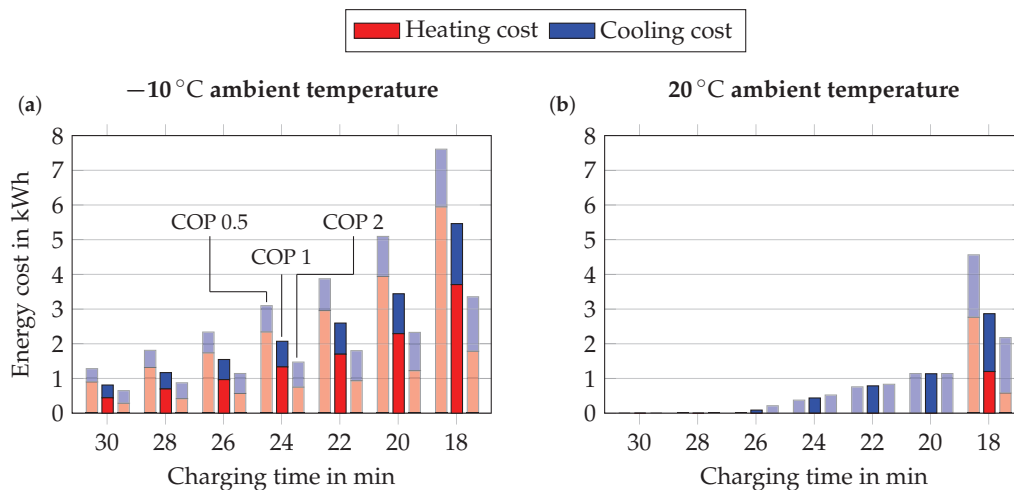


Figure 4. Energy cost for battery heating and cooling required to achieve different charging times from 10% to 80% SOC at ambient temperatures of (a) -10°C and (b) 20°C . Results are shown for battery heater COP values of 0.5, 1, and 2.

The energy cost of battery preconditioning is expected to strongly influence the resulting optimal thermal management and fast-charging strategy and is directly linked to the efficiency of the installed battery heater [12,34,35]. These can range from indirect methods, such as the so-called ‘waste heat mode’ in the Tesla Model 3, in which additional losses in the electric motor are generated and fed into the battery [36], to dedicated heaters, for example, using heat pumps, which are more efficient than resistance heaters as they utilize heat from ambient or other powertrain components.

To evaluate the impact of the installed thermal management system, we repeat the previous examination at -10°C for heater COP values of 0.5 and 2 instead of the initial value of 1, representing, respectively, a more inefficient and more efficient implementation. The resulting thermal management energy consumption for different charging speeds is also shown in Figure 4. With the less-efficient thermal management system, heating dominates the required energy to achieve higher charging speeds, leading to additional consumptions of up to 7.5 kWh per charge at -10°C ambient. Even at 20°C ambient temperature, achieving 18 min charging time costs over 4 kWh in additional thermal management energy, almost 3 kWh of which in heating energy, which lies in the same magnitude as the measured heating energy consumption in the Tesla Model 3 [36].

These results emphasize the importance of equipping next-generation electric vehicles with dedicated and efficient battery heaters, facilitating high charging speeds with reduced additional energy costs. For example, heat pump functionality could also be used for battery heating, which would increase costs and complexity but may offer long-term benefits regarding charging performance, especially in colder regions. Novel preconditioning technologies such as internal heating are increasingly being investigated, which may offer further benefits compared to current approaches [34]. Depending on the resulting energy balances, we expect different thermal management strategies to become more attractive,

necessitating the fast-charging behavior to be considered during the thermal management design phase and vice versa. For the remainder of this study, we assume a heater COP value of 1.

3.2. Impact of Vehicle Velocity on Charge Speed and Energy Consumption

Having established the beneficial impact of low initial SOC and high battery temperatures for fast-charging time, the impact of driving behavior can be evaluated. For this purpose, we simulate driving at a constant velocity between 115 km/h and 140 km/h at -10°C and 20°C for an initially full battery without preconditioning and a battery that is heated to 40°C just in time for the charge stop. The distance before the charge stop is defined in reference to a 30% stop SOC at 115 km/h to examine the impact of faster driving speeds without changing the vehicle route. The resulting charging times to 80% SOC, as well as the total energy consumption for driving, thermal management, and charging, are shown in Figure 5.

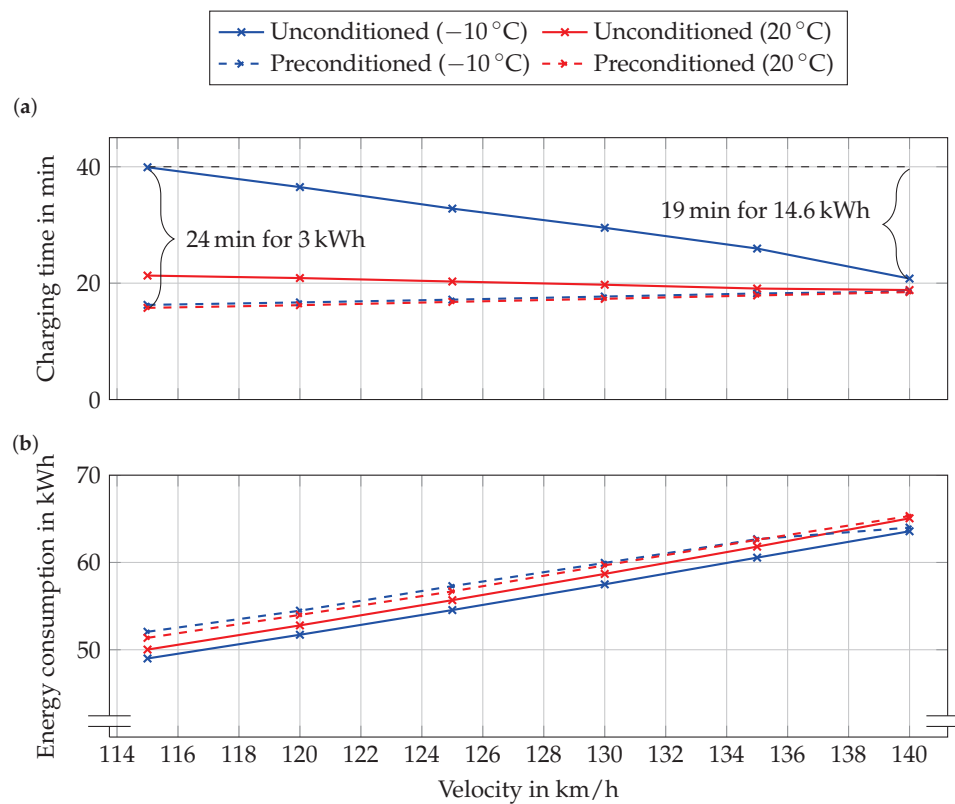


Figure 5. (a) Charging time and (b) total energy consumption for charge stops to 80% SOC with an unconditioned and 40°C preconditioned battery at ambient temperatures of -10°C and 20°C . Charge stops are performed at the same travel distance with different vehicle velocities.

Under cold ambient conditions, higher vehicle velocities result in faster charging times despite charging more energy. This is due to the lower charge-stop SOC caused by the higher energy consumption, as well as the higher battery temperature due to increased losses. This, however, coincides with significantly increased energy costs, which grow with the cube of the velocity due to air resistance. At warmer ambient conditions, higher velocities offer almost no benefit for charging speed. When preconditioning to 40°C is possible, the charging time becomes almost independent of the vehicle velocity, achieving greater time savings for only 20% of the energy cost of driving faster in the worst-case scenario. In this case, higher velocities slightly increase the charge duration, as more energy has to be charged without the added benefit of higher temperatures.

We thus conclude that if the vehicle is operated at high velocities, battery preconditioning becomes increasingly redundant. For this reason, the driving behavior has to be considered in the thermal management and fast-charging strategy to prevent unnecessary preconditioning costs, which could be taken into account through joint optimization [41]. Inversely, in the case of cold ambient conditions and constraints that prevent low-SOC charge stops, such as limited infrastructure, higher velocities can shorten the charge stop by up to 50%. This may also be the case for spontaneous charge stops without sufficient prior time for preconditioning. However, active heating achieves greater charge time benefits for significantly less energy than increasing the vehicle velocity. In this case, changes to the driving behavior are only relevant depending on the travel time versus energy cost preferences of the driver.

3.3. Proposed Thermal Management Strategy

By coupling electrochemical battery models that provide physics-based charging profiles and vehicle modeling, it becomes possible to design vehicle-level fast-charging strategies. To demonstrate this, we simulate an example long-distance journey of 400 km, which is approximately the distance for a typical holiday journey between the cities of Munich and Verona. To reflect realistic user behavior, we assume a departure in Munich with a full battery, a constant velocity of 120 km/h, and a single fast-charging stop en route with a targeted arrival SOC of 20% in Verona. Building upon this, we examine the impact of charge stop timing, preconditioning start time, and target temperature to derive recommendations for vehicle-level fast-charging strategies.

3.3.1. Timing of Charge Stop and Preconditioning

As previously shown, the achievable charging time depends strongly on the initial temperature and SOC of the battery. Given a predefined ambient temperature, the first step in deriving an optimized fast-charging strategy is the selection of the charge stop timing, e.g., the starting SOC of the charge process. Building upon the previously shown increase in charge speed at lower starting SOC, we examine the impact on charge duration and thermal management energy consumption for the defined example route. To decouple the effect of preconditioning, we only assume battery heating to a target temperature of 40 °C at the charge station during the charging process, as observed in the Tesla Model 3 when no preconditioning is performed [36]. The results of this can be seen in Figure 6. With both ambient temperatures, the previously observed sensitivity to the starting SOC leads to a doubling of the charge duration for 30% instead of 10% starting SOC, despite approximately charging the same amount of energy of 20 kWh. This is due to two effects, namely a shift of the charge stop target SOC towards higher regions, increasing the risk of lithium plating, and less potential for self-heating as the current needs to be reduced earlier in the charging process. The latter effect results in more energy being required to heat the battery parallel to the charging process, which results in longer charge durations and an almost twofold increase in energy consumption for lower temperatures. It can thus be concluded that the most significant increase in charge speed for a given route can be achieved by charging at the lowest possible SOC. This has to be weighed against available infrastructure considerations and range anxiety, which leads many vehicle owners to charge at higher SOC [31]. This conflict has been extensively addressed in past research in the context of the vehicle routing problem [42]. For future research, we propose extending existing charge stop optimization approaches for multiple charge events with nonlinear charging profiles derived from anode potential control with electrochemical battery models, allowing physics-motivated routing decisions to minimize charge and total travel duration based on the existing infrastructure.

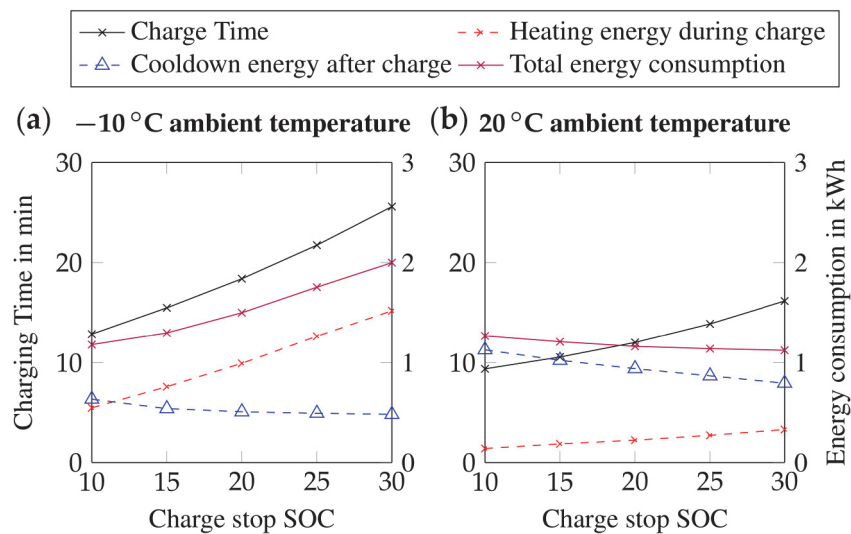


Figure 6. Charging time and thermal management energy consumption for different charge-stop SOC at (a) -10°C and (b) 20°C ambient temperature with no preconditioning and with heating during charge to a target temperature of 40°C . During each charge process, approximately 20 kWh of energy is charged.

After determining the charge stop location and SOC, the next option in thermal management strategy lies in the derivation of the preconditioning approach. For a given ambient temperature and preconditioning target temperature, optimization potential may be found in the timing of the preconditioning process. State-of-the-art electric vehicles such as the Tesla Model 3 have been observed to start heating the battery up to 1 h before the scheduled charge stop [9]. While earlier heating allows sufficient time for the battery to reach the desired temperature, it may also risk excessive energy consumption to maintain the temperature, as well as accelerated battery degradation due to longer periods at elevated temperatures [1]. To examine the trade-off between charging time and energy consumption, we simulate a charge stop at 20% of SOC for the example route at ambient temperatures of -10°C and 20°C . The battery is hereby heated to 40°C up to 90 min before the charge stop, the results of which can be seen in Figure 7. As more time is allowed for preconditioning, charge times decrease due to the battery reaching higher temperatures at the start of the charging process. This is accompanied by almost linearly increasing energy costs for heating en route and cooling after the charge is complete, as well as decreasing energy required to heat during the charging process. Once the preconditioning time is sufficient for the target temperature to be reached before the charge stop, no further benefits in charging time can be achieved, whereas the energy costs increase due to the energy required to maintain battery temperature. Using a preconditioning timing of 1 h would thus achieve maximum charging speed with acceptable energy consumption for the battery under study. Energy savings of up to 1 kWh could, however, be achieved by adjusting the heating time to the ambient temperature without compromising charge speed, such as heating 45 min in advance at -10°C and 20 min in advance at 20°C . We, however, note that further consideration must take deviations into account due to driving behavior, traffic conditions, or other uncertainties, such as the battery heat transfer coefficient, which supports increasing the preconditioning time to maintain a safety margin. The latter is especially expected to have a large impact on the optimal thermal management strategy, as a thermally more isolated battery pack requires less heating but more cooling. Furthermore, longer preconditioning times may be required to achieve temperature homogeneity within the battery pack, which is required to minimize the adverse effects of temperature gradients during fast-charging [43].

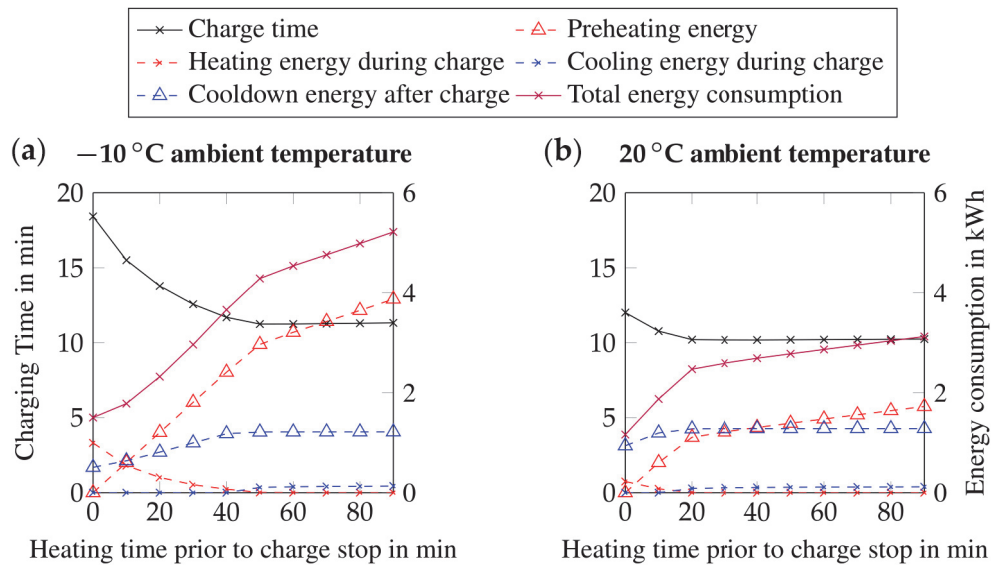


Figure 7. Charging time and thermal management energy consumption for different preheating start times prior to a charge stop at (a) -10°C and (b) 20°C ambient temperature and a charge stop at 20% SOC with preconditioning and heating during charge to a target temperature of 40°C .

3.3.2. Preconditioning Target Temperature

The final step in determining fast-charging preconditioning strategies lies in the temperature thresholds. As the cooling threshold is a safety factor that is usually defined in the battery datasheet, we assume a valid maximum temperature of 60°C and instead focus on the heating target temperature. As previously shown, higher heating target temperatures increase charging speed; however, this comes at the cost of growing energy consumption and aging. This leads to receding benefits of battery heating, causing charge speed costs to grow exponentially. While performance-oriented users may elect to heat to the highest target temperatures, allowing for the fastest charging experience, a more economical approach may be found in trading off the charge time reduction with the increase in energy consumption. This could be achieved by defining a minimum acceptable charge time reduction per additional kWh of thermal management energy required. To demonstrate this, we define the value as a 3 min minimum speed increase per additional kWh consumed for preconditioning. However, the concrete value can be defined based on user preference. By performing an extensive simulation study, heating thresholds that balance both energy consumption and charging speed can be selected. These can be seen in Table 2, assuming heating 1 h before the charge stop. For lower charge-stop SOC, the inherent self-heating of the battery during charging can be leveraged, requiring less external heating and thus less energy. The resulting charge speeds and energy consumptions can be seen in Figure 8a,b, as compared to a reference strategy of always heating to 40°C in Figure 8c,d. Using the cost-aware charging strategy, charging times of below 20 min can be achieved for almost all examined starting conditions, with both charging duration and additional energy consumption increasing for higher start SOC. By limiting the preconditioning target temperatures using the proposed cost factor, fast-charging can be maintained with increases of only up to 4 min in the low-SOC region compared to the reference, still allowing a total charge stop duration below 15 min to charge the required energy. At the same time, this can lead to energy savings of more than 3 kWh. This may pose a more attractive approach to deriving thermal management strategies in cost-critical use cases, such as commercial vehicles with frequent fast-charging requirements, or allow vehicle users to prioritize based on personal preferences.

Table 2. Cost-adjusted preconditioning thresholds.

	10% SOC	20% SOC	30% SOC	40% SOC
−10 °C ambient	10 °C	30 °C	40 °C	50 °C
0 °C ambient	10 °C	20 °C	40 °C	40 °C
10 °C ambient	20 °C	20 °C	30 °C	40 °C
20 °C ambient	30 °C	30 °C	30 °C	40 °C
30 °C ambient	-	40 °C	40 °C	40 °C
40 °C ambient	-	-	-	-

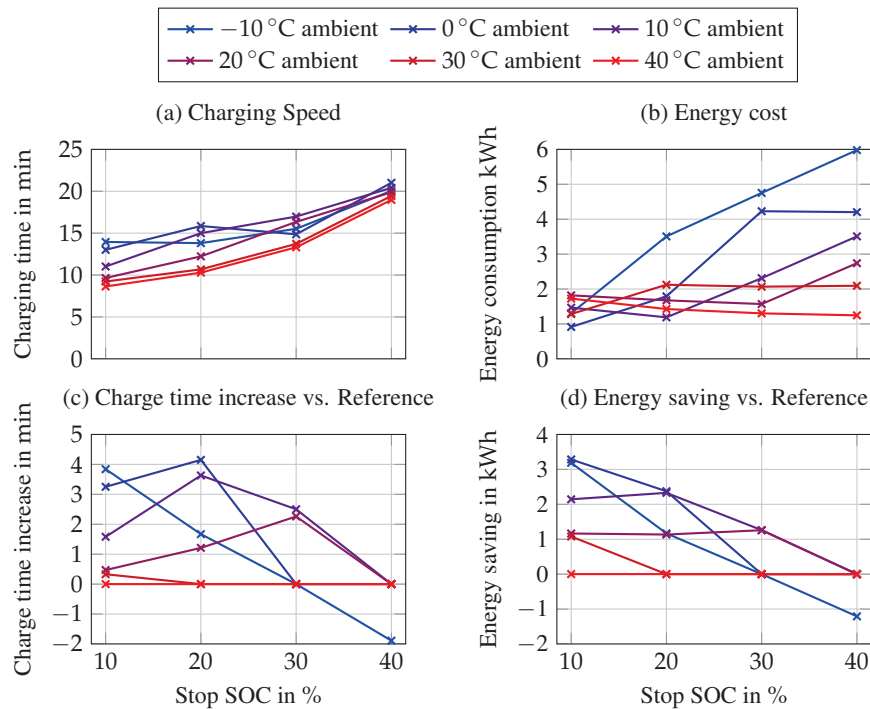


Figure 8. (a) Charging time and (b) energy consumption for the cost-aware preconditioning strategy, as well as (c) charge time increase and (d) energy saving for the proposed strategy compared to a reference thermal management strategy during which the battery is always heated to 40 °C. The results are shown for ambient temperatures of −10 °C to 40 °C, as well as charge-stop SOC of 10% to 40%.

4. Conclusions

By utilizing electrochemical battery models, physics-based fast-charging strategies can be derived that allow maximum charging speed while mitigating the risk of adverse side reactions such as lithium plating. Through coupling the derived information with vehicle-level considerations and ambient conditions, we demonstrate the impact of different thermal management and routing decisions on the achievable charging speeds and energy consumption, which can be summarized as follows:

1. Fast-charging should be performed at the lowest possible charge-stop SOC to prevent the increased risk of lithium plating at higher SOC and allow for maximum self-heating during the charging process, reducing the need for external heating and thus saving energy. This is especially critical at low ambient temperatures.
2. Preconditioning target temperatures should be chosen based on user preferences regarding energy cost vs. charging speed, preventing excessive energy consumption for receding charge speed benefits by leveraging the inherent self-heating during the charging process. For the battery under study, this can facilitate energy savings of over 3 kWh while only slightly impacting charging speed, which may be attractive in cost-critical use cases.

3. The preconditioning process should be initialized sufficiently early to achieve the desired temperature while minimizing the time maintained at elevated temperatures to reduce energy cost and degradation while maintaining identical charging speeds. However, an additional buffer should be considered to consider uncertainties and allow for homogeneous battery heating. A preconditioning time window of 1 h appears to offer a compromise between achieving maximum charging speed without excessive energy consumption. Further examinations are required to propose optimized preconditioning timing depending on battery pack effects and ambient conditions.
4. When the vehicle is operated at higher velocities, preconditioning offers diminishing charge time benefits. Vehicle manufacturers should thus take driving behavior into account when designing fast-charging strategies. For vehicles operated without active battery heating at low ambient conditions, increasing the velocity may allow for higher charging speeds but significantly increases energy costs. When active battery heating is available, higher vehicle velocities offer no benefit towards charge duration.
5. Charging speed and energy efficiency can be significantly increased by installing dedicated battery heaters, such as utilizing the vehicle heat pump. This has to be weighed against potential increases in weight, complexity, and cost, posing a design trade-off for vehicle manufacturers to consider depending on the concrete use case.

Future research will extend the proposed concept by examining the impact of different battery types, vehicle concepts, and mobility behaviors. Furthermore, the impact of battery degradation has to be considered, as well as the interplay between thermal management strategy and resulting thermal gradients within the battery pack. Finally, the proposed methodology can be embedded in vehicle routing algorithms to provide a methodology for integrating physics-based charging strategies in vehicle use cases, allowing for the derivation of optimal charge stop and operation strategies for any desired use case.

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Abbreviations

The following abbreviations are used in this manuscript:

BEV	battery electric vehicle
COP	coefficient of performance
SOC	state-of-charge
WLTP	Worldwide Harmonized Light Vehicles Test Procedure

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Article

Effect of Cell-to-Cell Internal Resistance Variations on the Thermal Performance of Lithium-Ion Batteries for Urban Air Mobility

Kuo Xin ¹ and Geesoo Lee ^{2,*}

¹ Department of Mechanical System Engineering, Tongmyong University, Busan 48520, Republic of Korea; 20237010@g.tu.ac.kr

² Department of Automotive Engineering, Tongmyong University, Busan 48520, Republic of Korea

* Correspondence: gslee@tu.ac.kr; Tel.: +82-10-2506-1537

Abstract: This study examines the thermal behavior of lithium-ion battery modules intended for Urban Air Mobility (UAM), a forthcoming urban transport system designed to facilitate efficient and secure passenger and cargo transport within city centers. UAM applications necessitate batteries with high energy densities capable of sustaining elevated discharge rates during critical phases such as takeoff and landing. The battery module evaluated in this study comprises four cells arranged in series and configured as a submodule for UAM applications. A three-dimensional thermal model was utilized to analyze the impact of external temperature fluctuations and high discharge rates on the performance of the battery module. The numerical findings indicated considerable variations in temperature and internal resistance among the cells, especially under high discharge rates at low temperatures, with a maximum temperature deviation of 32.952 °C observed at an 8 C discharge rate. These thermal non-uniformities were attributed to variations in cell capacity and internal resistance, which were amplified by manufacturing inconsistencies and operational conditions. The study underscores the necessity of robust thermal management strategies to mitigate the risk of thermal runaway and ensure the operational safety and reliability of UAM systems. The results emphasize the critical role of advanced Battery Management Systems (BMS) in monitoring and controlling cell voltage and temperature to achieve consistent performance across the battery module. This research contributes valuable insights into the design of more efficient and reliable battery modules for UAM, highlighting the importance of addressing cell-to-cell performance discrepancies to enhance overall module efficacy and durability.

Keywords: urban air mobility (UAM); lithium-ion battery; internal resistance; cell-to-cell variation; thermal behavior

1. Introduction

Urban air mobility (UAM) is a future air transport system that safely and conveniently transports passengers and cargo in the city center. It is expected to be a new means of transportation as collision avoidance and autonomous flight technologies develop along with the development of batteries with high energy density and high-efficiency motor technology [1,2]. The battery modules for UAM must be developed with careful consideration of power, energy density, safety, durability, and charging time, as these factors significantly impact the direct operating cost (DOC), which is essential for the commercialization of UAMs [3]. The cell-to-pack packaging efficiency of UAM batteries is approximately 60–70%, and based on this efficiency, battery cells with an energy density of over 300 Wh/kg are being developed [3,4]. As high discharge characteristics are required when UAM takes off and lands, a design that considers the heating characteristics due to high discharge along with the packaging design of the battery module is becoming increasingly important [5]. In addition, it is essential to develop a battery management system (BMS) that can

effectively monitor and control the voltage and temperature of cells constituting the UAM battery module. When a battery module composed of multiple lithium-ion battery cells is discharged at a high rate, inter-cell performance characteristics caused by the capacity and internal resistance deviations of cells constituting the battery module greatly affect the overall performance of the battery module. The deviation between cell capacity and internal resistance inevitably occurs in the process of manufacturing a battery cell, and the deviation of cells occurring after battery operation affects the battery performance and the deviation of heat generation between cells, resulting in overall performance degradation. Accordingly, there is a need for a technology to predict cell performance, deviations throughout the module, and corresponding responses. A change in the capacity and state of health (SoH) of the cells and a difference in internal resistance, which are inevitably caused in the process of manufacturing lithium-ion battery cells, affect the life of the battery module in which the cells are assembled. In general, a battery module for energy storage systems (ESSs) or electric vehicles (EVs) configures a plurality of lithium-ion batteries in series or in parallel, depending on the target applications. In general, battery cells configured in parallel are more difficult to monitor and manage deviations between cells than battery cells configured in series. When lithium-ion battery cells are connected in parallel, the current of the cell is imbalanced because it is difficult to measure and manage the current deviation. Therefore, when manufacturing a battery module, it is necessary to affect and manage it, and many related studies are being conducted.

Many researchers have studied the differences between battery cells and how they change over time and affect battery life and performance as a result. Paul et al. [6] studied the battery cells connected in series were studied to consider the capacity, initial internal resistance, life rate and heat of the initial battery cells. The analysis showed that the non-uniformity of cell aging was due to the current distribution of the non-uniform cells. Chiu et al. [7] focused on the series of battery cells, and it was confirmed that the decrease in battery capacity increased as temperature changed. Many studies have been conducted on battery cells configured in parallel. Offer et al. [8] reported that the contact resistance of the two internal cells was the cause of the non-uniform current flowing inside the pack. This led to a non-uniform load of each cell. Bruen and Macro [9] experimentally evaluated the imbalance of parallel cells. It was confirmed that a difference of 30% in impedance caused a change of 60% of the peak cell current and 6% during the cycle. Fernandez et al. [10] confirmed that the initial SoH 40% deviation decreased to 10% after 500 cycles because a lithium-ion battery experiment connected in parallel at 25 °C. Shi et al. [11] investigated parallel LIFePO₄ current imbalance. Rapid aging could reduce the imbalance by suppressing changes in temperature and current. Gong et al. [12] showed a large deviation between cells when discharging cells with different levels of deterioration composed of parallel, which could accelerate aging and lead to serious problems. Liu et al. [13] applied a thermal single-particle model to a parallel battery and found an irregular overpotential caused by internal connections and temperature gradients that affected the battery pack. Song et al. [14] analyzed the current, degradation rate, state of charge (SoC), and heat dissipation between cells using a thermal, electrical aging model and compared the long-term capacity.

Until now, numerous studies have been carried out on the impact of cell-to-cell variations in lithium-ion batteries connected in parallel on the overall electrical behavior of the module, SoC, degradation due to temperature variations, and SoH. The final structure of the UAM battery module in this research aims to configure 14 lithium-ion battery cells with a capacity of 90 Ah and an energy density of 300 Wh/kg in series. The target battery module will undergo high discharge under external temperature conditions ranging from −20 °C to 43 °C. Notably, the increase in internal resistance variation between cells at low temperatures significantly affects the temperature imbalance among cells, leading to a reduction in overall module performance; therefore, this must be carefully considered during battery module production. In this study, 109 lithium-ion battery prototypes were initially produced for UAM battery module development. Two sample cells from the first prototypes were selected for experiments to measure internal resistance under various tem-

peratures and were modeled for further analysis. Based on this data, a 4S series submodule was modeled. A lithium-ion battery submodule was then assembled, simulations were conducted, and the temperature imbalance during battery module operation was predicted.

2. Methodology

2.1. Lithium-Ion Battery Module

To meet technology requirements of higher energy density and cycle lifetime between 500 and 2000, the UAM needs to employ lithium batteries such as lithium nickel cobalt aluminum oxide (NCA) or different kinds of lithium nickel manganese cobalt oxides (NMC) batteries. Considering an integration factor of 0.75 from cell to module, the energy density of the battery cells must be at least 300 Wh/kg [15]. In addition, a new type of high-performance stretchable lithium-ion battery that can produce constant output power even in continuous dynamic tests is also being developed [16]. The lithium-ion battery manufactured for high discharge, while with the large energy density used in this study, was an NMC series with a maximum capacity of 90 Ah. The maximum voltage of the cell is 4.2 V, and the cut-off voltage is 2.7 V. The lithium-ion battery cell used in this study was developed for UAM with an energy density of 300 Wh/kg and was manufactured to discharge up to a rate of 8 C in consideration of the takeoff and landing conditions of the UAM flight profile. Detailed specifications of the lithium-ion battery cell are summarized in Table 1.

Table 1. Specifications of the lithium-ion battery cell specially designed for UAM.

Items	Specification
Nominal capacity	90 Ah
Nominal voltage	3.7 V
Energy density	300 Wh/kg
Max. charge voltage	4.25 V
Cut-off voltage	2.75 V
Material system	Cathode: NCM-811
	Anode: Graphite
	Electrolyte: Carbonate-based
Max. continuous discharge current	8 C

Figure 1 shows the cell-to-cell variations in internal resistance of 109 prototyped lithium-ion battery cells. The goal of this study is to predict the potential problems that could occur when applying modules to prototypes with significant variations in inter-cell internal resistance. A submodule composed of four serial cells (4S) composed of different internal resistances was constructed, and the thermal behavior performance according to the outside temperature and C-rate changes in the internal resistance deviation of the cell was examined.

Finally, to be applied, the battery module for UAM was composed of 14 serial 1 parallel (14S1P) cells to meet the design requirement of the applied system. Two cells with one thermal insulation pad are connected in series to prevent heat transfer between the cells as submodules, and seven submodules with aluminum covers are connected in series, as shown in Figure 2a. In this study, cells No. 42 and 46 were selected in consideration of the internal resistance deviation out of the 109 prototypes in Figure 1 to analyze the effect of the internal resistance deviation between cells on the module's thermal behavior performance. Submodules using cells No. 42 and 46 were organized into two groups and connected in series to model the module consisting of the four total serials, as shown in Figure 2b. Cells #1 and #2 belonging to submodule 1 were the cells with high internal resistance; cell No. 42 and cells #3 and #4 of submodule 2 were modeled as cells with relatively low internal resistance, such as cell No. 46. When the cells were connected in series, the tabs were welded using a laser welding machine, and the internal resistance between the tabs was about 0.1 mΩ. A submodule consisting of two cells and one pad was composed of a thin aluminum plate of 0.1 mm for active cooling of the battery cell configured to support two

modules so that cooling with external cooling air could be performed more efficiently. The cooling fin has the function of simultaneously serving as a support between the battery submodules along with cooling, as shown in Figure 2.

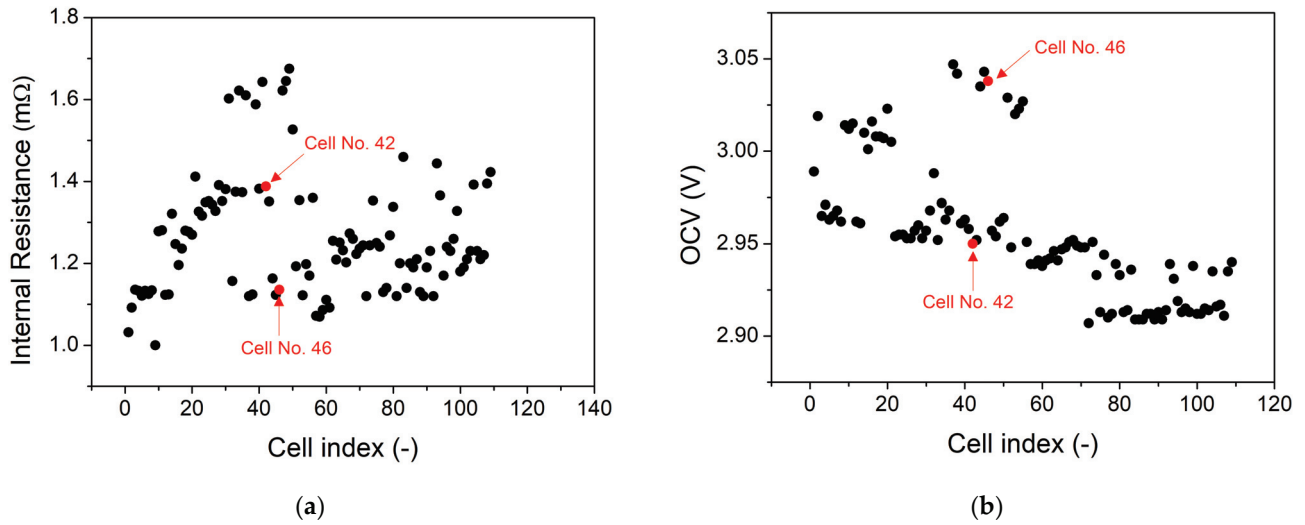


Figure 1. Cell-to-cell variations on the internal resistance of the first 109 prototyped lithium-ion battery cells. (a) Internal resistance; (b) Open current voltage (OCV).

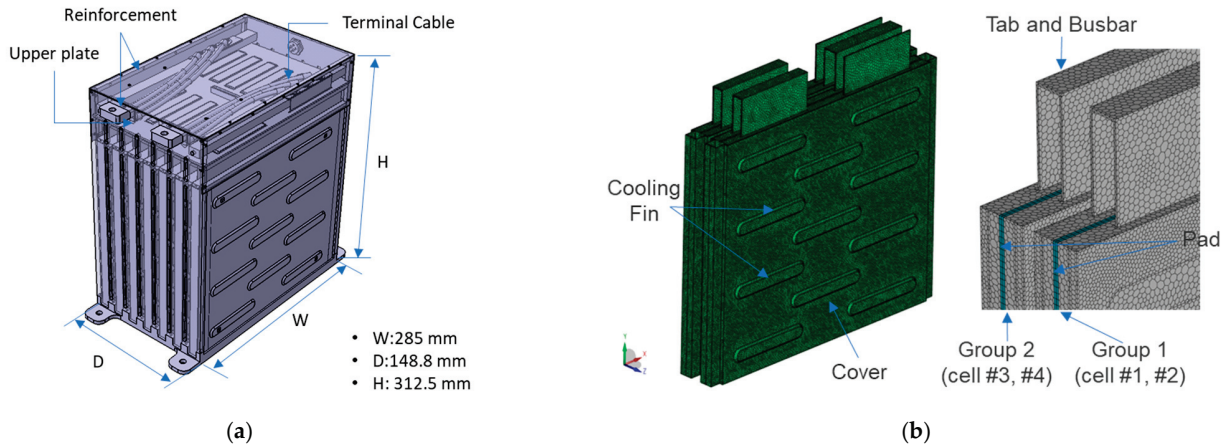


Figure 2. 3D model and computational grid system for UAM battery module. (a) Full model; (b) submodule model.

2.2. Governing Equation and Simulation Setup

In this study, a thermal analysis of the battery module was performed using AVL's FireM 2020R2, a software widely used for three-dimensional multi-physical analysis of batteries [17]. A hexagonal grid was constructed for the battery module, as shown in Figure 2. The total number of grids used for the analysis was about 840,000. The governing equation for the transient analysis of the battery module used a three-dimensional transient thermal conduction equation, as shown in Equation (1).

$$\frac{\partial(\rho_c C_p T)}{\partial t} + \nabla(-k \nabla T) = \dot{Q}' \quad (1)$$

where, ρ_c is the density (kg/m³), C_p is the specific heat (J/kg-K), k is the thermal conductivity coefficient (W/m-K), and $\dot{Q}' = \dot{Q}/V_{cell}$ represents the volumetric heating source (W/m³) inside the battery cells respectively.

Heat generation inside a battery cell is known due to the resistance to electrochemical reactions and the movement of species within the cell. The heat generation in a battery cell is usually modeled by two parts: the irreversible heat, including charge and mass transfer over-potentials and ohmic losses and the reversible heat caused by the entropy change [18]. Bernardi et al. [19] developed the following expression to calculate the heat generation inside the battery cell:

$$\dot{Q} = I(V_{oc} - V) - I\left(T\frac{dV_{oc}}{dT}\right) = I^2R_T - I\left(T\frac{dV_{oc}}{dT}\right) \quad (2)$$

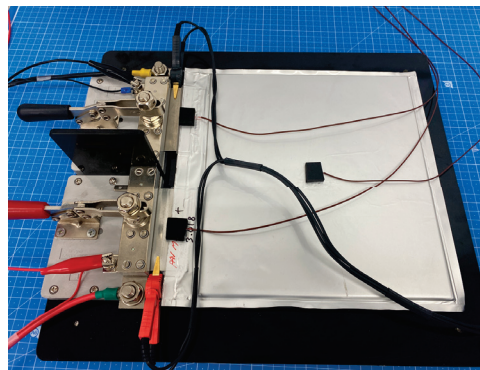
where I denotes cell current, V_{oc} open circuit potential, V cell potential, R_T the total internal resistance, and T absolute temperature of the cell. The current I is positive for discharging and negative for charging. The total internal resistance of the battery $R_T(\text{SoC}, T)$ depend on the SoC and temperature of the cell. The first term of Equation (2) represents heating due to the Joule effect and irreversible heat generation due to internal resistance to the current flow. The second term is the entropy change (reversible heat generation), attributed to electrochemical reaction [20].

The total internal resistance of lithium-ion batteries is significantly influenced by temperature changes, so the battery heat generation was simplified to the Joule heating value as a function of temperature, as $\dot{Q} \cong I^2R_T(T)$. The overall internal resistance was measured under different temperature conditions through experiments and was then modeled as the heat generation of the battery cells. However, in the case of taps, the change in internal resistance according to temperature was negligibly small, so a constant value was used. The battery cell was cooled to the outside through a thermal insulation pad and a cover, and it is cooled by convective heat transfer from the external cover to the cooling air. The convective heat transfer coefficient on the aluminum cover and tabs was specified as 20 W/m²K. The properties of the cooling air, the aluminum cover, the lithium-ion battery cell, and the thermal insulation pad between the cells used in the battery module thermal analysis are summarized in Table 2.

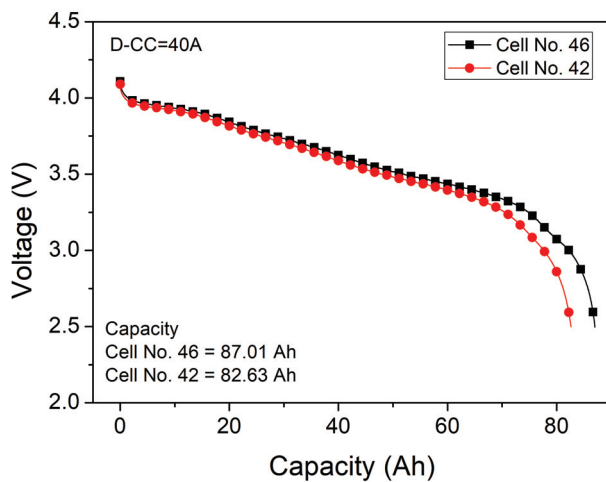
Table 2. Material properties of the pouch-typed lithium-ion battery (Reprinted from Ref. [15]).

Material	Air	Cover (Aluminum)	Cell (LIBs)	Thermal Insulation Pad
Density (kg/m ³)	1.1841	2702	2100	1060
Specific heat capacity (J/(kg·K))	1003.6	903.0	1100	796
Thermal conductivity (W/(m·K))	0.026	237	1/30/30	0.202

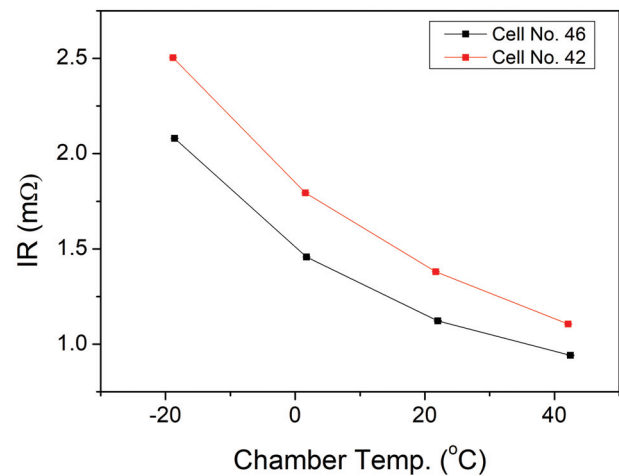
Figure 3 shows the capacity and internal resistance of the cell for two samples in Figure 1 through an experiment. As a result of the discharge under the condition of about 0.5 C (40 A), the capacity of cell No. 46 was 87.01 Ah, and the capacity of cell No. 42 was 82.63 Ah, as shown in Figure 3a. Figure 3b shows the result of measuring the internal resistance according to temperature change in the environmental chamber. As shown in the figure, the internal resistance of a lithium-ion battery increased as the temperature decreased and gradually converged as the temperature increased. The experiment is the result of measuring the internal resistance value according to the climatic chamber using Hioki's BT3562A precision resistance meter after mounting samples in the chamber. The resolution of the equipment is 0.1 μΩ. The internal resistance of cell No. 46 based on 20 °C was 1.1365 mΩ, and the internal resistance of cell No. 42 was 1.3853 mΩ, which was about 21.9% higher than that of cell No. 46. The internal resistance experimental data according to temperature were considered in the modeling of the heating value of the battery cell.



(a)



(b)



(c)

Figure 3. Cell-to-cell variations of the prototyped lithium-ion battery from the experiment. (a) Test rig and cell No. 42; (b) Voltage; (c) internal resistance—IR.

3. Simulation Results

Figure 4 depicts the final heat release in the cell according to the outside temperature change and C-rate change through steady-state analysis of a battery module. As illustrated in the experiment result of Figure 3b, as the internal resistance of a lithium-ion battery increases as the temperature decreases, the heating value also increases. However, when the internal temperature of the cell increased due to heat generation, the internal resistance of the cell also decreased, and the total heat generation also decreased, and the total heat generation had a constant value, as shown in Figure 4a. Based on the outside temperature of 20 °C, the heat generation of cell #1 was 71.4 W, and that of cell #4 was 60.1 W. In the case of 20 °C or higher, the change in the heating value was not large. Figure 4b shows the calorific value according to the outside temperature and C-rate changes, and the heat generation increases significantly as the C-rate increases. In the case of the same cell, the deviation of the internal resistance of the cell and the deviation for the C-rate were larger than the effect of the calorific value for temperature. In this study, the maximum heat generation of cell #1 under the 8 C condition was 4569.3 W, and the maximum heat generation of cell #4 was 3846.7 W. This was a value predicted during continuous discharge at 8 C condition, and the system was stopped before that because a thermal runaway occurred during the actual operation.

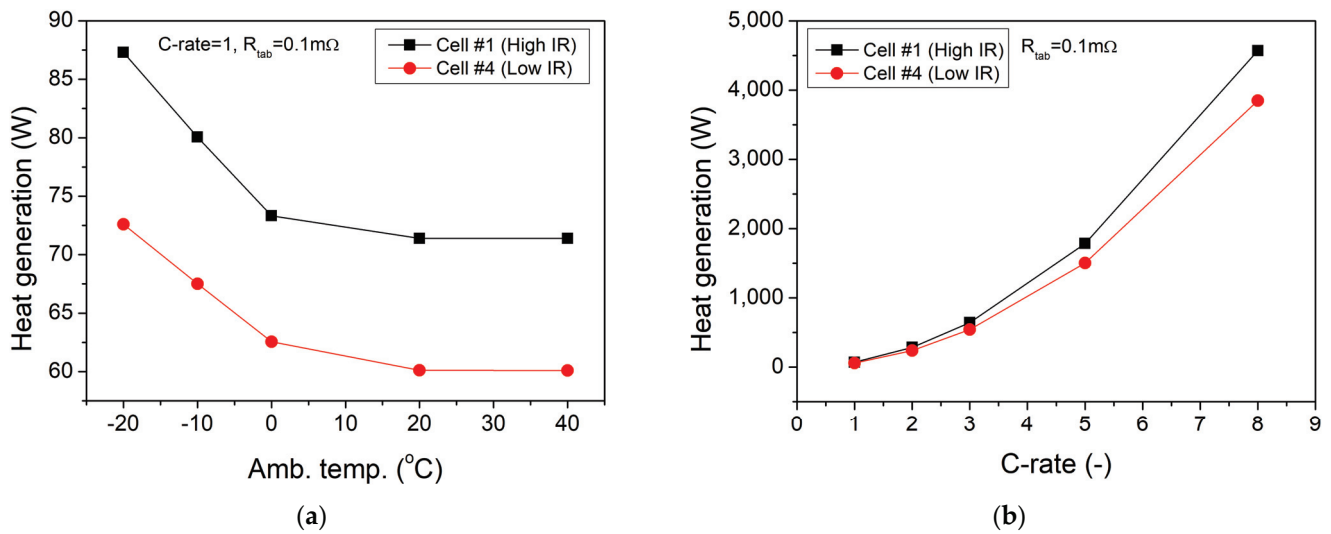


Figure 4. Heat generation variations of the lithium-ion battery for (a) ambient temperature and (b) c-rate on steady-state analysis.

Figure 5 shows the change of heating value over time in cells #1 and #4 under the outside temperature and C-rate conditions and shows the results of the transient analysis. The battery submodule generated heat in the cell according to the external air condition, the operating condition, and the C-rate. Therefore, it can be seen commonly that the initial heat generation increased significantly when the temperature of the cells in both cells decreased. The heat generation inside the cell gradually increases the temperature of the cell, thereby reducing the internal resistance of the cell. As a result, the heat generation of the entire cell was also gradually reduced. The figure shows that when the temperature reached 20 °C, there was little change in the internal resistance, and the heating value was maintained constant. As shown in Figure 5b, when the C-rate was increased to 8 C, the heating value or the temperature of the cell was greatly increased, resulting in a significant increase in the temperature of the cell, which resulted in a faster convergence of the heating value change. When high discharge was performed at a low temperature, an electrochemical reaction was slowed inside the cell and heat generation was accompanied by a large internal resistance.

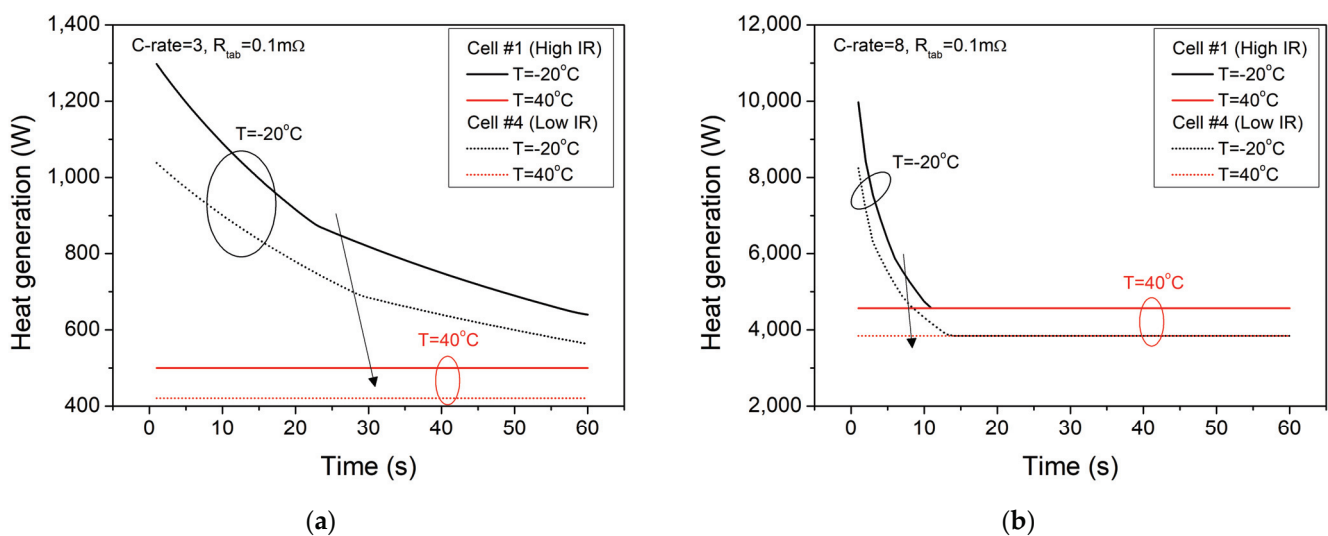


Figure 5. Heat generation variations of the lithium-ion battery for ambient temperature. (a) 3 C; (b) 8 C.

Figure 6 shows the result that the battery module surface temperature distribution after 1 min according to the C-rate change at an external temperature of 20 °C is predicted. As the cell discharged at the initial stage, the temperature rose due to the heat generated inside the cell, and the heat transferred along the thin aluminum plate surrounding the submodule was cooled through heat transfer with external air. The tab had a structure in which the temperature was increased by heat conduction by heat generation inside the cell, and heat transfer with external air was cooled by heat conduction by heat generation inside the tab.

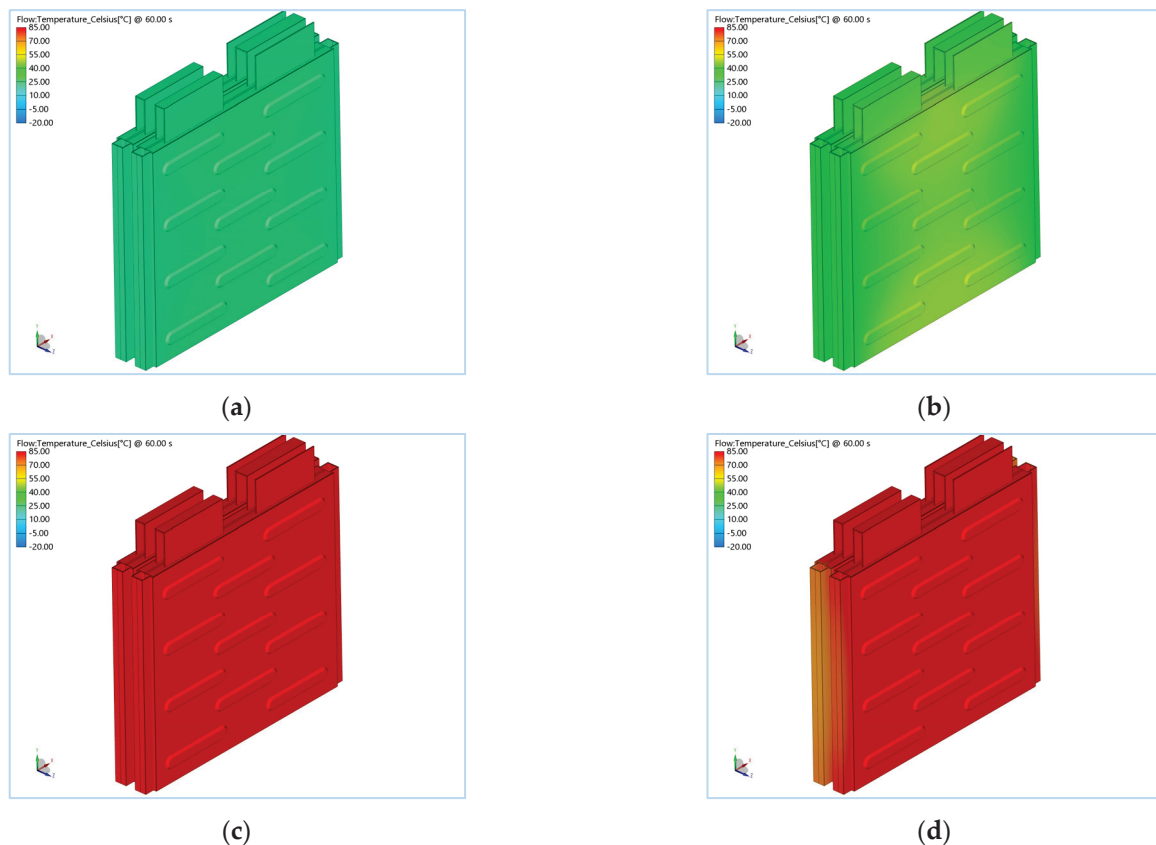


Figure 6. Temperature distributions of the lithium-ion battery for various C-rates at an ambient temperature of 20 °C. (a) 1 C; (b) 3 C; (c) 5 C; and (d) 8 C.

Figure 7 depicts the graph that predicts the average cell temperature and the temperature change in the tab, depending on the C-rate of the battery submodule according to the outside temperature change for 1 min. Since the heat generation was significant at low temperatures, the temperature rose significantly instantaneously, and after that, the temperature gradually rose gradually. Since the internal resistance of the tap was constant according to the temperature change, a gentle temperature increase was shown in the entire operation range. The heat generated by the cell was conducted to the tab, which increased the temperature as heat generated by its own resistance was added. The higher the discharge at low temperatures, the steeper the rise in the temperature curve of the initial cell. These characteristics can be seen because of reflecting the characteristics of internal resistance according to temperature. When the outside temperature reached 40 °C, the effect on the internal resistance was already small, so the temperature increase also had a gentler characteristic.

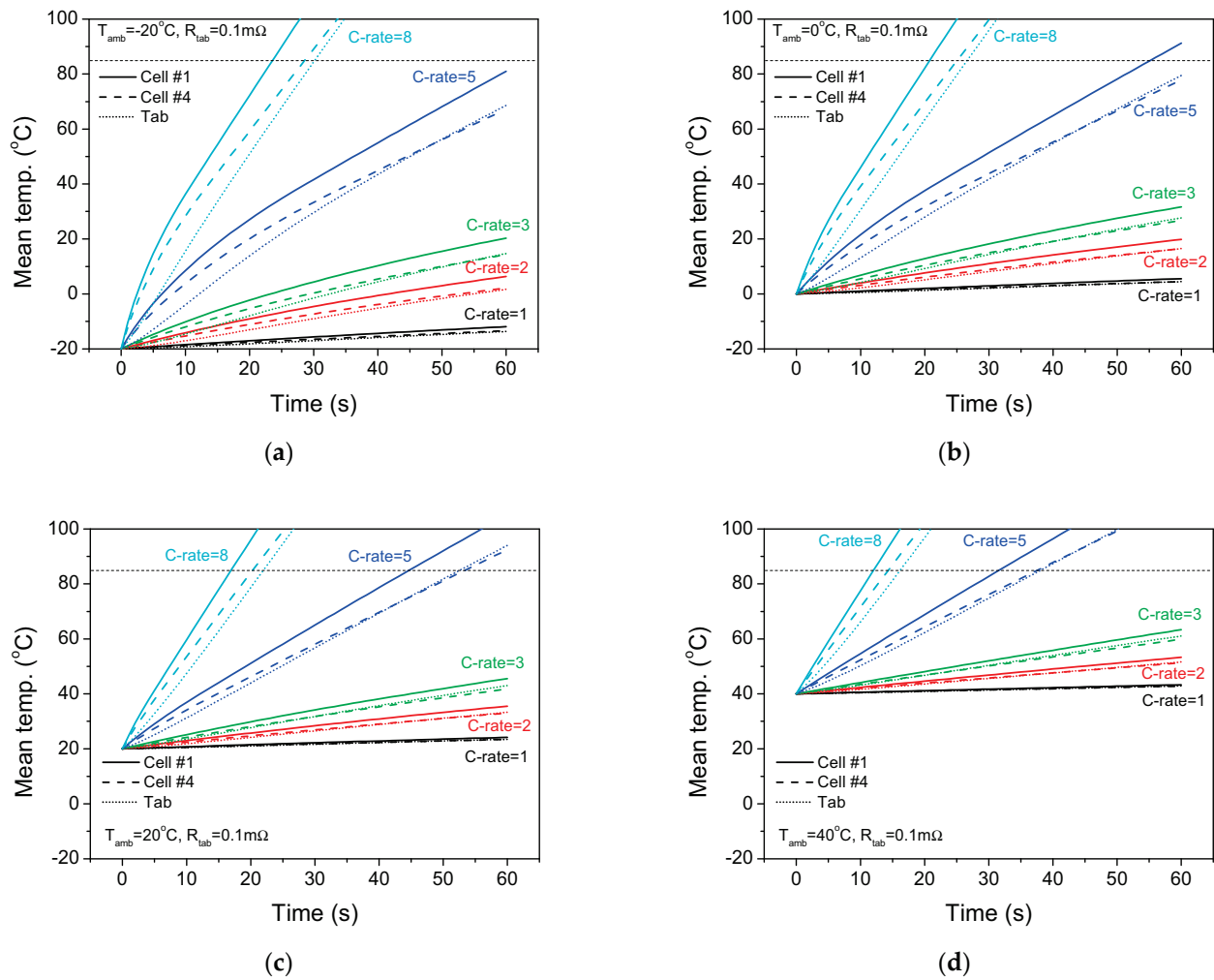


Figure 7. Mean temperature variations of the lithium-ion battery for ambient temperature. (a) -20°C ; (b) 0°C ; (c) 20°C ; and (d) 40°C .

Table 3 summarizes the results of the average temperature difference between the cells after 1 min according to the outside temperature and the C-rate change. The average temperature difference between cells increased as C-rate increased at the same ambient temperature and decreased as the temperature increased at the same C-rate. It was predicted that a maximum of 32.952°C temperature deviation would occur under -20°C during the 8 C condition.

Table 3. Mean temperature difference between Cells #1 and #4 for various ambient temperatures and C-rates at 60 s.

Ambient Temp.	Mean Temp. Diff. ($^{\circ}\text{C}$) at 60 s			
	1 C	3 C	5 C	8 C
-20	1.473	5.954	13.747	32.952
0	1.073	4.958	13.324	32.545
20	0.747	3.819	12.745	31.994
40	0.498	3.494	12.44	31.712

Based on the study on the temperature deviation of the internal resistance of the cells for manufacturing the UAM battery module, the product deviation between the cells was improved. The results are shown as a box plot in Figure 8.

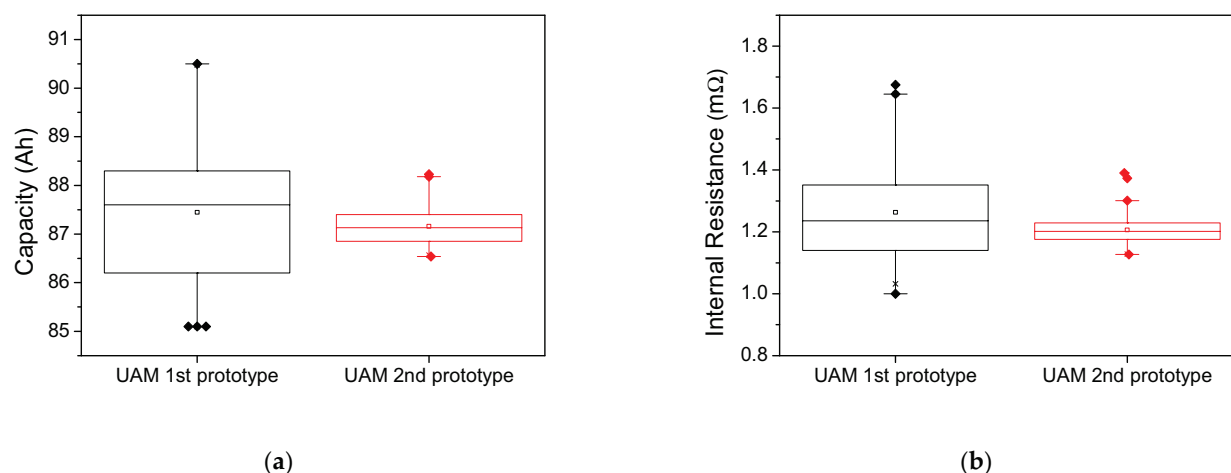


Figure 8. Cell-to-cell variations of the prototyped lithium-ion battery. (a) Capacity; (b) internal resistance.

4. Conclusions

As a study to develop a UAM battery module using pouch-type lithium-ion battery cells, a submodule composed of four cells composed of different internal resistances was constructed, and the thermal behavior performance according to the outside temperature and C-rate changes in the internal resistance deviation of the cell was examined. The initial heat generation of a lithium-ion battery increased as its internal resistance increased at low temperatures. There was little change in the internal resistance of the cell as the temperature increased. Since the heat generation was large at low temperatures, the temperature rose significantly after the temperature increased significantly. At low temperatures, especially as a high discharge was performed, a steeper temperature rise curve of the initial cell could be seen due to the reflection of the characteristics of internal resistance according to the temperature. When the outside temperature reached 40 °C, it had a constant internal resistance, so the rise in temperature also had a gentler characteristic. The average temperature differential between cells increased with higher C-rates and similarly escalated as the ambient temperature decreased under constant C-rate. The maximum temperature deviation of 32.952 °C was predicted at −20 °C during an 8 C-rate discharge. Based on the analysis of temperature deviations and internal resistance among cells in the manufacturing process of the UAM battery module, measures were implemented to reduce product variability between cells.

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Article

Barriers to Electrification: Analyzing Critical Delays and Pathways Forward

Beatriz Amante García ^{1,2,*} and Lluç Canals Casals ^{1,2}

¹ Department of Projects and Construction Engineering, ETSEIB and ESEIAAT, Universitat Politècnica de Catalunya, Carrer Colom 11, 08022 Terrassa, Spain ; lluc.canals@upc.edu

² INTEXTER, Carrer Colom 11, 08222 Terrassa, Spain

* Correspondence: beatriz.amante@upc.edu; Tel.: +34-937398686

Abstract: This paper extensively explores the intricate nuances surrounding the delayed transition to new business models for electric vehicles. While there is commendable clarity regarding stakeholders, model possibilities, emission-reduction strategies, state aid initiatives, and citywide prohibitions, the central challenge lies in the gradual pace of this transition. Notably, the persistent high costs of electric vehicles, primarily attributed to exorbitant battery prices and the raw materials involved, represent a formidable hurdle to widespread adoption. In this article, a comprehensive examination of the multifaceted aspects contributing to the delays in the shift towards electrified transport is proposed. By meticulously scrutinizing the intricacies of this delay, the aim is to provide valuable insights that can contribute to accelerating the adoption of electric vehicles. The exploration of these challenges is essential for fostering a nuanced understanding of the impediments hindering the transition and, subsequently, for devising effective strategies to overcome them. The analysis presented herein not only identifies the hurdles but also seeks to offer potential solutions and strategies that can drive the transformative change needed in the realm of electric transportation. Understanding and mitigating the barriers impeding the transition is crucial for fostering a rapid and successful shift towards electric mobility in Spain, ensuring a sustainable and efficient transportation landscape for the future.

Keywords: electric vehicles; business models; electric mobility

1. Introduction

In the rapidly evolving landscape of modern transportation, the ongoing transition to electrified transportation is a profound and paradigm-shifting development. This transition holds the promise of not only achieving environmental sustainability but also reducing dependence on traditional fuel sources. As governments, industries, and consumers navigate this transformative journey, it becomes increasingly evident that relying solely on state aid programs and citywide restrictions is insufficient to propel such significant shifts. Despite numerous analyses [1–3] underscoring the urgency of this transition in mitigating climate change, the actual pace of the shift remains suboptimal. Consequently, a nuanced examination of the diverse elements influencing this transformation is imperative.

A substantial impediment to the widespread adoption of electric vehicles (EVs) lies in the persistent and elevated costs, primarily dictated by soaring battery prices [4] and the intricate matrix of raw materials entwined in their production [5]. Moreover, the significant rise in demand for critical minerals for EVs raises concerns about sustainable extraction and supply chain reliability, especially regarding nickel and lithium production [6] and the risk of raw-material shortages [7]. Despite considerable advancements in battery technology, the barrier of insufficient battery capacity remains in the mindset of citizens [8], even though EV users rarely undertake long trips [9]. This social positioning contrasts with the fact that sizing high-capacity EV batteries is a contradiction regarding the sustainability of EVs [10]. As battery capacity grows, the expansion of fast-charging infrastructure for extended

journeys needs to increase. While commendable progress has been made, its deployment is still not covering peak demands [11], posing conceptual barriers to EV acquisition and driving planning needs, as well as a notable safety concern for users [8]. However, fast-charge infrastructure deployment has its own economic difficulties. According to Luiz Avelar [12], Senior Director of Strategy at Envision Digital, the charging infrastructure has high installation costs and logistical issues that limit the availability of charging stations, which will still be a problem, even with the expected cost parity with ICE vehicles by 2026, due to decreasing battery prices.

Additionally, the increased electricity demand from EVs poses a risk of grid overload [13], necessitating new investments in grid infrastructure and the improved management of intermittent energy supply. The high-carbon profile of current electricity grids undermines the environmental benefits of EVs [14], highlighting the need for grid decarbonization [15].

So many expectations lie in energy and mobility transition policies. “The Global EV Outlook” [16], supported by the EVI (the Electric Vehicles Initiative, a multi-governmental policy forum established in 2010), analyzes global electric mobility developments annually. The report explores EVs’ impact on energy consumption and emissions to offer insights for policymakers. It includes tools like the Global EV Data Explorer and Policy Explorer for the interactive exploration of EV data and policies. The key findings highlight a sustained growth in EV sales, projecting an overall increase of 31.1%, with potential reductions if incentives, particularly in Europe, diminish. They advocate increasing charging points to one per twelve vehicles and emphasize lowering EV acquisition costs by reducing operating expenses to spur adoption. The report concludes by stressing the necessity of policies to enhance affordability, expand charging infrastructure, and ensure sustainability in transitioning to electric mobility.

As observed globally, various authors underscore critical factors influencing the shift to electric mobility, such as infrastructure deficiencies, EV costs (especially batteries), state incentives, urban mobility policies proposed by local policymakers, sustainability concerns and raw-material shortages, and the various challenges associated with the electrical grid, as mentioned earlier.

Rogers’ Diffusion of Innovations theory [17] provides a valuable framework for analyzing the adoption of EVs within societies. This theory outlines several stages of adoption: knowledge, persuasion, decision, implementation, and confirmation, which can be applied to understand how EVs gain traction among consumers. Research indicates that factors such as perceived benefits, social influence, and compatibility with existing values significantly impact the adoption rates of EVs [18,19]. Together, these factors underscore the multifaceted nature of progress across various fields, integrating technology, policy, sustainability, consumer insights, and collaboration.

This article, as part of a comprehensive analysis, unravels the intricate complexities contributing to the delay in transitioning to electrified transportation. By meticulously dissecting the multifaceted challenges impeding progress, the aim is to shed light on these obstacles but also to illuminate potential strategies that can be employed to overcome them. Through this exploration, the goal is to facilitate a more expeditious and effective integration of electrified vehicles into mainstream transportation systems, thereby contributing to a sustainable, eco-friendly, and forward-looking future.

2. Materials and Methods

This study employs a comprehensive and systematic approach to analyze the critical transition to electrified transportation. The methodology begins with an extensive examination of the landscape, including key stakeholders, recent emission-reduction targets, governmental proposals for state aid, and the increasing number of municipal bans on high-emission vehicles.

This analysis informs the development of a business model that accounts for the second life of batteries [20]. To address the slow integration of electrified transport, this study adopts a multifaceted approach, structured around the following key areas:

- * **Stakeholder Identification and Analysis:** Key stakeholders are identified, with an exploration of their roles and vested interests in the transition to electrified transportation. The study also addresses the challenges in fostering collaboration among these stakeholders—a critical factor in the transition’s success.
- * **Market and Business Model Analysis:** Research into potential business models for EV, both in their primary and secondary life phases, is conducted [21]. This includes a detailed analysis of market trends [22], consumer preferences, and pricing dynamics within both primary and secondary markets. Additionally, the durability of batteries is scrutinized to challenge initially unfavorable estimates [23].
- * **Emission Reduction and Environmental Impact:** The study extends its focus to emission-reduction targets, with a thorough assessment of the environmental benefits of electrified transport. A comparative analysis of emissions between traditional vehicles and electric cars is undertaken, supplemented by a review of the literature on the challenges of meeting these targets.
- * **Policy and Incentive Evaluation:** The research also examines the impact of state aid, incentives, and municipal bans on reducing pollution and enhancing urban quality of life. This includes a critical evaluation of government initiatives and financial support programs, as well as an analysis of the effectiveness of municipal bans in curbing pollution [24–27].
- * **Battery Technology and Cost Analysis:** The study delves into the technical aspects of battery technology, focusing on battery durability and associated costs. This section analyzes the role of battery costs in the overall pricing structure of EVs [28], identifying the factors contributing to high vehicle costs, and reviews studies on battery aging and longevity [29].

By integrating these components, this study provides a holistic perspective of the challenges and strategies involved in the transition to electrified transportation. Through this research, we aim to offer actionable insights into accelerating this critical shift, emphasizing how to overcome the barriers related to cost, stakeholder collaboration, and policy effectiveness.

3. Results

As previously mentioned, a pivotal aspect involves the identification of various stakeholders within the system, focusing specifically on the Spanish territory. As illustrated in Figure 1, the relevant administrations offering incentives or punishing strategies are identified as key stakeholders. Subsequently, there are companies either receiving or providing aid, as detailed in Table 1. Another category comprises entities installing facilities for end-users, enabling qualification for assistance. These installations encompass chargers or systems for renewable energy generation, which are pivotal stakeholders for the transition towards the electrification of energy and mobility. Moreover, companies responsible for managing the electricity grid—Transmission and Distribution System Operators (TSOs and DSOs, respectively)—have to incorporate and oversee these changes. Furthermore, EV manufacturers are included along with associated sales centers. Lastly, research centers and universities contribute with the dissemination and transfer of valuable knowledge and innovations to propel the transition towards green electrification, receiving aid for technological advancements, even if not directly related to incentives.

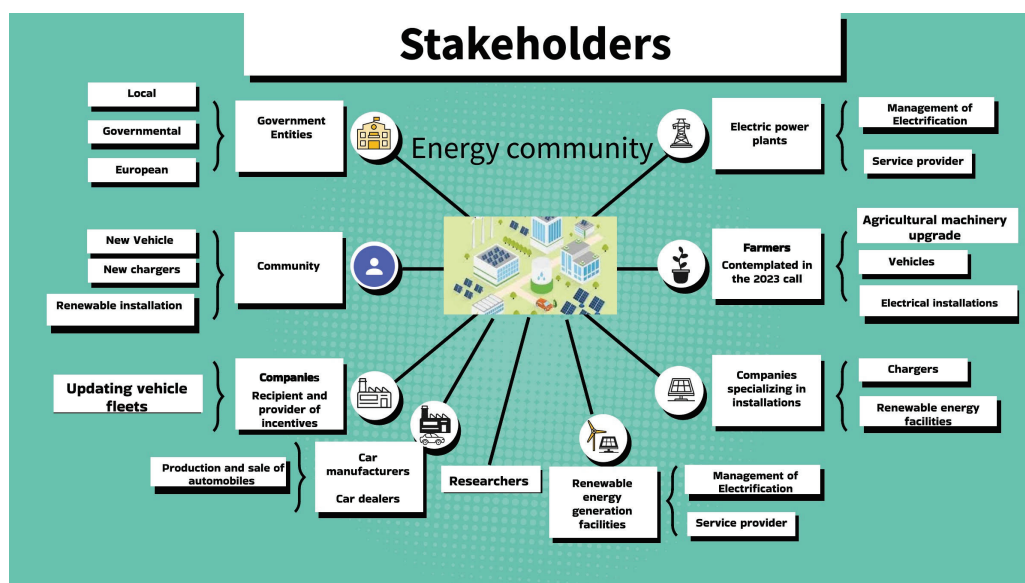


Figure 1. Identification of key stakeholders.

Table 1. Scrutinizing government initiatives and financial support.

Plan MOVES III (2022)	This program, promoted by the Spanish Government, offers aid for the purchase of electric vehicles, installation of charging points, and sustainable mobility projects.
Plan Renove (2024)	The Renove Plan incorporates incentives for acquiring fuel-efficient and environmentally sustainable vehicles, encompassing electric cars.
Local and regional support	Numerous cities and autonomous communities in Spain provide their own grants and discounts for the acquisition of electric vehicles. The availability and specifics of these programs may vary depending on the location.
Tax discounts	Some cities offer discounts on local taxes for electric vehicle owners.
Sustainable mobility programs in companies	Certain companies institute internal programs aimed at promoting the adoption of electric vehicles among their employees. These initiatives often involve offering financial incentives or establishing charging infrastructure within the workplace.

Regarding reward and/or punishment strategies, it is imperative to scrutinize the incentives predominantly provided by administrations, among other entities. While incentives at the European level are conceptualized, their execution and application fall under the purview of individual governments. As delineated in Table 1, various programs exist in Spain aiming to stimulate the acquisition of EVs and chargers. Noteworthy in this discussion are the farmers who, in recent years, underwent a fleet renewal, encompassing 1083 vehicles and machinery at a total cost of EUR 957,165. To gauge the efficacy of these incentives, four key indicators are proposed: the quantity of vehicles procured during the incentive period, the reduction in greenhouse gas emissions attributed to the transition to EVs, the utilization of charging infrastructure, and the return on investment. At a governmental level, this return could be measured by a reduction in overall environmental impact, calculated with CO₂ equivalent emissions, while, in terms of economic benefits, it could be quantified through a decrease in pollution-related taxes.

The global trajectory of EV purchases is evident [30]. Focusing specifically on Spain [31], there has been a notable surge in EV acquisitions in recent years, as validated by [32]. In 2023, a significant purchase of 120,000 units was recorded, representing a 26% increase in contrast to the previous year and an impressive 84% growth when compared to 2020. A

paper from the Banco de España [33] showcases the increase in vehicle purchases following incentive plans, which effectively play an important and useful role in the transition of vehicle fleets to cleaner mobility. Before any plan was in place, the share of EV sales in Spain was about 1%; just after the MOVES I program, it grew up to 3% on average per month during the 8-month duration of the plan; with the MOVES II program, it increased up to 5% in 5 months; and the last MOVES III topped the share up to 8%.

Innovative policy measures have also been used to accelerate the adoption of EVs worldwide. Zero-emission vehicle (ZEV) mandates, for example, require automakers to produce a certain percentage of EVs, pushing the industry toward cleaner transportation options [34]. Urban low-emission zones (LEZs) are another effective strategy, restricting the access of high-emission vehicles to certain areas, thereby encouraging the use of EVs. In Spain, large cities, such as Barcelona, have implemented these so-called low-emission policies that have driven the purchase of electric, hybrid, and even gas-powered vehicles by both individuals and companies operating in urban areas. These policies have proven effective in reducing emissions, although user acceptance remains limited [35].

Additionally, measures to enhance urban mobility have been introduced, including the increase in the percentage of EVs used in procurement processes for both small-scale mobility and public transportation. These subsidies, along with the incentives outlined in Table 1, represent the strategies that have been successful in Spain in recent years.

Concerning the charging infrastructure, a discernible deficit in the number of charging points has been observed. However, metropolises such as Madrid, Barcelona, and those along the Mediterranean coast are demonstrating readiness for the transition. On a global scale, a pressing need for a 30% increase in the number of charging points has been identified. These figures could be affected by an additional issue identified during the summer period: the queuing time at charging stations. The user-to-charger ratio ranged from six to eight, leading to waiting times of over two hours in addition to the approximately 20 min required for the actual charging process. In this sense, public–private partnerships have proven useful in developing the necessary infrastructure for EVs, such as expanding charging networks and offering incentives for businesses to install charging stations, even though it might not be the best option from a societal perspective. These policies promote EV adoption as they raise awareness of the commitment of both the public and private sector to electric mobility [36].

Shifting the focus to CO₂ emissions data, the transport sector stands out as a major contributor to greenhouse gas (GHG) emissions, which have experienced a consistent rise since 1990. The sector currently contributes nearly 20% of the total GHG emissions of the EU. In 2021, CO₂ emissions in Spain reached 19,447 megatons, reflecting a notable 9.15% increase compared to those in 2020.

Overall, C₂ emissions in Spain amounted to 272,244.4 Mt CO₂ Eq. in 2021, positioning the country in the 159th position among 184 countries in a global ranking by CO₂ emissions, arranged from least to most polluting. The subsequent reduction in emissions observed in 2023 (271,629.5 MtCO₂Eq) stands in stark contrast to the prevailing global trend of escalating C₂ emissions. This notable reduction in Spain is attributed largely to the increasing prominence of renewable energies within the energy mix. As elucidated by OTEA [37], the ascendance of solar energy in Spain has witnessed a more than fivefold increase since 2018, while wind energy has doubled during the same period.

Examining the evolution of CO₂ emissions per USD 1000 of GDP, which gauges the “environmental efficiency” of a country’s production over time, Spain emitted 0.13 kilos per USD 1000 of GDP in the previous period. Although this is higher than the 2020 figures, the reduction observed in 2023 indicates an encouraging improvement in these environmental efficiency metrics.

Focusing on future trends for EVs, sales are increasing, but several issues still affect consumer decisions. Major concerns include battery costs and capacity [5], as well as recharging infrastructure. To mitigate these issues, fiscal aid strategies have been implemented to reduce the impact of battery costs. Additionally, promoting the reuse and

reevaluation of batteries aims to lessen their environmental and economic impact during their first life. Ref. [27] evaluates the cost and carbon footprint associated with the second-life use of EV batteries in both residential and utility-level applications. The study highlights that repurposing EV batteries can significantly reduce waste and lower carbon emissions compared to traditional disposal methods. By extending the life cycle of these batteries, municipalities can postpone pollution and enhance sustainability efforts. The findings suggest that municipal bans on the disposal of EV batteries could further amplify these benefits by promoting recycling and reuse, thereby decreasing the overall environmental impact. However, the study also notes potential challenges, such as the economic feasibility of second-life applications and the need for a robust infrastructure to support battery repurposing [28]. These factors must be considered when analyzing the effectiveness of municipal bans in reducing pollution and fostering a circular economy in battery management.

However, as the number of EVs and second-life batteries increases, the stationary market may become saturated. To address this, utilizing battery capacity while still in the car is suggested through Vehicle-to-Grid (V2G) strategies. Current car batteries often exceed daily needs, allowing part of this capacity to be used in the energy market throughout the day, thus providing additional user benefits and reducing vehicle costs [10].

Another approach involves producing vehicles with smaller batteries that meet daily needs [21], although manufacturers are hesitant due to consumer concerns about insufficient capacity. Moreover, the development of small mobility solutions for urban areas will become increasingly important.

From the perspective of the electrical network, technological advancements can mitigate challenges in EV adoption by enhancing intelligent and cleaner charging infrastructure, ensuring a steady and stable power supply, and reducing electricity costs. Smart and flexible charging technologies enable EVs to distribute the charge over time and to supply unused power to the grid during peak demand and recharge during off-peak hours. This reduces both grid congestion and consumer costs [38]. Additionally, smart energy management systems integrate renewable energy sources and demand assets, optimizing load management and providing grid stability. AI-enabled battery monitoring and analytics support predictive maintenance, extend battery life, and improve recycling processes, thereby reducing the demand for new batteries and alleviating supply chain pressures.

As the transition to electric mobility accelerates, AIoT-assisted technology, smart charging, energy management, and advanced battery solutions address infrastructure, grid management, and mineral supply challenges [39]. These innovations support global efforts to reduce emissions and positively position the EV environment, especially considering the potential bans on combustion-engine vehicles by 2030 in some countries.

The reduction in emissions resulting from the incorporation of EVs is dependent on the energy mix of each country. Consequently, the benefits of adopting EVs may be limited in countries with an energy mix that relies heavily on non-renewable energy sources.

In this sense, from the various stakeholders described in Table 1, governmental entities are responsible for providing funding and implementing policies that support and promote this shift. Researchers are dedicated to advancing technological improvements and studying the impacts and effects of the different alternatives, whether in terms of charging systems, energy storage solutions, battery recycling, or overall energy optimization. However, considerable progress is still required in these areas, particularly in reducing the reliance on scarce materials and developing more-efficient recycling systems with lower energy consumption.

As the EV fleet expands, the electrical grid will need to be thoroughly reviewed and upgraded, and a comprehensive optimization of charging points, based on the projected global fleet, will be essential. This process involves both utility companies and installation firms. In this identification, the agricultural sector has also been included, as significant efforts have been made in Spain to update the machinery used, as previously discussed. Moreover, there is a need for greater awareness among consumers and society as a whole.

Thus, current efforts have not yet met expectations; consequently, continuing the same policies, albeit with greater stringency, is essential to accelerate the process of change. This should be accompanied by incentives, whether for renewable energy installations, charging infrastructure, or the renewal of vehicle fleets.

When focusing on the costs associated with EVs, it becomes evident that these expenses can be attributed to several interconnected factors. Primarily, the production costs of EVs are heavily influenced by the prices of battery components, which represent a significant portion of the total vehicle cost. The dependence on rare materials, such as lithium and cobalt, intensifies these costs due to volatile market prices and vulnerabilities in the supply chain [40]. Moreover, research indicates that economies of scale have not yet been fully achieved in the EV market, resulting in higher per-unit costs compared to conventional vehicles. The initial investment required for EV infrastructure, including charging stations, further compounds the financial burden on both consumers and manufacturers. Additionally, consumer perceptions and the limited availability of affordable models deter potential buyers, despite the long-term savings associated with fuel and maintenance. Addressing these challenges is essential for improving the affordability and adoption of EVs.

Recent advancements in battery technologies highlight the growing interest in lithium–sulfur (Li–S) batteries, which utilize sulfur as a cathode material. Li–S batteries are noted for their high theoretical capacity (1675 mAh/g) and energy density (2600 Wh/kg), making them a promising alternative to conventional lithium-ion batteries (LiBs) that face limitations in energy density and resource availability [27]. Note that sulfur is abundant and low-cost compared to cobalt in LiBs. However, Li–S batteries face challenges such as the shuttle effect, poor conductivity, and volume expansion during cycling, which hinder their practical application [20]. Recent trends also indicate a focus on sustainability and environmental impact in battery production, as seen in the EU’s proposed regulations. Table 2 summarizes the current load capacity and development status of various battery technologies.

Table 2. Summary of the current load capacity and development status of battery technologies.

Battery Type	Load Capacity (mAh/g)	Development Status
Lithium-Ion (LiB)	150–250	90%
Lithium–Sulfur (Li–S)	1675	60%
Metal–Sulfur	Varies (up to 1000)	50%

These emerging technologies also are playing a crucial role in overcoming the current barriers to the widespread adoption of EVs. Advancements in battery technology, such as solid-state batteries, are not only significantly enhancing energy density but are also reducing charging times and improving overall vehicle range. Meanwhile, the integration of smart grids is facilitating more-efficient energy distribution and management [23], enabling EVs to interact dynamically with the power grid, which helps in load balancing and reduces charging costs [22]. Additionally, the development of wireless charging infrastructure is poised to make electric vehicle ownership more convenient by allowing vehicles to charge seamlessly without needing physical plugs. These innovations collectively contribute to a more accessible future for electric mobility.

4. Conclusions

The ongoing transition towards the electrification of transportation in Spain marks a promising trajectory, supported by strategic government incentives. Despite the positive momentum, challenges persist. While commendable reductions in emissions and improvements in environmental efficiency have been achieved, the scale and efficiency of the charging network emerge as pivotal determinants for the sustained and widespread adoption of EVs.

The success of the electrification movement hinges on the seamless availability and accessibility of charging points throughout the country. A comprehensive expansion of the charging infrastructure is not just a logistical necessity but a strategic imperative to alleviate range anxiety among potential EV adopters, even though they would rarely undertake these trips. It also plays a crucial role in facilitating long-distance travel and supporting the integration of EVs into diverse urban and rural landscapes.

A well-developed infrastructure network can significantly contribute to reducing the required capacity of batteries, thereby optimizing the use of rare materials and improving efficient resource management.

Until such a reduction in capacity is achieved, the proposal includes utilizing batteries (inside the cars in their first life) as a primary support for grid stability.

Furthermore, there should be a concerted effort to enhance the development and implementation of small-scale mobility solutions within urban centers. This initiative aims to reduce emissions, alleviate traffic congestion that impedes smooth circulation, and mitigate associated stress for users.

Moreover, the emphasis on renewable energy sources, particularly the noteworthy surge in solar- and wind-energy contributions, underscores a commendable commitment to a sustainable and eco-friendly energy matrix. This transition not only aligns with global environmental goals but also positions Spain as a proactive player in the broader context of mitigating climate change.

In conclusion, while Spain has made commendable strides in the electrification of transport, the journey ahead necessitates a comprehensive and collaborative approach. Strengthening the charging infrastructure, coupled with sustained government support and technological innovations, will be instrumental in solidifying Spain's position at the forefront of sustainable and electrified mobility.

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Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric vehicle
GHG	Greenhouse gas
MDPI	Multidisciplinary Digital Publishing Institute
V2G	Vehicle-to-Grid

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Article

Sustainable Business Models for Innovative Urban Mobility Services

Adriano Alessandrini ¹, Fabio Cignini ^{2,*} and Fernando Ortenzi ³

¹ Department of Civil and Environmental Engineering, University of Florence, 50139 Florence, Italy; adriano.alessandrini@unifi.it

² Italian National Agency for New Technologies and Environment (ENEA), 00123 Rome, Italy

³ ENEA—Italian Agency for New Technologies, Energy and Sustainable Economic Development, 00123 Rome, Italy; fernando.ortenzi@enea.it

* Correspondence: fabio.cignini@enea.it

Abstract: Any sharing mobility service aims to make urban mobility sustainable to help reduce environmental impacts and improve the quality of life for all in cities. Many transport services are not currently self-sustainable. The Life for Silver Coast (LifeSC) opened its mobility services on 22 May 2021 and offered electric mobility services during the summer for a few cities in Tuscany. E-bikes and e-scooters can be financially neutral, and even profitable, thanks to the low costs of the vehicles, but they only see a high utilization rate in winter. Shared electric cars, meanwhile, are not profitable. A new shared service that is viable must be profitable to become widely adopted and significantly contribute to sustainability. A few key characteristics have been identified, and one has been tested with a new business model that combines ride-sharing and car-sharing. The innovative Ride Sharing Algorithm (RSA) has been tested based on data from a potential city, Monterotondo, where many commuters travel daily to Rome by train. The Italian census and local survey data allowed for the simulation of the scheduling of vehicle rides and an evaluation of the economic results, which could be positive if enough interest for such a system exists among the people, as at least 400 commuters from Monterotondo go to the train station daily in the morning and return in the afternoon. Such a transport demand would justify a new commercial sharing service by using the model tested with the RSA algorithm.

Keywords: shared mobility; transport services; business model; sustainability; ride-sharing; car-sharing; transportation

1. Introduction

The transport sector, as the largest carbon emitter ([1,2]), is central to the climate crisis and the transition to a Net Zero economy [3], yet it has shown no clear emissions reduction. This implies a rapid and radical action is needed to decarbonize transport. More intensive use of fewer vehicles can effectively cut emissions, but there is currently no coherent national or local policy framework for the integration of shared car use with other mobility options. This lack of integration, especially where public transport is limited, hinders progress. Resistance to sharing is due to the wrong questions being asked; the focus should be on enabling greater levels of sharing and innovations that make not owning a car more accessible [4].

This article is an extended version of a conference paper presented at the EVS37 Symposium (COEX, Seoul, South Korea, 23–26 April 2024) [5]. The paper aimed to review the literature on sharing vehicles (mostly electric). Then, it analyzed the Life for Silver Coast (LifeSC) results, which involved the authors through direct design and experimentation, survey, data collecting, and results evaluation. The results promise positive benefits for commuters, entrepreneurs, and, last but not least, the environment. However, the economic results of e-car sharing are still negative.

This article suggests that several business and transport-sharing models may bridge the gap uncovered by LifeSC and other experimental projects. It proposes a use case combining project outcomes, authors' experiences, and available commercial solutions. It also simulates a real case scenario, based on Italian census data, of a feasible business model with a dedicated algorithm.

The Life for Silver Coast (LifeSC) project began its public mobility services on 22 May 2021, and focuses on developing and testing new electric vehicles and mobility services in the regions of Orbetello, Monte Argentario, and Isola del Giglio. It provides land and water electric transport services (like minibuses, e-boats, e-bicycles, e-scooters, and e-cars). All these services are integrated into a single mobility platform, allowing users to plan their travel, purchase tickets, and book and use the services through a "one-stop-shop" system. Professional drivers provided the minibus and e-boat services, which worked via fixed scheduling. So the literature review in this article focuses on commercial sharing services for urban mobility, especially e-cars.

As expected from the literature, the LifeSC ended with negative results for e-car sharing services, while e-scooter and e-bike sharing services were positive. These positive results do not properly take into account the winter period, and so the real results with a year of service average would be worse.

Our research efforts focus on increasing the efficiency of sharing systems, which are too underutilized today, but do not involve new business models. This article discusses possible features and technological solutions to make the business positive, even in small peripheral areas or towns. A new business model was therefore tested with dedicated simulations and real transportation data; the purpose of this simulation was to demonstrate its feasibility as a commercial solution for a sharing service.

Beyond this introduction, this paper is organized into four sections. Section 2 details the literature on sharing transport services, models, and their benefits. Section 3 describes the LifeSC project, its results and lessons learned, and identifies a few solutions to make electric vehicle sharing profitable. Section 4 is devoted to the algorithm description and simulations of the new ride-sharing business model. The Section 5 concerns conclusions and future development.

2. Literature Review

The concept of car-sharing, first defined by Susan Shaheen, explores the impacts of vehicle-sharing systems on society and mobility (one of the latest publications [6]). No single business model for sharing services dominates ([7]), suggesting that these services aim to reduce vehicle ownership by encouraging infrequent car users to opt for shared vehicles. These models can vary significantly in tourist areas due to seasonal demand fluctuations. Shaheen's research indicates that the initial motivation for sharing services was to provide the benefits of car mobility without the associated purchase and maintenance costs [8]. Advances in digital technologies have made car-sharing more attractive, enabling remote bookings, vehicle access, and real-time tracking. These developments have established car-sharing as a viable alternative transport mode in various urban areas [9].

Business car-sharing models are typically categorized into round-trip, point-to-point, non-profit/cooperative, and peer-to-peer (P2P) sharing. However, differences exist even within these categories. Remané proposed a detailed classification scheme in 2016 [6] to address this, as shown in Table 1.

It translates the aforementioned technological advances into creating value-added economic solutions; it can be used for more accurate analysis than existing operators and the systematic discovery of new business models. This taxonomy, later adopted by SAE International in 2018, aims to standardize terms and definitions [10].

The paper [11] describes the socio-demographic factors influencing the demand for different car-sharing services. A study titled "I like it, but I don't use it" suggests that free-floating electric vehicle services are generally preferred [12]. It also notes that the decision to use car-sharing services depends on service characteristics, trip type, and service quality. High-quality

services with accessible vehicles are crucial for maintaining active users. Research [13] has shown that fare is critical in attracting users. As the references [14–16] suggest, the attractiveness decreases in sprawled cities with low inhabitants where transport lacks frequency and capillarity. Many studies have investigated the attractiveness of a sharing service in areas not covered. These studies are based on surveys and various demand transport models [17–19].

A simulation method was developed and tested in Turin to define optimal fares based on user profiles, considering mobility needs, usage hours, frequency, and urban congestion levels [20].

Low utilization rates are a common issue in car-sharing, often due to demand polarization. A proposed solution involves user-based vehicle relocation, where users are incentivized ([21]) to park in high-demand areas, increasing vehicle availability and operator profits.

Table 1. Taxonomy of the different car-sharing services and business models (Reprinted from Ref. [22]).

Dimension		Characteristics					
Value proposition	Destination	Roundtrip		One-way		Roundtrip with option for one-way	
	Minimum duration	At least 1 day or longer		Hourly		By the minute	
	Vehicle types	Identical or very similar vehicle available			Very different vehicle available		
	Additional benefits	Free/discounted parking		Delivery by owner		No additional benefits	
Interface	Vehicle booking	Reservation and fixed return time		Instant access and fixed return time		Instant access and open ended	
	Vehicle access	Manual key handover		Lock box for key		Automatic	
Service platform	Booking platform	Proprietary			Open for other providers		
	Parking infrastructure	Dedicated carsharing station	Only attached to other stations		Street parking		Private homes
Organizing model	Vehicle ownership	Operator owned			Private customers		
	Vehicle maintenance	Maintained by operator			Maintained by private customer		
	Vehicle refueling	Refueled and paid by owner		Refueled by driver and paid by owner		Refueled and paid by driver	
Revenue model	Price structure	By duration only			Combination of duration and distance		
	Transaction-based revenues	Service fee (including insurance)			Commission and/or insurance		
	Continuous revenues	Membership fee from drivers	Service fee from car owners	Subsidies	Advertising	Combination of multiple sources	No continuous revenues
	Organizational ownership	Private company		Cooperative		Government owned	

Another strategy is to offer different services at different times, catering to commuters in the morning and central city activities during the day. The analysis of the (simulation) results shows that, with a user-based relocation strategy, the number of rejected bookings can be significantly reduced, even with a relatively small number of vehicles, and, at the same time, the operator's profit can be increased by satisfying more demand with the same vehicle fleet. Another way to improve the utilization rate of shared vehicles is to guarantee different services by the same fleet at different times. In the early morning, the service is oriented towards commuters and would be conceived to have them driving toward the attractive destinations of the city.

In contrast, in the middle of the day, the service remains concentrated in the center of the main centrality. The research [23] has studied an interurban car-sharing service by modelling the behavior of potential users through a stated preferences survey, demonstrat-

ing the considerable theoretical attractiveness of a service aimed at bringing commuters from other smaller municipalities of the same province to Salerno city.

P2P sharing services, where individuals share vehicles, have gained attention. In 2012, Shaheen [24] found 33 personal vehicle-sharing operators worldwide, indicating the potential of these services to enhance transport sector connectivity and reduce vehicle ownership.

Car-sharing services have demonstrated various positive impacts, including:

- Environmental benefits [25,26];
- Reduction of car-ownership rates [9,27];
- Reduction of vehicles-miles travelled [25,26];
- Efficient transportation alternative, particularly when it complements existing transportation modes or supplements off-peak public transit services [28,29];
- Decreasing the demand for cars, reducing traffic and parking congestion, and increasing social cohesion among sharers [9,26,30–32].

A recent evaluation [33] identified 245 car-sharing operators worldwide; 58% station-based, 30% free-floating, and 11% P2P. The I Share Life project [34] has at least three fundamental objectives in common with LifeSC. These are:

- Maximize vehicle utilization rate;
- Serve customers with different needs who would not guarantee intensive use of the vehicle but who, having complementary needs, can do it together;
- Identify a main customer (preferably a business) who acquires (buys or rents) electric vehicles and who, not using them entirely, makes them available to others on certain days and within certain time slots so that they contribute (even if minorly) to lowering the overall costs of vehicles.

Other considerations come from sharing the same space; sharing a vehicle reduces privacy as well as security [31] and personal safety. For example, sharing raises the risk of contagion, as demonstrated by the COVID-19 pandemic, which lowered people's sharing propensity in LifeSC (evaluated with surveys), which opened its service in the summer of 2021 with the first re-openings of public transportation.

This effect was partially mitigated in LifeSC thanks to explicit (and well-publicized) sanitization protocols, convincing people to re-commence sharing rides through information and education.

Two noteworthy papers have addressed the issue of education and the problem it poses for the use of shared services [35] and electric vehicles [36]; both will be needed with technological solutions to share rides without any contagion risks.

Lastly, several papers have investigated the role of the legal framework (see [15,37,38]), which sets up the basis for behavioral change in people. It could “help” with pushing measures (Limited Traffic Zone—LTZ, circulation taxes, parking lot absence, enforcement in traffic control, and no parking zones, etc.) These measures force people to find other solutions for transport that they had not yet considered, such as giving up their car and using public sharing systems. It is worth noting that a specific information and education campaign for people and stakeholders should accompany these solutions. It should aim at understanding people's needs, spread knowledge of the benefits of sharing, and avoid misunderstandings (see [39,40]).

In conclusion, effectively managing and integrating car-sharing services are essential to attracting and retaining users, ultimately contributing to more sustainable urban mobility solutions.

3. Life for Silver Coast Project: Outcomes, Lessons Learnt, and New Business Models

This section concerns the Life for Silver Coast project, the lessons learnt from this experience, technical parameters, performances, costs, revenues, and economic results. It also discusses possible solutions to achieve viable commercial models in real applications.

LifeSC introduced three vehicle-sharing services: e-bikes, e-cars, and e-scooters. Initially, all journeys were round-trips with pre-established parking areas, but the system

transitioned to a free-floating model for flexibility. Initially, it was cluster 1 ([22]), where all journeys were round-trip.

The Life for Silver Coast (LifeSC) project began its public mobility services on 22 May 2021, and focused on developing and testing new electric vehicles and mobility services in the regions of Orbetello, Monte Argentario, and Isola del Giglio. The services provided included collective options, such as electric minibuses and boats in the Orbetello lagoons and at sea, and individual services, like sharing e-bicycles, e-scooters, and e-cars. All these services were integrated into a single mobility platform, allowing users to plan their travels, purchase tickets, and book and use the services through a “one-stop-shop” system. The vehicles were different and multipurpose, so the project switched to a service that covers two types: cluster 4 (free-floating services) and cluster 5 (one-way services), with stations to pick up and leave the vehicles (hubs for bicycles and charging stations for cars and scooters).

This section is divided into three parts: the economic results and outcomes from the LifeSC project, the lesson learnt from LifeSC, and new business models to bridge the gap.

3.1. The Economic Results and Outcomes from the LifeSC Project

The tariff structure used is challenging to classify compared to others in the past; those applied in LifeSC demos are indicated below (<https://www.lifeforsilvercoast.eu/en/summer-2021/>, accessed on 30 August 2024):

- E-bikes were rented for €0.21 per minute up to the first hour of use, for €19.90 from 1 to 3 h, for €26.90 from 3 to 6 h, and €34.90 after 6 h for the daily rate;
- E-scooters were rented for €0.25 per minute up to the first hour of use, €22.90 from 1 to 3 h, €29.90 from 3 to 6 h, and €39.90 after 6 h for the daily rate;
- E-cars were rented for €0.28 per minute up to the first hour of use, €26.90 from 1 to 3 h, €32.90 from 3 to 6 h, and €49.90 after 6 h for the daily rate.

The tariffs changed with the rental time, covering more business models with the same service. The pay-by-minute model typical of free-floating services and used for short trips to move quickly in a selected area was supplemented by the tourist-excursions model typical of the short-term rental for bicycles and (mostly) scooters in tourist areas to reach a faraway beach or another tourist attraction and by the daily-rental model typical of people needing to travel by car for one or a few days.

This last model was mostly used to drive to Florence or Rome because the car was rented in Orbetello with the battery fully charged and driven for almost its entire available range (from 200 to 300 km), where the electric car could access the central LTZs and be parked for free in a parking spot reserved for EV charging.

The person would then spend the entire day in the city center and retrieve the car fully charged to drive back to Orbetello. It is an unconventional use of electric vehicles but has significantly increased the rental hours (and therefore the utilization rate) and responded to a specific need. Naturally, from the point of view of sustainability, it might have been better to favor the use of the train to reach both Florence and Rome, but financially, it helped the service.

Table 2 shows the overall results of the LifeSC sharing service. The project usage rates were: e-bikes 22%, e-cars 16%, and e-scooters 7%.

Table 2. LifeSC main results.

Parameter	Unit	Car	Scooter	E-Bike
Number of rents	#	907	116	110
Average rents per vehicle	#	302.3	4.64	4.78
Total rental time	-	587 h 29' 24"	586 h 41' 31"	298 h 51' 10"
Total distance travelled	Km	9394	5543	1300
Service period	Day*vehicle	156	349	57
Utilization rate	%	16	7	22

Overall, the three vehicle-sharing services collected €12,120 in revenues, divided as follows:

- €4986.49 was collected from the cars over 156 total days of availability for all vehicles, which, extended throughout the year, would make the estimated income of a car over the course of a year 11,650 €/year*vehicle;
- €5387.30 was collected from the scooters in 349 total days of availability for all the scooters, which extended over 365 days, would make the estimated income for a scooter 5635 €/year*vehicle;
- €1764.10 was collected from bikes, with bikes available for a total of 57 days, which extended over the 365 days of a year, brings the expected income for a bike to 11,500 €/year*vehicle.

The annual costs of sharing services were the following:

- **Vehicle Depreciation Costs:** These costs were determined by dividing the purchase cost of the vehicle by its years of use. Shared cars typically travel 10,000–12,000 km/year for a maximum of 5 years, after which they require replacement due to obsolescence and safety concerns. Scooters and bikes have even shorter lifespans. So the purchase cost was divided by five for cars and three for e-scooters and e-bikes.
- **Fixed Ownership Costs:** These encompass property taxes and insurance. Insurance expenses vary based on the number of vehicles insured, usage patterns, and the initial cost. A standard cost of €1000/year per vehicle has been applied here. Smaller, cheaper scooters and bikes, despite their lower value and speed, incur higher insurance costs due to unfavorable accident statistics.
- **Maintenance:** based on local market research, maintenance is typically calculated as a percentage of the vehicle's purchase price, about 5% for traditional vehicles and 2% for electric ones annually.
- **Washing Costs:** each car required a weekly wash at €6 per wash. Scooters and bikes can be cleaned every two weeks, with each wash costing €4.
- **Personnel Costs:** this covers vehicle repositioning, washing, recharging (where applicable), maintenance, and emergency interventions. The number of people required depends on the service offered. In the LifeSC, a person managed 3 cars, 25 scooters, and 23 bikes. the exact time allocation for each service is unknown, so it was assumed to be evenly distributed for calculation purposes.
- **Energy Costs:** actual energy consumption costs were not billed to the service manager during the project, as the energy provider was a project partner and specific energy consumption data for each vehicle was unavailable; these were therefore estimated based on average energy consumption.
- **Infrastructure Investment Costs:** These were evaluated by dividing the total infrastructure expenditure by the useful life of the infrastructures (including depots, workshops, and charging stations). In this project, only the e-bike sharing service required a dedicated infrastructure to be maintained and amortized; the others were demanded by third parties, which also managed other services.

Table 3 compares the vehicle and operation costs of the three services and shows the energy evaluation. For example, the energy costs were 0.45 €/kWh. This parameter is an average value based on billing data provided by EnelX, the partner of the project, across the whole experimentation period. Public data by the Italian Regulatory Authority for Energy, Networks and Environment (ARERA) are available at: <https://www.arera.it/dati-e-statistiche/dettaglio/andamento-del-prezzo-dellenergia-elettrica-per-il-consumatore-domestico-tipo-in-maggior-tutela>, accessed on 20 August 2024), and the cars had an average consumption of 0.2 kWh/km; so a car costed 0.09 €/km. The car fleet travelled (overall) 9394 km in 156 days*vehicle of operation, expanding from 156 to 365 days; each vehicle was expected to travel 21,980 km/year, costing 1980 €/year of energy.

Table 3. Operation and energy cost comparison between the three services.

Cost Per Vehicle	Unit	Car	Scooter	E-Bike
Purchase (VAT included)	€	34,000	2460	1200
Number of vehicles	#	3	25	23
Years of depreciation	Year	5	3	3
Depreciation cost	€	6800	820	400
Insurance and circulation	€	1000	1000	1000
Maintenance	€	680	50	24
Washing (52 weeks/year)	€	312	104	104
Personnel	€	3333	400	440
Infrastructure	€	0	0	330
Sub-Total Operational Costs	€	12,125	2374	2298
Energy cost	€/kWh	0.45	0.45	0.45
Energy consumption	kWh/km	0.20	0.05	0.02
Distance travelled	km	9394	15,510	1330
Days of operation	days	156	349	57
Equivalent yearly distance	km	21,980	16,221	8516
Sub-total energy costs for a year of service	€	1980	130	80

In the LifeSC demonstrations, bikes were stored and recharged within technological hubs; each costed €20,000 and accommodated 6 bikes with 10-year life expectancies. Amortizing the cost of the infrastructure on the 6 bikes over 10 years added a further cost of 330 €/year*vehicle to the e-bike costs.

The annual cost of sharing one vehicle is the sum of operation and energy costs (sub-total from Table 3).

It equals 14,105 €/year*vehicle for cars; 2504 €/year*vehicle for scooters; and 2378 for e-bikes, €/year*vehicle. Though costs (and revenues) are commercially sensitive data not commonly publicly available, validating their share in the balance is possible.

Table 4 shows the share of the different costs, with data collected by the Rome mobility agency (Roma Servizi per la Mobilità) [41].

Table 4. Direct cost component shares, translated from the Rome Car-sharing Service (slide 25).

Direct Costs Component Share	Percentage
Fuel	14%
Car wash	2%
Vehicle rental (depreciation, maintenance, insurance, and taxes)	36%
Personnel	24%
Call center	12%
Technologies	10%
Administrative costs	2%

Table 5 compares results from the Rome service with the ones from LifeSC, where this latter used only the first four categories and accounted for the first.

Table 5. Results comparison between Rome and LifeSC use cases.

Direct Costs Component Share	Rome	Rome Re-Scaled Value	LifeSC
Fuel/energy	14%	18.4%	13.1%
Car wash	2%	2.6%	2.1%
Vehicle depreciation	36%	47.4%	60.1%
Personnel	24%	31.6%	22.0%
Total	76%	100%	100%

The difference in categorizations between the Rome and LifeSC use cases forced us to re-evaluate the Rome results to fit with LifeSC (see the relative column “Rome re-scaled

value”) by using a linear proportion. The Rome car-sharing service cost of technologies, administration and the call center are (overall) 24% of the total service costs (Table 4), but in LifeSC they were neglected. The linear proportion method neglects the same categories of LifeSC in the Rome case and re-scales their percentages to 76% (i.e., Rome personnel represent 31.6% of the 76%).

LifeSC car costs, including depreciation, taxes, insurance, and maintenance, equal 60% of the annual cost; in Rome, it was only 47%. On the contrary, fuel/energy accounts for 13% of LifeSC’s costs, and 18% of Rome’s. These differences align with expectations as the LifeSC vehicles were electric (more expensive than traditional ones), and they were not leased or rented but purchased, which had a higher overall cost, but electric energy is cheaper than fuel. Car wash costs were in line, and LifeSC’s personnel costs were cheaper (22%) than Rome’s (32%).

The personnel cost is a highly relevant factor; one person did manage the services in the demonstration, but the demonstration period was too short to consolidate the value. On the other hand, Rome had a much more dispersive environment, and even the easy task of reaching the carwash might have required much longer than in Orbetello. Overall, the magnitude of the calculated shares is in line with expectations and the Rome experience.

Financially, the services generated revenues of €12,120, divided among e-cars (€4986.49), e-scooters (€5387.30), and e-bikes (€1764.10). Costs included vehicle depreciation, insurance, maintenance, washing, personnel, and energy, totaling annual costs of €14,105 for e-cars, €2504 for e-scooters, and €2378 for e-bikes. The balance between costs and revenues per year is extraordinarily positive, so positive that it is unlikely. These are as follows:

- The cars have 11,560 €/year*vehicle of prospective revenues and 14,105 €/year*vehicle of prospective costs, losing 2455 €/year each; i.e., just over 17% of the annual cost is not covered by the revenues;
- The scooters have 5635 €/year*vehicle of prospective revenues and 2580 €/year*vehicle of prospective costs, earning 3131 €/year each or more than 125% of the expenses is profit;
- The bikes have 11,500 €/year*vehicle of prospective revenues and 2318 €/year*vehicles of prospective costs, earning 9122 €/year each, i.e., the net profit is almost four times the cost invested.

3.2. The Lesson Learnt from LifeSC

From LifeSC data, e-bikes were used 22% of the time they were available, cars 16% (also thanks to several multi-day rentals that extended the rental times encouraged by the maximum daily rate), and scooters 7%. The e-bike data is less robust than the others because not all bikes were available at the same time as there were not enough active stations, and the e-bike sharing model was station-to-station; their availability is therefore calculated as a sum of the times each e-bike was made available for rental. However, over nearly four months, from May the 22nd to 21st September (when data were collected), 23 e-bikes, instead of being available more than 2500 e-bike*days, were available for only 57.

These data are from the summer of 2021, in the thick of the COVID-19 pandemic. The tourist flow has been verified to check whether the summer of 2021 was less attractive for tourists than the preceding ones going back to 2019. According to the local Chamber of Commerce data for 2021, the tourist flow was slightly above the data for 2019.

The decrease in international tourist presence was more than compensated for by the increased presence of Italian tourists. There was marginally less presence in hotels and more in summer houses (whether rented or owned). Overall, the COVID-19 pandemic did not influence the tourist flow into the area for the summer of 2021.

The e-bike balance is biased by only 57 days of availability for 23 bikes (less than 3 days per bike on average), maybe due to the hub (the rental stations) being late and the 23 bikes not being available altogether, which had increased the utilization rate of the few bikes available. These rates were influenced by the limited availability of the e-bikes and the differing rental purposes for each vehicle type, such as daily rentals for long-distance trips to cities like Florence and Rome.

As reported in the Chinese study, a realistic service has an average utilization rate of 4% to 10%; it reaches 15% (only in peak hours with some other conditions). So the average of 20% measured in Orbetello seems overestimated. The e-scooter service had a very positive balance, with a utilization rate of only 7%. The bike service would have a positive balance with a similar utilization rate. Each bike would collect about 4200 €/year*vehicle, still nearly twice the costs.

The utilization rate is the cornerstone of the profitability of any sharing services.

The studies [42–44] suggest a few ways to raise the utilization rate by optimizing intermodal hub vehicle location with predictive analysis of traffic and transport demand and using an operator that can relocate the vehicles just in time for their utilization; indeed, such approach could solve the problem in short term, but it requires wide investigations of the territory and its peculiarity (it cannot be applied everywhere) with real data simulations on booked services, and it should be repeated with change of boundary conditions.

Another way to raise the utilization rate is reducing the number of vehicles, but this affects the quality of service with a twofold negative impact. Firstly, it reduces the transport demand, and even the remaining demand loses confidence in the system, which would negatively impact the possibility of users making radical choices like giving up private vehicle ownership, which is the main contribution to sustainability sharing services. This utilization rate, obtained for the summer months, was considered constant throughout the year. This assumption can be plausible for cars (a limited number of vehicles used mainly by permanent residents even in summer) but is much less so for scooters and bicycles, which will be affected by weather and environmental conditions.

If the utilization rate for bikes and scooters were 7% in summer (3 months of the year) and 1% in the other 9 months of the year, this means an average value of 2.5%, the equivalent revenues being 1800 €/year*vehicle for bikes and 1900 €/year*vehicle for scooters. These more realistic projections for using scooters and bicycles over the year would bring all three balances into negative territory.

It is worth noting that the budgets of the three shared services are neutral if the company costs, mobile APP and IT services costs, and remuneration of capital and personnel are not paid by the service revenues but “offered” by local (or not local) supporters and partners. Such a situation is typical of services organized by municipalities or municipal companies that use existing staff, structures, call centers, and public funds to purchase (or build in-house) IT services for mobility.

To make any of these services an appealing investment for private investors, who use their risk capital and expect remuneration, supplying these services is not convenient. The critical parameter remains the utilization rate, which should be enhanced. Separate studies are required to improve it due to significant differences in vehicle costs between cars, scooters, and bicycles. The utilization rate measured for cars (16%) is insufficient to even the balance. Increasing it above 16% for the whole year is extremely difficult; as a comparison, the car-sharing service managed by the mobility agency of Rome (a much more populous municipality), directly measured by CTL of La Sapienza University in 2012, has a utilization rate between 13% and 19%, and for a sharing business model with fixed stations this extends rental times. Those rates are also aligned with other services, such as free-floating car-sharing, which varies between 15% and 25% during peak hours [45].

Repositioning vehicles dynamically to follow demand can increase the rate. Still, enabling automatic cars requires either many human resources that worsen the balance or a technological revolution. The 7% utilization rate measured for scooters would be widely sufficient to ensure profitability if it could be maintained throughout the year. For example, this goal seems difficult to achieve in winter without a full (or partial) relocation. In any case, sharing bikes and scooters in winter is less doable due to climate conditions.

On-demand management and a personalization of the relationship between customer and carrier would allow for the development of several new connected business lines that would never be applicable otherwise.

3.3. New Business Models to Bridge the Gap

This section discusses how to deploy a potentially profitable sharing service based on background and LifeSC experience; thus, it outlines the key features a vehicle-sharing service must have to be profitable outside the central areas of large cities where the isotropic demand allows for a free-floating sharing model. Vehicle sharing is beneficial when it allows citizens to live without owning cars.

Any such service should not compete against conventional mass transit but be complementary, especially when and where transits are less effective. Generally speaking, transport demand is highly variable throughout the day, the week, and the year. Dimensioning the fleet based on maximum demand would have a negative financial impact; dimensioning it on its lower levels would mean not supplying a good enough service to build customer loyalty.

To deploy a profitable vehicle-sharing service outside central urban areas can be done using five key strategies, each described in the following paragraphs:

- Sharing rides at peak hours and in directions complementarily to public transport;
- Self-repositioning of empty vehicles;
- Shortening or eliminating charging times;
- Differentiating vehicles to lower costs and allowing different uses;
- One integrated service to cover all mobility needs.

3.3.1. Sharing Rides at Peak Hours and in Directions Complementarily to Public Transport

One solution would be to mix car-sharing and ride-sharing. At peak times (and for prevalent directions), the customer rents a seat instead of renting the vehicle. In contrast, the standard free-floating business model is adopted in off-peak times and directions.

The ride-sharing model can work even better if the service is integrated with other “scheduled” transport modes (such as trains or metros). This way, all people from one area travel together toward the transport hub (or vice versa, getting off the train to reach their home). One of the customers drives the car, and the others are passengers. Rental costs are shared (and therefore, services can be used daily), and fewer vehicles are needed because some of them are relocated and can be used again.

A second innovation is also needed to enable this business mode to work. It can be the “on-the-fly” driver exchange. When a pool of customers travels, their trip foresees at least one stop for each destination required by the person involved. The innovation could be adding one more stop (is necessary and if it does not match other scheduled stops) to pick up the driver of the next pool. So, this little detour allows the customers in the first pool to reach their destination, and the vehicle can continue its trip without parking and the customer is picked up before (they have to drive).

Vehicle parking includes the parking slot search, parking, and the closing of the rent (and other non-remunerative actions that require a small amount of time), which could lead to time wasted. If the next driver is not picked up during the trip, when the vehicle is available, it can be too far from the vehicle, while if the previous pool reaches him directly at his home, it can be more productive in terms of time and quality of service.

When looking for a vehicle to rent, each customer must state the origin, destination, desired travel time, and drive availability if required. This service can be implemented quickly thanks to recent improvements in ICT technologies. This new feature can solve the repositioning problem studied in Genova [21] without the inconvenience of parking the car far from the desired destination and could increase the perceived quality of service, which has been demonstrated [12] to be crucial to customer satisfaction.

3.3.2. Self-Repositioning of Empty Vehicles

Vehicles already need much less repositioning with the ride-sharing and the on-the-fly exchange, especially in small places like the LifeSC locations, where picking up the next customer at the “other end” of the municipality only increased the travel by no more than

5 min, while reaching the doorsteps of the destination without the need for parking saves much more than that.

However, having a customer wait for a car when the other one is arriving is still a matching problem with uncertain results and off-peaks; when the demand is deficient, empty-vehicle repositioning might still be needed.

As described in [46–48], technology exists for empty automated vehicles driving at low speeds along pre-certified infrastructures. For example, the patent [49] aims to convoy multiple vehicles (of various types together) with a safeguard mechanical connection to guarantee the same trajectory for all. It also uses a steering mechanism as a backup for automated vehicles (with a steer-by-wire system).

Though this is less certain, even the legal framework might allow it (up to a certain extent and in specific locations). The other technological option to reposition empty vehicles at low cost is to have one driver driving a convoy of up to 10 vehicles (depending on the country and its road regulations, the convoy can be up to 18.5, 32, or 60 m long).

There must be a large enough fleet and a big enough demand to justify repositioning that many vehicles simultaneously. It would be difficult to pay a driver for less than six vehicles at once to reposition. Besides, even to ride an automated vehicle (sharing or not) will cost more than a traditional one, but the people willingness to pay for such a service could be higher and this could justify the investment [50].

3.3.3. Shortening or Eliminating Charging Times

The utilization rate can rise by decreasing vehicle idleness, even for recharging. It is not just a matter of increasing a vehicle's mile range with one charge; the charging strategy must change. There are several technological options to do this, ordered from the easiest to the most complicated:

- Use hybrid vehicles instead of electric ones. Bringing back refueling (customers can do it in exchange for discounts) and extending the range when the vehicle is used for longer trips.
- Faster wireless automatic charging at high power would reduce charging times and the burden on the customer. However, this requires a feasibility investigation because such charging infrastructures are not easy to implement everywhere; e.g., one of LifeSC's issues came from the legal and formal authorization (on-the-road installations) of "static" charging stations and bicycle hubs.
- Online fast charging, analogous to the overhead electricity line used by trams, a few main corridors can be electrified (i.e., be "energy-active") and recharge the passing vehicles. Those technologies would eliminate any need for charging stops, especially in urban settings.

3.3.4. Differentiating Vehicles to Lower Costs and Allowing Different Uses

The vehicle purchase cost impacts the profitability of the models proposed. A mixed fleet composed of many lighter vehicles (slower and cheaper, such as mopeds or microcars); standard vehicles (cars); and a few larger vehicles (mini-vans of up to nine seats) can be a good trade-off. Urban service exploits small vehicles assisted by the larger ones to fulfil most peak-hour transport demand by using car-sharing mixed ride-sharing. Moreover, this second vehicle type expands the covered area by offering interurban trips, especially for off-peak rentals.

Such a mix allows for the selection of different power trains for the various vehicle types, and, as demonstrated in [51], allows for increased efficiency (reduced energy consumption and circulating vehicles for the same transport demand). Larger and standard vehicles can be hybrid, and lighter ones can be electric and have fast charging.

3.3.5. One Integrated Service to Cover All Mobility Needs

Overall, the new service will need to respond to all the customers' mobility needs wherever they need to go with whoever (e.g., pets or babies) at whatever time. This means that every trip needs a vehicle appropriate to its size.

A convenient mobility solution for a standard commuter journey may be a train trip with a shared car waiting for the last mile trip at the arrival station. A crucial requirement is that the customer can plan, book, manage, and have all the information through the same integrated tool.

This solution will increase customer confidence in the service and boost the probability of convincing them to give up vehicle ownership and completely embrace sharing, which will positively affect urban space consumption.

Even more important is that increasing customers' use of shared vehicles can make the balance of the services positive, thus relieving the need for cities to subsidize and sustain shared mobility services.

Many attempts to create a MAAS (Mobility As A Service) integrated platform to have a one-stop-shop platform to access all transport services are underway. However, the main problem has been to "force" every service to be reachable by the same platform. An interesting approach to open innovation and data sharing has been proposed by [52].

4. The New Business Model: Algorithm Description and Simulation of Transport Service in Monterotondo (Rome)

The Ride-Sharing Algorithm (RSA) aims to optimize vehicle use, reduce operational costs, and provide a reliable, integrated service, promoting sustainable urban mobility.

This model intends to offer alternative transport to those users who must reach the station daily (and must return from there in the afternoon or evening). At the same time, other people come to the station and need to reach other locations around the city.

This section consists of five steps: the algorithm description, data collection, Origin–Destination matrices generation, iterative simulations to size the fleet (depending on transport demand and using a random calls generator), and results evaluation for each step.

4.1. Algorithm Description

This RSA for local public transport combines car-sharing and ride-sharing for those areas where the demand does not justify a bus. Such a transport concept is feasible, assuming a demand for counter-flow. When the user calls for a ride, they can either be told to drive a shared car parked nearby or that somebody else driving it will pick her up. Up to nine people share the same ride to the station, with one driving the others (and having a free ride for doing this). The maximum number of people in the same vehicle is limited by street regulations, allowing up to nine people in the same car with the type B license (the most diffused required to drive a car).

After the first ride, the vehicle is left at the station or exchanged "on the fly" so it is picked up by a person driving counter-flow called "User1". They leave the train station, and while reaching their destination, they pick up the driver, "User 2", of the next ride (directed again to the station). Both users go to the destination of User 1, where they leave and give the driver seat to User 2 or another person picked up in the meantime and drive back to the station. The on-the-fly exchange allows a user to close their ride while another user opens theirs up, and such a feature eliminates the search for parking and time losses for people to reach their destination (from the parking slot to their house and vice versa).

Such a transport scheme complements a bus service because it is tailored to areas (or times of the day) where the demand would not justify a busload. To correctly size the vehicle fleet and fine-tune the RSA for planning each user's daily travel requests, simulations were carried out, starting with a zoning exercise of an actual city with distances and conditions of a real use case. The city of Monterotondo (30 km from Rome) was used as a test. The numbers mentioned concern the city of Monterotondo, which has a population

of almost 40,000 inhabitants and sees 8222 of them travel to Rome daily. Of these users, about 40% use the train, so they reach the railway station daily using their own transport.

Table 6 identifies the reported categories of trips in the commuting matrix: incoming, outgoing, and internal.

Table 6. Trip categories.

Cat.	Name	Description
A	Internal	They reside in the municipality under consideration and move within it.
B1	Outgoing	They reside in the municipality and move towards an attractor pole (e.g., Rome is an attractor pole for municipalities bordering the ring road).
B2	Outgoing	They reside in the municipality and move to another municipality other than the pole of attraction.
C1	Ingoing	They reside in the attractor pole and move towards the municipality under consideration.
C2	Ingoing	They reside in another municipality other than the attracting pole and move to the municipality under consideration.

Table 7 shows those categories for Monterotondo, divided by mode of transport. The simulations (Section 3.3) were carried out using only outgoing and ingoing trips by train, with B1 plus B2 equal to 3364 and C1 plus C2 equal to 378 users. From now on, internal trips will be neglected. Each category of Table 3 must have an Origin–Destination Matrices (ODM) for each mode of transport.

Table 7. Matrix of trips divided by mode of transport and by reason (study or work).

Cat.	Train	Cars	Bus	Bikes	On foot	Tot	Workers	Students
A	0	6279	823	248	3504	10,854	47%	53%
B1	3199	4561	302	518	160	8740	87%	13%
B2	154	1965	202	34	9	2364	89%	11%
C1	184	910	84	24	0	1202	93%	7%
C2	164	3927	2122	120	67	6400	52%	48%

The following paragraphs describe the data collection, the ODM generation, methods of simulations, and results.

4.2. Data Collection, Assumption, and Simplification

This chapter explains the data collection and elaboration used to feed the algorithm. The primary data sources are the Italian national census entity (ISTAT) through the 2011 census and a local survey of urban travel carried out in cooperation with the Municipality of Monterotondo and the ENEA research department. The following paragraph describes these data sources, the files for graphical processing and the first processing of them, i.e., a simplification concerning the aggregation (graphical and numerical) of the census section data aimed at reducing the computational burden of the simulations.

The Italian census (ISTAT) provides these data, which help design transport services for the Italian territory:

- Commuting matrix (<https://www.istat.it/it/archivio/139381>, accessed on 15 December 2023), mainly includes the number of individuals who commute daily between one or two cities, their reason (e.g., study or work), and the mode of transport used (vehicle);
- Population data by census section (<http://datiopen.istat.it/>, accessed on 10 December 2023): This contains information on the number of residents for each section, age, gender, number of persons with income, number of students, buildings, etc. In addition, there is specific data on commercial activities by census section;
- Census of Industry and Services (<https://www.istat.it/it/archivio/104317>, accessed on 15 January 2024) provides the number of workers and activities available for

each “ATECO” code (Source Italian Chamber of Commerce: <http://atenco.infocamere.it/ateq/home.action>, accessed on 9 November 2023) for each section. The latter categorizes the type of each activity;

- Geo-fenced graphic files (shapefiles) for processing the census sections, allowing the census information to be analyzed geographically.

For example, Figure 1 shows the 65 sections of Monterotondo (identified by the smaller numbers on the map) that have been reduced into 20 more extensive sections to decrease the computational effort.

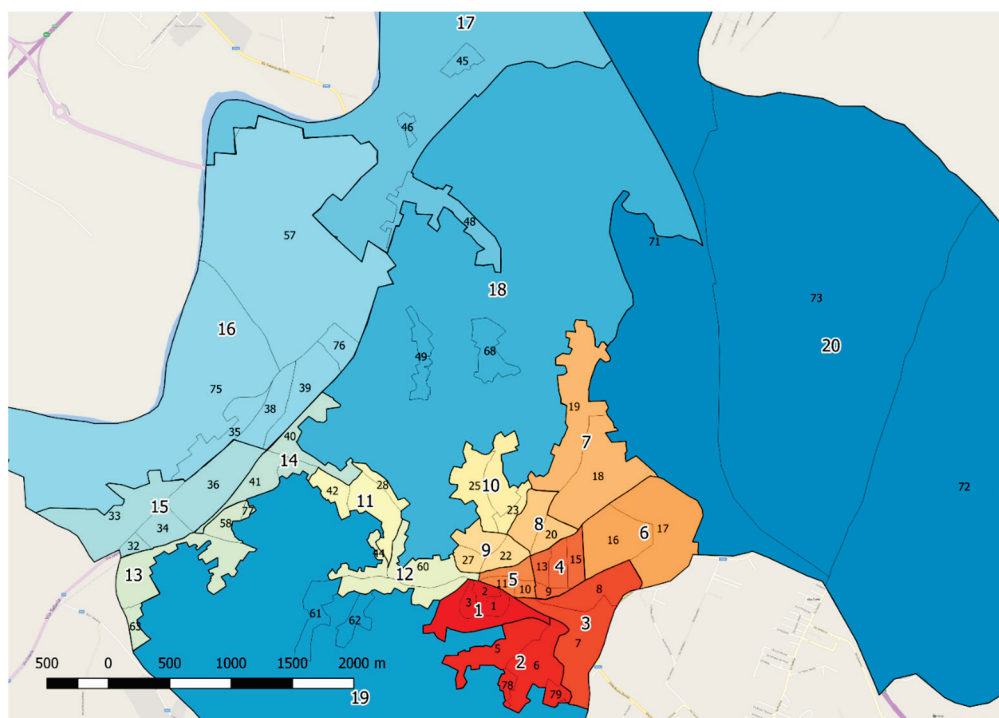


Figure 1. Graphical representation of census area shapefiles, with evidence of census sections. Numbers identify the section and colours have no meaning.

Monterotondo has a resident population of 39,502 (year of reference 2011), and the 65 sections have an average resident population of 607; by applying the abovementioned areas, the average number of residents per zone increased to 1974.

The construction of areas where there is a high residential density (greater than 500 inhabitants per square kilometre²) has been done by trying to keep the maximum width of the area within 1 km so that it can be considered a single point of generation and attraction of movements to and from that area. While areas with low residential density (less than 500 inhabitants/km²) were constructed by analyzing the road graph and the travel time by car, e.g., between the two furthest points of the area, the travel time by car should be lower than 5 min.

The survey processing results in:

- Table 8 regarding travel from Monterotondo to Rome by any mode plus train and by car (outgoing);
- Table 9 shows journeys from Rome to Monterotondo by train (incoming) and from Monterotondo to Monterotondo by any mode (internal).

For example, as shown Table 8 for those leaving by train (outgoing), of the 97 valid responses to the question concerning possible interest in the new transport service, 52% went to the station by car, 30% by bus, and 19% on foot, and, respectively, 80%, 86%, and 78%, would be interested in using the service. Those who might be willing to drive are 54%, 28% and 28%, respectively. This proportion applied to the ISTAT numbers (3353 commuters

to Rome and other destinations by train from Monterotondo) yields a potential user pool of 1200 people (about 41%), while the incoming commuters by train are 126 (about 33% of the 378).

Table 8. Survey results in Monterotondo: Potential users of the service proposed by Medium (outgoing users).

	Mode of Transport	Survey Answers	Interested in the Service	Willing to Drive	Total ISTAT	Inhabitants Potentially Interested in Driving
52%	Car + train	50	80%	54%	1728	933
30%	Bus + train	29	86%	28%	1002	277
19%	Feet + train	18	78%	28%	622	173
	TOTAL outgoing by train	97	81%	41%	3353	1383
	Outgoing by Cars	38	80%	26%	4561	1200

Table 9. Survey results in Monterotondo: Potential users of the service proposed by Medium for users travelling to Monterotondo by train (incoming) and within Monterotondo (internal).

	Mode of Transport	Survey Answers	Interested in the Service	Willing to Drive	Total ISTAT	Inhabitants Potentially Interested in Driving
	Incoming by Train	11	50%	33%	378	126
62%	Internal by Cars	89	12%	8%	6279	494
14%	Internal by Bus	20	50%	10%	823	82
24%	Internal on foot	34	56%	18%	3504	618
	TOTAL internal users	143	28%	10%	10,606	1113

A few assumptions of RSA to reduce complexity:

- Each random generation of calls is repeated three times, so the result indicators represent the average values;
- The RSA based the vehicle availability for accepting new trips in the relocation. Each vehicle is pre-located the night before near the location of the first passenger. Once they reach the station, the incoming user or the operator relocates the vehicle. The operator can also use the cited patent [49] to convoy up to 6 vehicles at a time, and it is estimated that in 1 h, an operator can relocate up to 12 vehicles;
- The fleet dimension (number of vehicles) should be the same all day; during the afternoon, the transport demand is spread out over a longer time: the same commuters departing from 6:00 a.m. to 9:00 a.m. arrive in the afternoon between 1:00 p.m. and 8:00 p.m.;
- Vehicle size is the same, with a maximum of 7 passengers simultaneously. Even if bigger vehicles exist (up to 9 passengers) those are too large and usually difficult for average drivers to drive, whereas the 7-passenger vehicle is more or less an ordinary SUV or of station wagon size;
- As a first approximation to give more flexibility to the RSA, the algorithm could ask the user if she can change her train after the call assigning is carried out. RSA assumes the user will accept the change indiscriminately, with the previous or right after her first train choice. In the real world, such possibilities can be implemented with commercial strategies that make the time shift advantageous for the user and gather enormous advantages for the business (otherwise, they could need more vehicles to satisfy the same calls);
- Travel time to reach the train station is equal to 300 s;
- Safety coefficient time: traffic time loss 1.3, detour time for passenger collecting 1.2;
- Passenger boarding time is equal to 30 s;
- The tolerance time between two consecutive trips of the same vehicle is equal to 180 s;

- The alert time for the operator (or a counter-flow user who relocates the vehicle) starting from the depot/station with a new vehicle is 600 s;
- The counter-flow demand is sometimes too small to satisfy an efficient relocation, so the RSA evaluates the operator's requirement. They also proceed to other duties such as vehicle services (bringing them to maintenance or washing in off-peak hours);

This new business model can have a tariff model with a user fare equal to $0.5 \text{ €/pax} \cdot \text{km}$ (minimum 1.2 €/trip and maximum fare of 2.5 €/trip), which is waived for the driving user.

The costs are:

- Operator 27,000 €/year, used to move vehicles to the depot for maintenance and wash and to relocate when necessary (average gross annual remuneration of a pro driver);
- Vehicle 6500 €/year, using a leasing formula, which includes maintenance, tax, and insurance costs (quotation of a 9 seat vehicle for a rental period of 4 years);
- Average vehicle consumption is 15 km/L of diesel, with an average value of 1.5 €/L.

4.3. Procedure for Generating Origin–Destination Matrices (ODM)

This chapter concerns the generation of a set of ODM representing the demand for mobility. The matrices were constructed using a bi-proportional method [53] and then simplified to reduce their size and constitute the database for the simulation.

The simulations are limited to analyzing only the trips needed for simulation, and they are outgoing and ingoing trips by train.

Attraction percentages were applied to each category to produce a travel demand for the simulations. The first hypothesis is for outward journeys by train (outside the municipality) and internal (within the municipality). The initial percentage of interest was set at 10%, and it increased by 5% in each iteration. The reasons for these attraction hypotheses are social and economic, and sometimes, they are due to the needs of individuals (e.g., the need to accompany a relative or child) and introduce a further degree of randomness to the survey. Therefore, partly as a matter of caution, because specific categories of travelers (mainly those who use cars) are challenging to attract, even if they have stated that they are interested in a new service, these values have been used. During the simulations, the attraction hypothesis varies to analyze the impacts on results (number of vehicles, takings, kilometers travelled, filling coefficients, etc.) when demand changes. A similar assumption was made for the return journey, so travel occurs between the railway station and the census area. ISTAT origin data are only available for the morning, but it is assumed that users who have left must return on the same day to the same origin from which they left.

Tables 8 and 9 report total potential trips by applying the attraction percentage to the ODM for each iteration step, making it possible to build and achieve the simulation of trips.

The number of workers and students that originate within the city and go to the train station can be estimated by multiplying:

- The total outgoing trips by train (shown in Table 8);
- The ISTAT value 'Resident population that commutes daily outside the municipality' (available for each section);
- The inverse of total "residents income earners" from ISTAT is available in the municipality.

The destination of these outgoing trips is the census section, including the train station.

The incoming trips are opposite to the previous ones. They begin in the train station and go to a section with commercial activities. Monterotondo has high schools and only a small university, attracting local students from neighboring cities (especially mid- and high-school students). Usually, they come together with a parent (same vehicle) or use an extra-urban bus, so these trips are neglected due to the difficulty of predicting them.

4.4. Simulation Methods of RSA

The simulation phases are as follows:

1. Assigning a random time to each trip, named call, up to reach the total trips expected, and assigning each call to a train;

2. Organize pools of users who are assigned to the same vehicle, even if they come from different areas;
3. Calculate the number of vehicles to meet the generated demand and plan the trips;
4. Generate calls for incoming commuters and assign them to the vehicles to be relocated;
5. Repeat all previous steps for the afternoon trips using the same morning numbers with inverted roles between outgoing and ingoing.

Step 1 generates the calls for each train. Starting from the users who make their first trip during morning rush hour, between 6:15 a.m. and 9:15 a.m., the percentage of interest in the service was applied, with an initial attraction percentage of 20%. Figure 2 shows the distribution measured at the train station during a working day, with the number of people departing and arriving by train; data are collected directly at the Monterotondo train station. The morning hours seem to have a Gaussian-similar distribution for departure trips, while the arrival people seem to have almost a steady value. Outgoing and ingoing trips in the afternoon therefore follow a similar distribution.

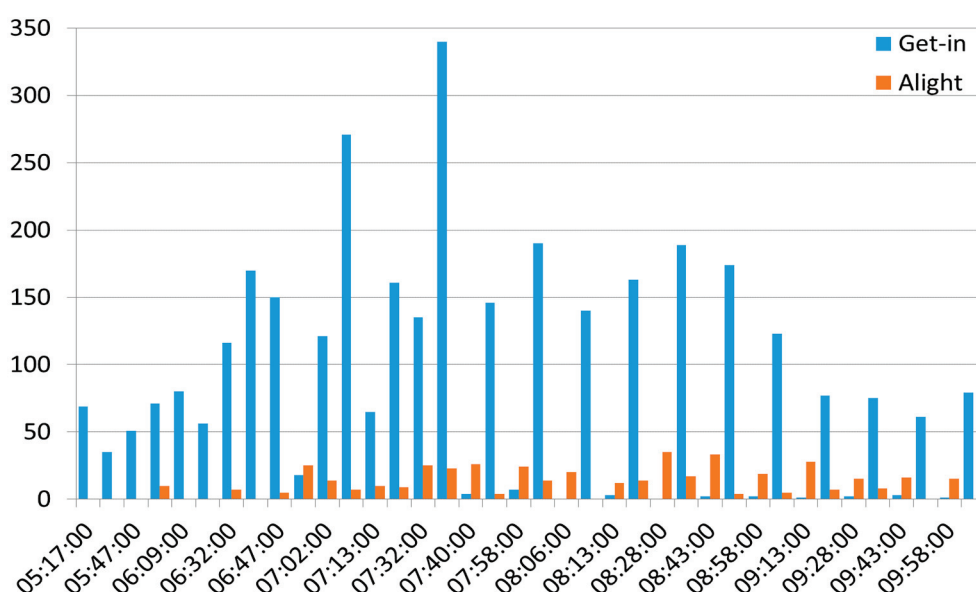


Figure 2. Distribution measured at the Monterotondo train station in the morning hours.

Table 10 shows the random calls generated with an attraction percentage of 28%, the commuter's willingness to drive a vehicle with this new service (399 of 1383). The rows represent the trips generated by the origin area and directed to the station (14), divided into the trains that pass between 6:00 a.m. and 9:00 a.m.

Step 2 concerns the pool scheduling. It is conducted iteratively by evaluating the following six possibilities, which identify the type of schedule:

TYPE 1: Minimum number of people. The first pools are those with trips generated by the same origin–destination pair (OD pair) filling the vehicle. It has assumed at least four people to constitute a new pool and a maximum of seven (as the maximum available seats);

TYPE 2. Change the train from the next to the previous. From the newly generated TYPE 1 pools, the algorithm searches for those that can accommodate other users by adding these users of the next train who want to anticipate their departure. These users are part of the same pool generated with TYPE 1.

TYPE 3. Change the train from the previous to the next. This step is similar to TYPE 2 and involves reassigning the randomly generated train with the previous one available in the station (instead of the next one as in TYPE 2).

TYPE 4. This step identifies the possible OD pairs that can be satisfied from the previously generated pools by collecting users along the route to the station without any significant detours (only with intermediate stops). This merging can only occur if the users

in the already generated (but still incomplete) pool and those potentially included have been assigned to the same train.

TYPE 5. As in the previous case, but with a train change from the next to the previous.

TYPE 6. Once the previous steps have been completed, new pools must be generated to collect the remaining people unserved. This schedule contains users who might change trains and/or come from different zones.

Step 3 sizes the fleet and involves an iterative calculation to plan individual vehicle rides; each ride contains a pool. The following parameters are identified: travel time, waiting time, kilometers travelled, passengers per kilometer (pax*km), people not served, and ride revenue. At the end of each scheduling process, the algorithm checks the availability of vehicles, and if one is not available, it activates another one. Ride revenue is determined with a simplified model of a fixed cost per km travelled by each passenger and two saturation parameters: maximum and minimum trip costs, which limit the user's cost between two values. Revenue is determined by the sum of the cost incurred by each passenger on the ride.

Table 10. Trips matrix with hourly random generation from Monterondo by train.

Orig Area	Dest Area	Total Trips	Train Timetable at Monterotondo Station											
			6:15	6:24	6:30	6:46	7:05	7:12	7:25	7:32	7:37	8:08	8:33	9:02
1	14	22	1	1	2	3	4	3		4	1		2	1
2	14	28	4		1		1	5	1	6	4		3	3
3	14	16	1	1	1	2	4	3			1	1	2	
4	14	20	1	1	4	3		2	5	3				1
5	14	14	1	2		1	2	3		1	1	2	1	
6	14	24	2	2			4	5	2	4	1		1	3
7	14	25			1	2	4	2	4	3	2	1	2	4
8	14	9	1	1		1		2			2		2	
9	14	18	2			1	2	1	4		2	1	2	3
10	14	24	3	1		1	4	4	4	2	2	1	1	1
11	14	21	1	1		2	2		1	5	6	1		2
12	14	29	4		3	4	3	2	3	4	1	1	3	1
13	14	25	3	3	3	2	2	1		1	2	3	4	1
14	14	6	1		1			1	1		1		1	
15	14	57	6	3		4	7	3	6	8	3	12	3	2
16	14	38	5	4	2	4	3	3	6	3		3	3	2
17	14	12	1	2	1	2		1	2	1		1	1	
18	14	2				1				1				
19	14	8	1		1	1		1	1		2		1	
20	14	1					1							

The random generation of the previous steps provided a vehicle schedule such as the one summarized in Table 11.

The first vehicle (column “Id veh” and row value equal to 1) during the time slot 6:00–9:00 transports 50 users, covering 47 km with eight rides. The vehicle's occupation time is just under 2 h (taking into account all travel times and tolerance times to ensure a smooth operation of the service and to allow for any minor delays), just under 1 h is the time the vehicle is stationary, i.e., waiting to be picked up by users.

Step 4 simulates the incoming trips similarly to the outgoing ones. The algorithm is the same as seen for outward travel and uses the same vehicles arriving at the station. The types of planning are equal, but the purpose of this simulation is to relocate the vehicles that will be the origin of the movements leaving the municipality immediately afterward.

Firstly, random calls are generated and assigned to the train. The last step is checking the vehicles available that require relocation and matching between OD pairs of the incoming user with the vehicle pre-scheduled for the outgoing trips. The matching between the departure times from the station towards the Monterotondo areas (thus incoming

transport demand) and the arrival times at the station of residents (outgoing) are inherently predetermined; in fact, trains arriving at Monterotondo then depart towards Rome, or if they terminate, there is bound to be at least one more train in the opposite direction (the railway line is double-tracked with an average frequency of one train every 15 min).

Table 11. Extract of simulation results and vehicle indicators.

Id Veh	Pax Tot Veh	Total km	Pax*km	N Rides	Vehicle Time (s)	Waiting Time (s)
1	50	47	132	8	7548	3302
2	37	33	76	7	5833	4881
3	40	23	86	6	4411	4699
4	19	21	52	4	3298	3932
5	26	28	71	4	4858	3830
6	25	28	67	4	4718	3987
7	25	25	71	4	4282	4568
8	19	27	48	4	3952	4718
9	16	13	39	3	2224	2983
10	9	31	30	3	3682	1739
11	16	15	41	3	2776	1874
12	21	13	40	3	2312	2537
13	5	16	22	2	2124	983
14	8	15	30	2	2226	1876
15	7	4	28	1	775	140

The simulation uses the incoming trips measured by train, using the numbers available from ISTAT on commercial activities divided by census section with the application of an attraction percentage and a measured interest through the public survey. Generally speaking, the proposed service could affect trips from other municipalities only via the railway station, probably also a small fraction are traveling from outside using their own vehicles. In the case of Monterotondo, about 63% of incoming trips are made by car. The value of potential interest in this new service of these users is difficult to quantify. This demand could only be generated after the creation of the offer; subsequently, other variables could affect this attractiveness, but at this preliminary stage, they have not been considered.

In the fifth and final step, the number of vehicles needed for afternoon service is less than that required for morning service (due to higher people concentration). Using the number of vehicles required for morning service implies that a few are not used in the morning; vice versa, a small part of morning people will not be served. The RSA accepts those people as unserved to reduce costs.

4.5. Results of the Simulations

The RSA has been reiterated by changing the potential market, which is calculated as the attraction percentage (or demand) that multiplies the potential users measured with the survey and the commuting matrix method. Figure 3 shows the results of simulations in terms of vehicles required and people not served by varying the attraction percentage. It shows the economic results (€/year) compared with the number of vehicles required and personnel costs per vehicle by changing the attraction percentage.

Instead, Figure 4 shows the passengers (served and not served) compared with the vehicle filling rate; this latter indicator measures the average value of passengers transported for the same distance travelled. The greater this indicator is, the greater the vehicle utilization and the lower the possibility of enhancing the results.

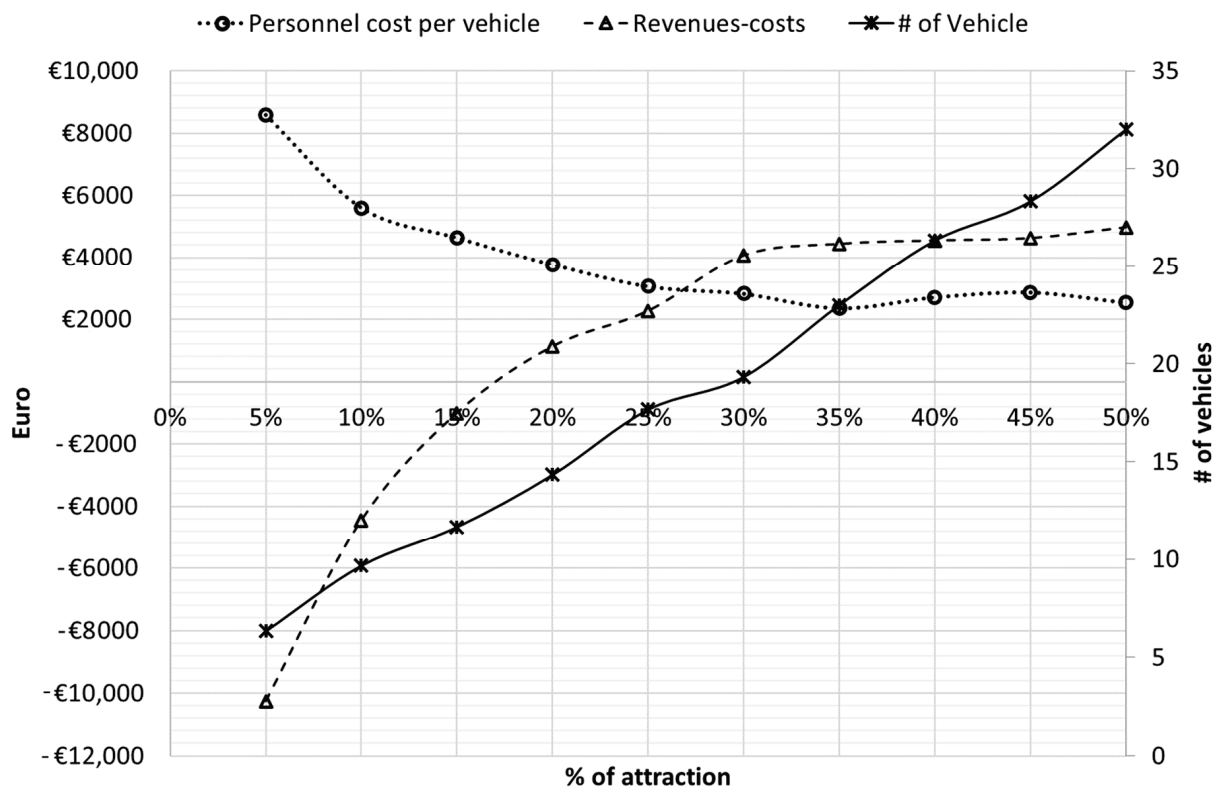


Figure 3. Results of simulation by varying the attraction percentage in terms of revenues and vehicles.

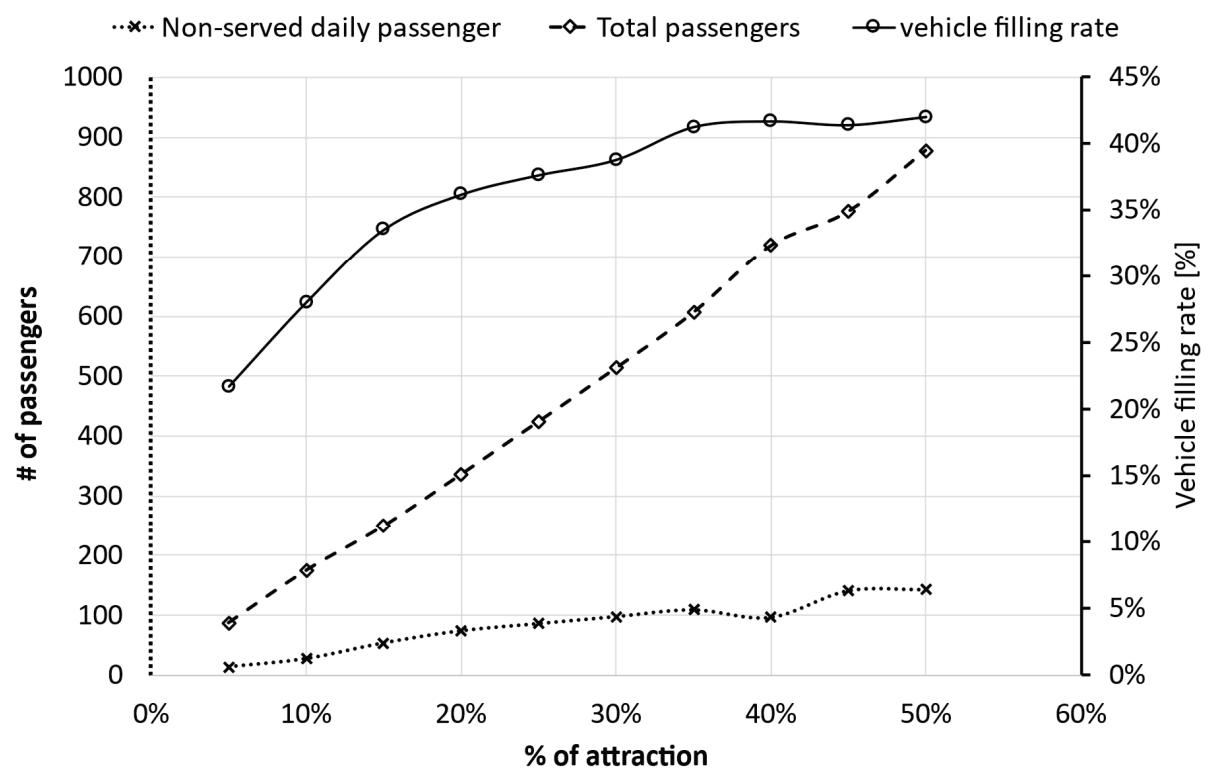


Figure 4. Simulation results by varying the attraction percentage in terms of vehicle filling rate and passengers.

For example, an attraction percentage of 10% means less than 200 people a day (20 not served); they travel from Monterotondo to Rome in the morning and return in the afternoon, requiring a fleet of 13 vehicles, filled at 55%. It has a negative economic result, with losses of 4500 €/vehicle per year.

If the attraction percentage increases to 20% (400 served passengers), 15 vehicles will be required, and the positive economic results will be about 1000 €/year. Greater attraction percentage increases positive results, but the difference between the revenues and costs trend seems to reach a plateau above 30%.

5. Conclusions and Future Developments

This paper has investigated the business models of vehicle-sharing services through a literature and project review and then presented the results of the financial analysis of the electric vehicles-sharing demonstration done by the LifeSC Project in the municipalities of Orbetello, Monte Argentario, and Isola del Giglio on the southern Tuscany Tyrrhenian coast of Italy. These financial analyses showed how the investigated sharing services can be profitable, but with difficulty and with the support of public subsidies. These findings hold for most sharing services outside the centers of large cities. However, the findings also highlight how lowering the purchase price of shared vehicles and increasing the service utilization rates could be profitable. A few features are suggested as the best chances to organize a vehicle-sharing service based on the latest developments in ICT technologies and strategic choices.

The new “Ride-Sharing Algorithm” has been tested through dedicated simulations. It combines ride-sharing and car-sharing into one service. It offers a sharing service for people moving from a city center to reach an attraction pole (typically an intermodal hub like a train station). From this pole, other people relocate vehicles parked here to the city center (this former demand is in counter-flow); when this demand is not enough, an operator relocates the vehicles using innovative solutions that enable a driver to relocate up to six vehicles simultaneously with vehicle automation.

Responding to a fluctuating demand without increasing the fleet can improve the utilization rate without lowering the quality of the service. Such a solution can be done by introducing ride-sharing at peak times, using an on-the-fly driver exchange, and relocating empty vehicles. Selecting the most appropriate vehicle type, powertrain, and charging method also influences the utilization rate. An integrated service would help build customer confidence, impacting urban mobility sustainability.

The economic result of simulations is positive when attraction demand reaches 20% of the potential transport demand, which means about 400 served passengers, less than 30 rejected passengers; the fleet size required is 15 vehicles, and revenues are 1000 €/year greater than costs. Higher costs for leasing the vehicle or increasing the number of operators could worsen the economic results to neutral or negative outcomes that could drive away investors and sharing companies. Still, they can enhance their incomes with ancillary services selling (on-board or at the collection point) or long rental vehicle services during off-peak hours or weekends, primarily because the ride-sharing daily service covers almost all its total cost (vehicles and operators).

To use such a service, people can book their travel through a one-stop-shop interface, for example, a smartphone app, allowing them to follow the vehicle in real-time, purchase an ancillary service, manage their booking and provide feedback. The cost factor of app development and maintenance has not been evaluated due to the high innovation associated and difficulty quantifying the required development time. Moreover, the transport company offering this service could have other sharing services and applications that can be modified to achieve this scope.

The new algorithm proposed here promises to achieve positive economic results and fill the gap of underused vehicles in classic or mixed car-sharing models.

Future work will include simulation with different and changed parameters, testing other relocation strategies and simulating the variation of counter-flow demand. Other

simulations will do a sensitive analysis of the parameters adopted. ISTAT data for potential transport demand will be updated, and a further survey about personal preferences in sharing vehicles and/or ride availability will be conducted.

Moreover, the authors plan to deploy a transport service analog to the one proposed in an experimental project called TUSS (<https://www.tuss.unifi.it/p1.html>, accessed on 28 August 2024). This will help improve our understanding of the feasibility and tangible economic impact of such a model.

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Article

Sizing a Renewable-Based Microgrid to Supply an Electric Vehicle Charging Station: A Design and Modelling Approach

Amirhossein Khazali ^{1,*}, Yazan Al-Wreikat ¹, Ewan J. Fraser ¹, Mobin Naderi ², Matthew J. Smith ², Suleiman M. Sharkh ¹, Richard G. Wills ¹, Daniel T. Gladwin ², David A. Stone ² and Andrew J. Cruden ¹

- ¹ School of Engineering, University of Southampton, Southampton SO17 1BJ, UK; y.m.y.al-wreikat@soton.ac.uk (Y.A.-W.); e.j.fraser@soton.ac.uk (E.J.F.); s.m.sharkh@soton.ac.uk (S.M.S.); rgaw@soton.ac.uk (R.G.W.); a.j.cruden@soton.ac.uk (A.J.C.)
- ² Department of Electronic and Electrical Engineering, University of Sheffield, Sheffield S10 2TN, UK; m.naderi@sheffield.ac.uk (M.N.); matt.j.smith@sheffield.ac.uk (M.J.S.); d.gladwin@sheffield.ac.uk (D.T.G.); d.a.stone@sheffield.ac.uk (D.A.S.)
- * Correspondence: a.khazali@soton.ac.uk

Abstract: In this paper, an optimisation framework is presented for planning a stand-alone microgrid for supplying EV charging (EVC) stations as a design and modelling approach for the FEVER (future electric vehicle energy networks supporting renewables) project. The main problem of the microgrid capacity sizing is making a compromise between the planning cost and providing the EV charging load with a renewable generation-based system. Hence, obtaining the optimal capacity for the microgrid components in order to acquire the desired level of reliability at minimum cost can be challenging. The proposed planning scheme specifies the size of the renewable generation and battery energy storage systems not only to maintain the generation–load balance but also to minimise the capital cost (CAPEX) and operational expenditures (OPEX). To study the impact of renewable generation and EV charging uncertainties, the information gap decision theory (IGDT) is used to include risk-averse (RA) and opportunity-seeking (OS) strategies in the planning optimisation framework. The simulations indicate that the planning scheme can acquire the global optimal solution for the capacity of each element and for a certain level of reliability or obtain the global optimal level of reliability in addition to the capacities to maximise the net present value (NPV) of the system. The total planning cost changes in the range of GBP 79,773 to GBP 131,428 when the expected energy not supplied (EENS) changes in the interval of 10 to 1%. The optimiser plans PV generation systems in the interval of 50 to 63 kW and battery energy storage system in the interval of 130 to 280 kWh and with trivial capacities of wind turbine generation. The results also show that by increasing the total cost according to an uncertainty budget, the uncertainties caused by EV charging load and PV generation can be managed according to a robustness radius. Furthermore, by adopting an opportunity-seeking strategy, the total planning cost can be decreased proportional to the variations in these uncertain parameters within an opportuneness radius.

Keywords: microgrid; renewable energy; battery energy storage system; optimisation; information gap decision theory (IGDT)

1. Introduction

The interest in reducing carbon emissions generated by fossil fuels has resulted in the adoption of new development strategies in the energy and transportation sector. While in the former this strategy is based on increasing the penetration of renewable energy sources (RES) in power grids, the latter pursues increasing electrification of the transportation sector [1]. These policies, coupled with a generally congested National Grid, have led to significant interest in establishing carbon-free microgrids for charging electric vehicles. However, sizing renewable sources to supply EVC stations can be challenging. On one

hand, a system can be oversized, and additional costs can be incurred by the stakeholders' oversizing of renewable energy sources (RESs). On the other hand, if the capacities of these elements are underestimated, it results in a system that cannot provide adequate energy to the EVC station [2]. Hence, appropriate optimisation frameworks must be developed to determine the best capacity for each element [3,4].

The capacity sizing problem of microgrids has been investigated by several researchers. In [5], Bandyopadhyay et al. present a techno-economic framework for obtaining the optimal size of photovoltaic (PV) generation systems and BESS capacities in a microgrid. In the paper, they study the effect of the geographical location of the microgrid on capacity sizing of these components.

A stand-alone system composed of wind turbines (WTs), a PV system, and a battery energy storage system (BESS) is sized in [6], incorporating demand-side management. The results indicate that for various combinations, the plan composed of WTs, a PV system, and BESS is the best plan from the economic point of view. Particle swarm optimization (PSO) is used in this paper; however, reaching the global optimal point cannot be guaranteed by this approach.

An analytical sizing approach is introduced in [7] for sizing the capacity of vanadium redox batteries for microgrid systems. The nonlinear efficiencies and operating characteristics are considered in this study. The microgrid, nonetheless, is not off-grid and the optimisation problem is solved by dynamic programming. Planning of isolated BESSs for isolated microgrids is studied in [8]. Alharbi et al. solve a two-stage mixed integer linear programming (MILP) formulation where, in the first stage, the capacity of the battery is specified, and the second stage determines the installation year of the battery, but the microgrid is not renewable-based. In addition, the reliability of the system is not adjustable for it. An analytical approach for sizing BESS in microgrids is presented in [9] with the aim of minimising the unused capacity of the BESS and maximising renewable consumption. The results indicate that the solution ensures that there is no wasted energy storage capacity and shows how energy leakage affects the sizing of long-term storage. Nevertheless, Ref. [9] does not regard the net present value of the system. Battery degradation is studied in [10] for microgrid optimal planning to increase the precision and economic feasibility of the microgrid capacity sizing problem. Degradation of lithium-ion batteries for another capacity planning problem is also studied in [11] where a new battery degradation model is presented for microgrid planning. The amount of unmet load is controlled by the value of loss load included in the objective function for this method. A stochastic programming approach is presented in [12] where Habib et al. include smart prosumers and electric vehicles in the microgrid planning problem. Multi-dimensional uncertainties are used in [13] for the microgrid capacity planning problem. Chen et al. use a novel technique for generating scenarios which are similar to the real data, but the planning is not for a renewable-based system. Also, there is no possibility for adjusting the unmet load in [13].

The integration of electric vehicle charging stations in energy grids has also been studied in several papers. For instance, the integrated planning of electricity networks and fast charging stations is studied in [14]. The planning scheme is based on the cost of the system and the quality of service to the customers. Plug-in electric vehicle load modelling is presented in [15] for charging scheduling strategies. This modelling is used in smart charging algorithms and to increase the knowledge of future behaviours to aid charging scheduling. A load modelling scheme is presented in [16] for electric-vehicle fast charging stations. The method utilises the measured data and an iterative optimisation approach to acquire an accurate load model for these stations. An optimal EV charging station planning scheme based on EV load forecasting is studied in [17] where the spatial-temporal EV load is forecasted according to the road topology.

Specifying the level of uncertainty for decision-making problems with stochastic parameters is challenging. While considering high levels of uncertainty increases the operation cost, underestimating the uncertainty level of the system results in decreasing the robustness of the plan [18]. On the other hand, accurate statistical data are used

for evaluating the uncertain space of the problem, which is not always available. The information gap decision theory (IGDT) approach is an uncertainty management approach that is suitable for problems which deal with the scarcity of data and can provide solutions for various levels of robustness (or opportunity-seeking levels) [19]. IGDT has been used in several types of research for microgrid operation and planning [20]. In [21] the IGDT approach is used for operating a microgrid with liquid air energy storage; in this research, the capacity of microgrid elements is pre-specified but microgrid capacity planning is not considered. In [22], IGDT is used for microgrid planning for e-mobility infrastructure; however, in this research, the IGDT is only used for managing the uncertainty caused by EV charging load. In [23], the author uses IGDT for operating a combined cooling, heat, and power microgrid; this study also focuses on microgrid operation and only takes the load uncertainty into account. Also, in [24] a similar uncertainty management scheme is used for capacity planning; however, the research does not mention how the renewable generation uncertainty is harnessed by this approach.

In this paper, a reliability-constrained optimisation model is presented for sizing renewable generation systems and battery energy storage systems within EVC stations at a visitor attraction site near Southampton, UK. In this paper, reliability refers to the proportion of EV charging load that is met by the system during the planning horizon. The main contribution of this research is presenting a MILP formulation where the decision maker can adapt the desired plan according to the reliability level of the system for electric vehicle charging stations. Two scenarios are investigated, with and without reliability constraints, to quantify and demonstrate their significance. In addition, a linear model is presented for utilising IGDT for managing uncertainties caused by EV charging demand and renewable generation.

The next section of this paper is dedicated to explaining the structure of the problem. The third section presents the microgrid capacity planning formulation. Simulation results are presented in Section 4. Section 5 concludes the paper.

2. Stand-Alone Microgrid Planning

In this section, the proposed model for the microgrid planning is illustrated. Figure 1 shows the structure of the microgrid which is composed of wind turbines, PV panels, batteries, and the EV charging stations all connected to a common busbar with power electronic interfaces. It is worth mentioning that other miscellaneous loads can also be supplied by this system. In this system, the EVC stations are supplied by PV generation and wind turbines. When there is a surplus of energy, the excess is used to charge the BESS. If the battery state of charge (SOC) is greater than a specified level, the excess energy will be curtailed. Conversely, when there is a shortage of renewable energy production, the battery will discharge to supply the EVC stations. If the battery SOC falls beneath a specified value, load shedding is inevitable. It is the case that PV panels and wind turbines are interruptible and volatile generation sources, and their generation depends on the geographical location of the system. Also, it is true that battery energy storage systems have a more deterministic behaviour, and they can be scheduled if they do not reach the state of charge limitations. However, these components complement each other, and their performance should not be considered separately. Without the renewables, the batteries cannot be charged, and without the batteries, the generation of the renewables is not manageable.

Two scenarios are investigated. In the first scenario, the maximum amount of unmet load is constrained. In the second scenario, a cost-benefit model is formulated where the income acquired by charging EVs is included in the objective function, but without reliability constraints. Figure 2 shows an overview of the optimisation planning problem of a microgrid including the objective function elements, constraints, and decision variables. As illustrated, the objective function consists of the CAPEX and OPEX of various components of the system.

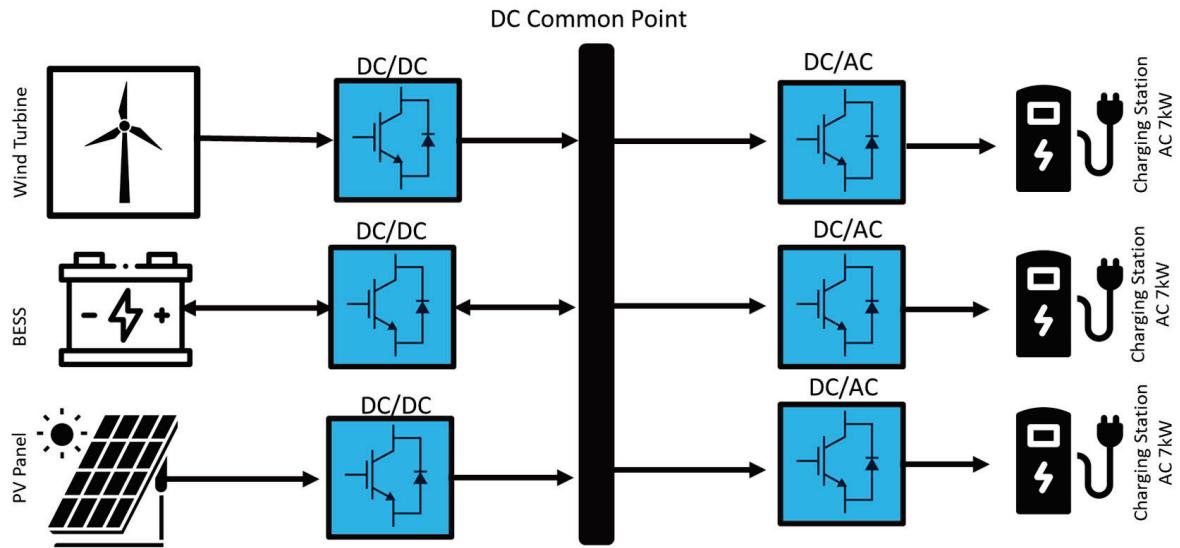


Figure 1. Structure of the stand-alone microgrid.

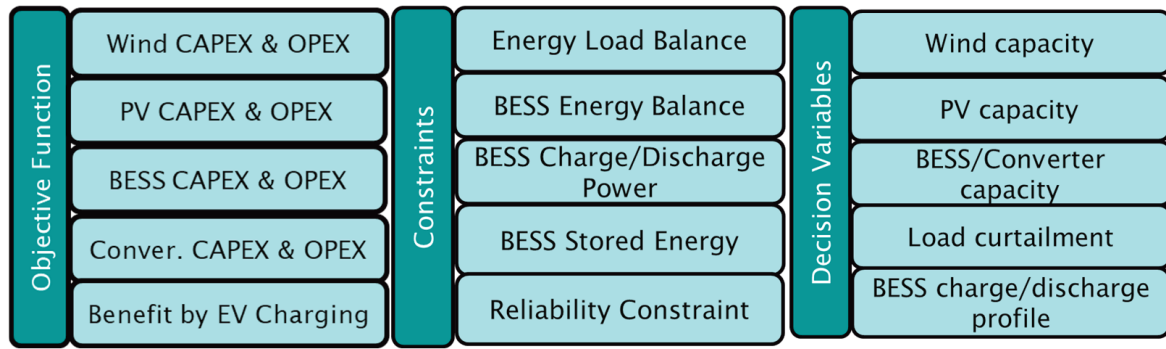


Figure 2. Overview of the optimisation problem.

The respective mathematical formulations of the two scenarios are presented in the next section.

3. Mathematical Formulation

3.1. Scenario1: Unmet Load Reliability Constrained Model

In this section, the microgrid capacity planning scheme for reliability-constrained formulation is presented. The objective function for this study case is defined in (1). This relation is composed of the total CAPEX and OPEX. The CAPEX and OPEX for each element of the microgrid are calculated using the following equations:

$$MinOF = CAPEX + OPEX \quad (1)$$

$$CAPEX = CAPEX_W C_W + CAPEX_{PV} C_{PV} + CAPEX_{BESS} C_{BESS} + CAPEX_{Conv} C_{Conv} \quad (2)$$

$$OPEX = OPEX_W + OPEX_{PV} + OPEX_{BESS} + OPEX_{Conv} \quad (3)$$

$$OPEX_W = \sum_{y=1}^{N_Y} \sum_{t=1}^{N_T} (OPEX_{W,F} C_W + OPEX_{W,V} C_W Wind(y, t) \Delta t) \quad (4)$$

$$OPEX_{PV} = \sum_{y=1}^{N_Y} \sum_{t=1}^{N_T} (OPEX_{PV,F} C_{PV} + OPEX_{PV,V} C_{PV} PV(y, t) \Delta t) \quad (5)$$

$$OPEX_{BESS} = \sum_{y=1}^{N_Y} \sum_{t=1}^{N_T} OPEX_{BESS,F} C_{ConV} + OPEX_{BESS,V} (P_{ch}(y, t) + P_{dis}(y, t)) \Delta t \quad (6)$$

The capacity of each of the microgrid elements is restricted by the following relations:

$$C_{PV} \leq C_{PV,max} \quad (7)$$

$$C_W \leq C_{W,max} \quad (8)$$

$$C_{BESS} \leq C_{BESS,max} \quad (9)$$

$$C_{ConV} \leq C_{ConV,max} \quad (10)$$

It is the case that renewable energy generation systems, especially PV panels, occupy a lot of space and one of their main challenges is finding appropriate sites for their installation. However, the presented model is able to cope with this challenge by the constraints presented in relations (7)–(10). In these relations, the capacity (or number of elements) of each component can be restricted to a maximum value which can be determined by the amount of provided space for installation. By doing so, the optimiser is able to find the capacity size of each element with the least cost while satisfying the capacity constraint.

The energy balance for the system needs to be maintained:

$$C_W Wind(y, t) \Delta t + C_{PV} PV(y, t) \Delta t + P_{dis}(y, t) \Delta t + UL(y, t) = P_{ch}(y, t) \Delta t + EV(y, t) + RS(y, t) \quad (11)$$

In the above equation, the sum of energy produced by renewable sources and the energy discharged by the battery must be equal to the load and the amount of energy charging the battery. In addition, the unsupplied load and renewable spillage terms in (11) are used to make this relation feasible in case of energy shortage or when there is a surplus of energy, respectively.

The operational limitations of the BESS are as follows:

$$P_{ch}(y, t) \leq C_{ConV} \quad (12)$$

$$P_{dis}(y, t) \leq C_{ConV} \quad (13)$$

$$P_{ch}(y, t) \leq Mu_{ch}(y, t) \quad (14)$$

$$P_{dis}(y, t) \leq Mu_{dis}(y, t) \quad (15)$$

$$u_{ch}(y, t) + u_{dis}(y, t) \leq 1 \quad (16)$$

$$E(y, t) = E(y, t - 1) + (\eta_{ch} \eta_{ConV} P_{ch}(t) \Delta t) - (P_{dis}(t) \Delta t / \eta_{dis} \eta_{ConV}) \quad (17)$$

$$SOC_{min} C_{BESS} \leq E(y, t) \leq SOC_{max} C_{BESS} \quad (18)$$

In (12) and (13) the power charged and discharged by the BESS is limited by the converter size. Equations (14)–(16) specify linearised formulations for determining the operation state of the BESS. Relation (17) calculates the stored energy in the BESS for each time of each year, taking the losses in the converters and batteries into account. Finally, the stored energy in the BESS is limited in (18) by the maximum (SOC_{max}) and minimum (SOC_{min}) states of charge.

The reliability constraints of the problem are as follows:

$$EENS(y) = \sum_{t=1}^{N_T} UL(y, t) \quad (19)$$

$$EENS(y) \leq EENS_{max} \cdot \sum_{t=1}^{N_T} EV(y, t) \quad (20)$$

In these relations, (19) calculates the percentage of unmet load for each year and (20) limits this variable to a maximum value $EENS_{max}$ ($0 \leq EENS_{max} \leq 1$).

3.2. Model 2: Cost–Benefit Scenario without Reliability Constraints

The second scenario includes the benefit acquired by this system for the stakeholders. It is defined by subtracting the objective function defined in (1) from the income acquired by charging electric vehicles and considering the discount factor r as follows:

$$MinOF = CAPEX + \sum_{y=1}^{N_Y} \frac{1}{(1+r)^y} \left(OPEX - \sum_{y=1}^{N_Y} Pr_{EV}(TEV(y) - EENS(y)) \right) \quad (21)$$

$$TEV(y) = \sum_{t=1}^{N_T} EV(y, t) \quad (22)$$

In this scenario, the reliability constraint in (20) is not considered, which maximises the obtained profit, specified by the objective function (21). Hence, this scenario uses the objective function (21) and the relations (2)–(19), and (22).

3.3. Information Gap Decision Theory for Optimal Microgrid Capacity Planning

This section presents the formulation using the IGDT approach for managing the uncertainties caused by renewable generation (as will be seen later, the contribution of wind generation is trivial according to the results that will be presented in section four, and therefore only the uncertainty of the PV generation system is considered) and EV charging load. Information gap decision theory is an uncertainty management approach applied to optimisation problems with a high degree of uncertainty. This method specifies for a specific amount of exacerbation of the objective function (in this case increasing the total planning cost), how much the negative effect of the uncertain parameters on the objective function can be intensified (decrease in renewable generation and increase in EV charging load for this case). Therefore, the decision maker can make a risk-averse plan which is robust against the worst assumed scenario defined in terms of variations in uncertain parameters according to an uncertainty radius. Conversely, for the opportuneness strategy, the decision maker is optimistic about the uncertain parameters. This strategy calculates for a certain amount of improvement in the objective function (decreasing total planning cost for this case), how much should the uncertain parameters improve (decrease for the EV charging load and increase in renewable generation).

Using the envelope-bound information-gap model [25] and assuming a maximum variation in the uncertain parameter proportional to the parameter used for the deterministic model, the uncertain models for EV charging and PV generation can be formulated as (23) and (24).

$$U(\alpha_{EV}, EV) = \left\{ EV : \frac{|\hat{EV}(y, t) - EV(y, t)|}{EV(y, t)} \leq \alpha_{EV} \right\}, \alpha_{EV} \geq 0 \quad (23)$$

$$U(\alpha_{PV}, PV) = \left\{ PV : \frac{|\hat{PV}(y, t) - PV(y, t)|}{PV(y, t)} \leq \alpha_{PV} \right\}, \alpha_{PV} \geq 0 \quad (24)$$

In (23) and (24), EV and PV show the uncertainty set for the EV charging load and the PV generation system. α_{EV} and α_{PV} show the uncertainty radius for the EV charging load and PV generation systems, respectively. $\hat{EV}$ and $\hat{PV}$ show the uncertain electric vehicle charging load and the uncertain PV generation for each hour of each year. According to the uncertainty sets that are defined for the EV charging load and the PV generation, the decision maker is seeking a solution which is robust against the variations in the uncertain

parameters. The risk-averse strategy for microgrid capacity sizing can be formulated as follows:

$$\hat{\alpha}_{EV}(X, B_C) = \max \left\{ \alpha_{EV} : \left(\max_{\tilde{EV} \in U(\alpha_{EV}, EV)} OF < OF_D \left(1 + \sigma_{EV}^{RA} \right) \right) \right\} \quad (25)$$

where OF_D is the total planning cost for the deterministic case (obtained by solving the model in Section 3.1), and σ_{EV}^{RA} shows the uncertainty budget for the case that the uncertainty caused by the EV charging load is studied.

Relation (25) can be written as a single-level optimisation problem as (26)–(28) and considering relations (2)–(10) and (12)–(20).

$$\max \alpha_{EV} \quad (26)$$

$$OF < OF_D \left(1 + \sigma_{EV}^{RA} \right) \quad (27)$$

$$\begin{aligned} C_W Wind(y, t) \Delta t + C_{PV} PV(y, t) \Delta t + P_{dis}(y, t) \Delta t + UL(y, t) \\ = P_{ch}(y, t) \Delta t + (1 + \alpha_{EV}) EV(y, t) + RS(y, t) \end{aligned} \quad (28)$$

The presented optimisation model shows, for an uncertainty budget of σ_{EV}^{RA} , how much the EV charging load can increase without violating any constraints of the main microgrid optimal sizing problem.

Like the EV charging load, for the PV generation, the risk-averse optimisation framework can be formulated as (29)–(31) and considering relations (2)–(10) and (12)–(20).

$$\max \alpha_{PV} \quad (29)$$

$$OF < OF_D \left(1 + \sigma_{PV}^{RA} \right) \quad (30)$$

$$\begin{aligned} C_W Wind(y, t) \Delta t + C_{PV} (1 - \alpha_{PV}) \cdot PV(y, t) \Delta t + P_{dis}(y, t) \Delta t + UL(y, t) \\ = P_{ch}(y, t) \Delta t + EV(y, t) + RS(y, t) \end{aligned} \quad (31)$$

Equations (29)–(31) shows, for an uncertainty budget of σ_{PV}^{RA} , how much the PV generation can decrease while all the constraints are still feasible. In (31), there is a nonlinear term caused by the multiplication of two variables ($\alpha_{PV} \cdot C_{PV}$). To linearise this term, a binary expansion scheme is used. To do so, the robustness radius α_{PV} is defined as

$$\alpha_{PV} = \left(\frac{1}{2^{N_z} - 1} \right) \sum_{z=0}^{N_z} 2^z \gamma_{RA}(z) \quad (32)$$

In (32), N_z is the total number of binary variables. $\gamma_{RA}(z)$ is the corresponding binary variable of each z . By multiplying C_{PV} and the equivalent relation in (32) for α_{PV} , a nonlinear variable is obtained by the multiplication of the binary variable $\gamma_{RA}(z)$ and C_{PV} . By defining this product of these two nonlinear variables as $\rho_{RA}(z)$, α_{PV} , C_{PV} can be replaced by the following linear relationships:

$$\alpha_{PV} \cdot C_{PV} = \zeta_{RA} = \left(\frac{1}{2^{N_z} - 1} \right) \sum_{z=0}^{N_z} 2^z \rho_{RA}(z) \quad (33)$$

$$-M \gamma_{RA}(z) \leq \rho_{RA}(z) \leq M \gamma_{RA}(z) \quad (34)$$

$$-M(1 - \gamma_{RA}(z)) + C_{PV} \leq \rho_{RA}(z) \leq M(1 - \gamma_{RA}(z)) + C_{PV} \quad (35)$$

Eventually, in (31), the terms α_{PV} , C_{PV} are replaced by ζ_{RA} and the relations in (33)–(35) are added to the main optimisation problem.

In the second strategy, the decision maker has an optimistic view of the stochastic parameters. The model shows, for a decrease in the planning cost according to an oppor-

tunistic factor of σ_{EV}^{RA} , how much the EV charging load has to decrease according to an opportuneness radius of β_{EV} of the EV charging load. The formulation for this model is as (36)–(38) and considering (2)–(10) and (12)–(20).

$$\min \beta_{EV} \quad (36)$$

$$OF < OF_D(1 - \sigma_{EV}^{os}) \quad (37)$$

$$\begin{aligned} C_W Wind(y, t) \Delta t + C_{PV} PV(y, t) \Delta t + P_{dis}(y, t) \Delta t + UL(y, t) \\ = P_{ch}(y, t) \Delta t + (1 - \beta_{EV}) EV(y, t) + RS(y, t) \end{aligned} \quad (38)$$

Finally, for an opportuneness radius of β_{PV} and an opportunistic factor of σ_{PV}^{os} , the opportunity-seeking model for the variations in the PV generation system can be formulated as (39)–(41) and regarding relations (2)–(10) and (12)–(20).

$$\min \beta_{PV} \quad (39)$$

$$OF < OF_D(1 - \sigma_{PV}^{os}) \quad (40)$$

$$\begin{aligned} C_W Wind(y, t) \Delta t + C_{PV}(1 + \beta_{PV}) PV(y, t) \Delta t + P_{dis}(y, t) \Delta t + UL(y, t) \\ = P_{ch}(y, t) \Delta t + EV(y, t) + RS(y, t) \end{aligned} \quad (41)$$

Similar to the risk-averse strategy formulation, the nonlinear term $C_{PV}\beta_{PV}$ can be linearised according to the following relations:

$$\beta_{PV} \cdot C_{PV} = \xi_{OS} = \left(\frac{1}{2^{N_z} - 1} \right) \sum_{z=0}^{N_z} 2^z \rho_{OS}(z) \quad (42)$$

$$-M\gamma_{OS}(z) \leq \rho_{OS}(z) \leq M\gamma_{OS}(z) \quad (43)$$

$$-M(1 - \gamma_{OS}(z)) + C_{PV} \leq \rho_{OS}(z) \leq M(1 - \gamma_{OS}(z)) + C_{PV} \quad (44)$$

4. Simulation Results

The visitor attraction site of the microgrid has ten chargers, each with a capacity of 7 kW. In this study, 6.2 kW wind turbines and 200 Wp PV panels with an efficiency of 15.6% are used [26]. The wind speed–power curve for the wind turbines is extracted from [27]. The capital costs of the wind turbine and PV panels are 5000 GBP/kW and 730 GBP/kW, respectively [28]. In addition, the ESS uses lithium-ion batteries with a capital cost of 146 GBP/kWh [29] and an efficiency of 97.5%. Finally, the capital cost for the converter is 90 GBP/kW with an efficiency of 95%. The price of each EV charger is GBP 1500, and 10 chargers are installed. The total CDM (construction, design, and management) cost is assumed to be GBP 20,000 and the EV modelling is fulfilled according to [28]. The planning horizon is 10 years, and the total capacity of each technology is installed in the first year. The optimisation problem regards a load profile over a ten-year period. Hence, there will be no concerns about the growth of the EV charging load and there will be no need for upgrading the system. All components are sized and installed at the first operating year to last for ten years. The normalised renewable generation profiles for 1 year are shown in Figure 3 with 30 min resolution. It is worth mentioning that various geographical locations can change the results and the size of each component. Each geographical location has its own solar radiation and wind speed profile for each year. These parameters change the power generated by PV panels and wind turbines at different times of the year. Accordingly, the size of various elements including the PV panels, wind turbines, and battery energy storage systems change, which results in variations in the total capacity planning costs. The more the geographical locations differ, the greater the change for different geographical coordinates in terms of component sizes and planning costs. The formulation is modelled

as an MILP formulation in Python and solved using the GUROBI solver [30]. The following sub-sections present the results for the two scenarios for the FEVER project [31].

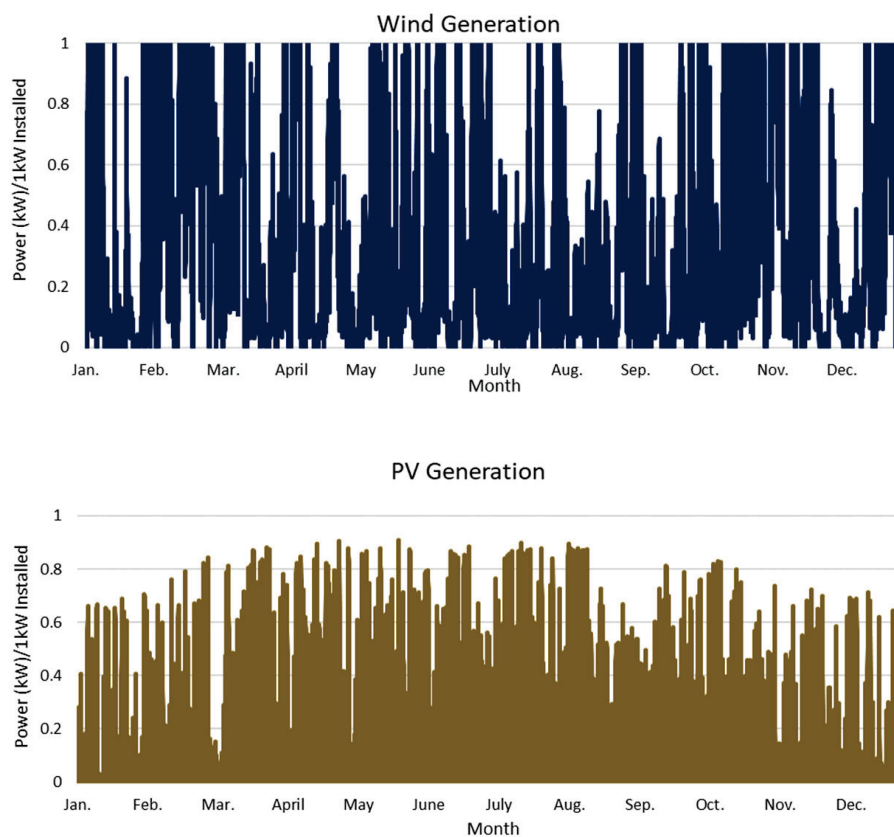


Figure 3. Normalised wind and PV generation profiles for one year (30-min interval).

4.1. Results for the Unmet Load-Constrained Scenario

In this section of the study, the results are presented for a range of EENS from 1% to 10%. Figure 4 indicates the variations in the total and planning cost for each of these reliability levels. In this figure it is observed that for the highest level of reliability, the total cost and planning cost of the system are GBP 131,428 and GBP 116,669, respectively. Conversely, for an EENS of 10% for each year, these costs drop to GBP 79,773 and GBP 68,743, respectively. In addition, in this scenario, the capacity of each element for each level of reliability is shown in Figure 5. In this figure, it is shown that for all levels of reliability, the PV generation capacity fluctuates around 50 kW. When a reliability level more than 97% is desired, nonetheless, this capacity increase to 63 kW (100% reliability). Also, the variation in the BESS capacity shows that for reliability levels from 90 to 97%, the optimiser increases the battery capacity to cope with decreasing the EENS, and for the highest reliability level the BESS capacity increases to 280 kWh. The wind capacity for all levels of reliability is under 6.2 kW, which is less than the capacity of one turbine, and when the level of reliability changes, the variations in the wind generation capacity are trivial. The reason that the required wind generation capacity is so small is not only because of the higher price of wind turbines compared to PV panels but also the load characteristic of the microgrid site. The load for the visitor attraction site is concentrated in the diurnal hours which makes it manageable by PV generation systems and batteries. Hence, instead of sizing expensive wind turbines, the optimiser prefers to use PV generation and BESS to minimise the cost of the system.

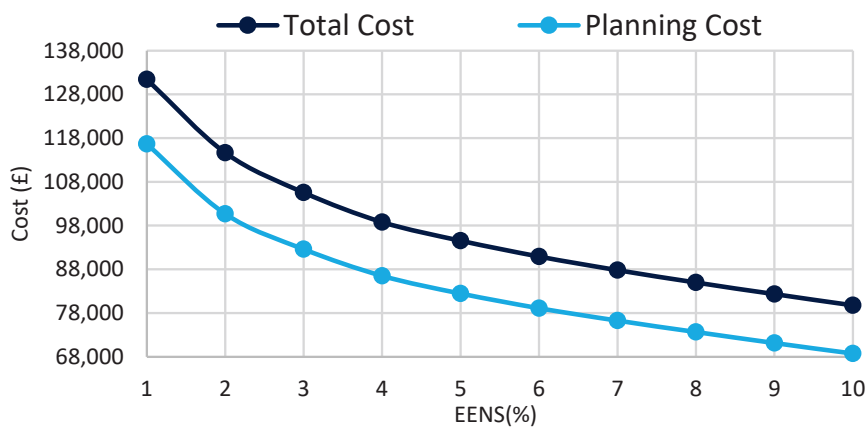


Figure 4. Total cost and planning cost for each level of reliability.

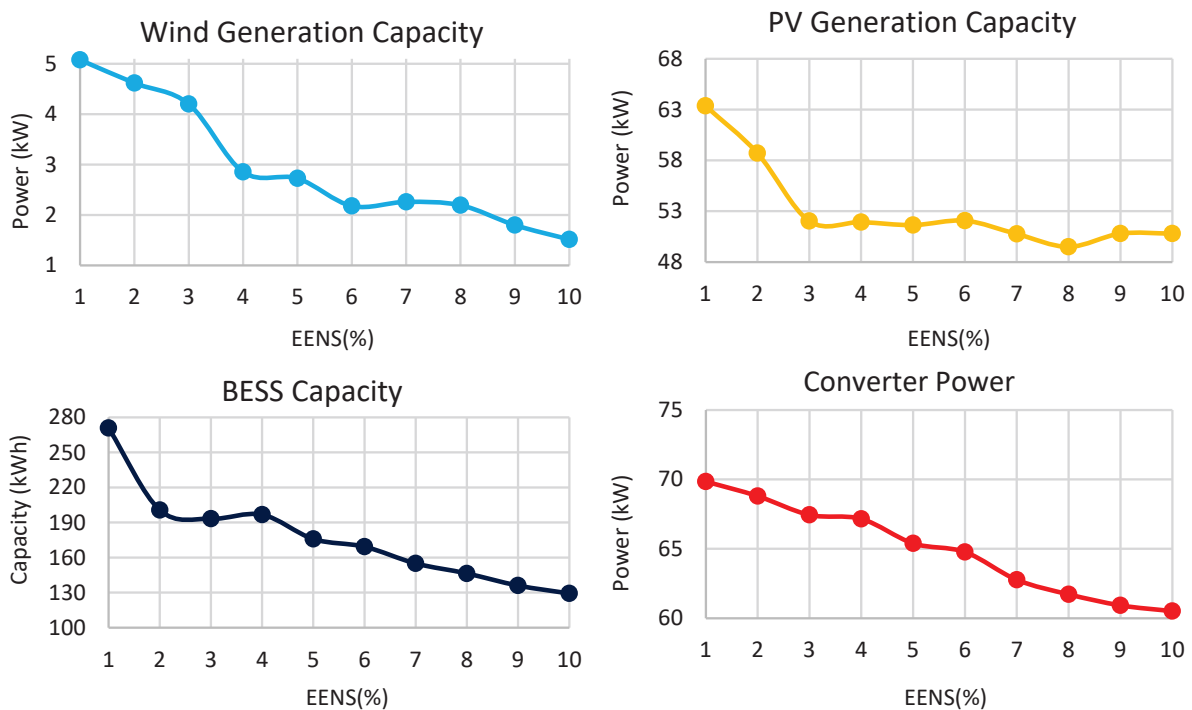


Figure 5. Capacity of each component of the microgrid versus EENS.

For the converter, as the peak load is 70 kW, the size of the converter is near to this value, especially when the EENS is more restricted. It is worth mentioning that if an EENS of 0 is sought after, the total planning cost of the system increases to GBP 265,891 with 233 kW PV and 401 kWh BESS capacity and no wind generation. The size of the converter for this case remains at 70 kW.

For the battery, the charge and discharge profiles are shown in Figure 6 for the last year of the simulation. The total energies charged and discharged when EENS is restricted to 1% are 26,745 kWh and 22,860 kWh, respectively. The stored energy for these two cases is shown in Figure 7.

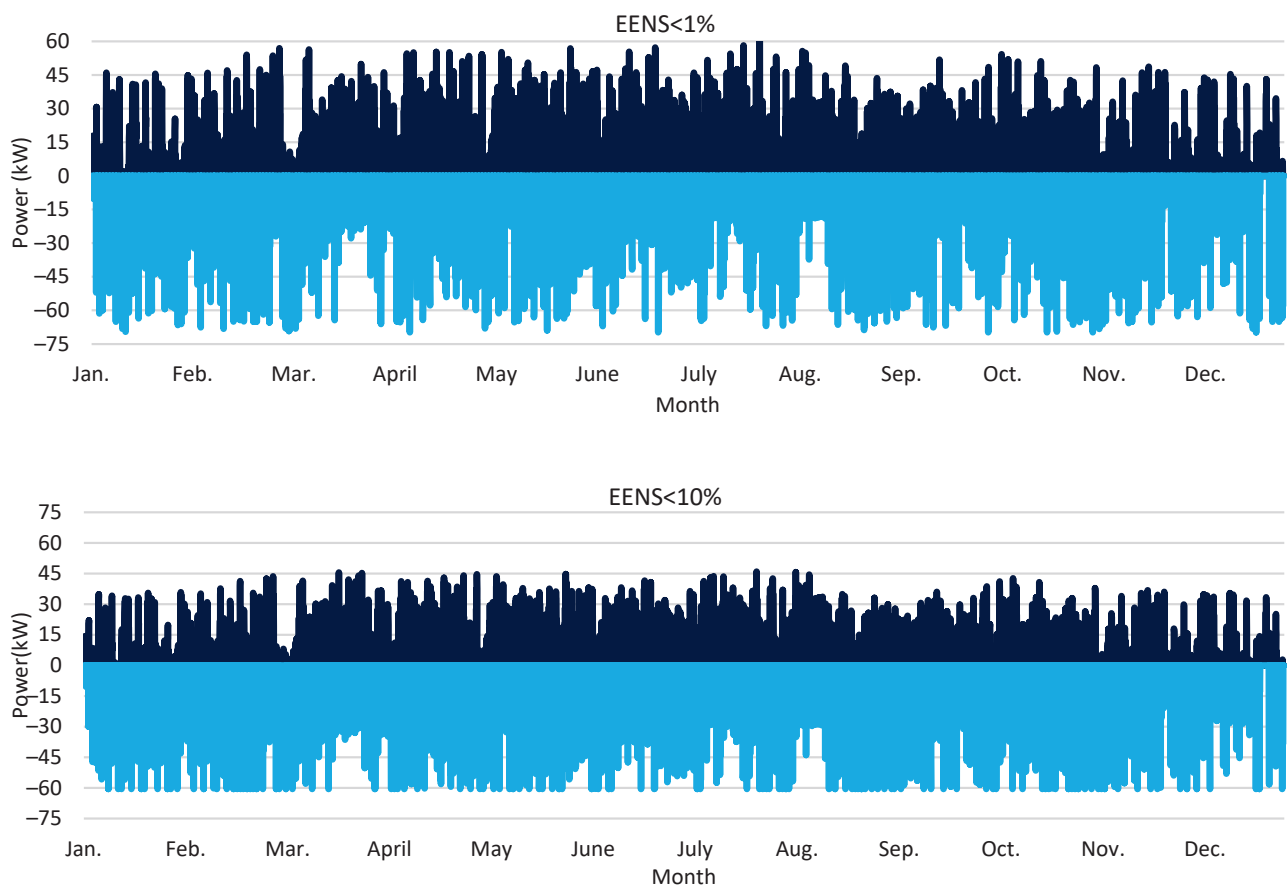


Figure 6. BESS power charge (positive values)/discharge (negative values) for the last year and for two levels of reliability.

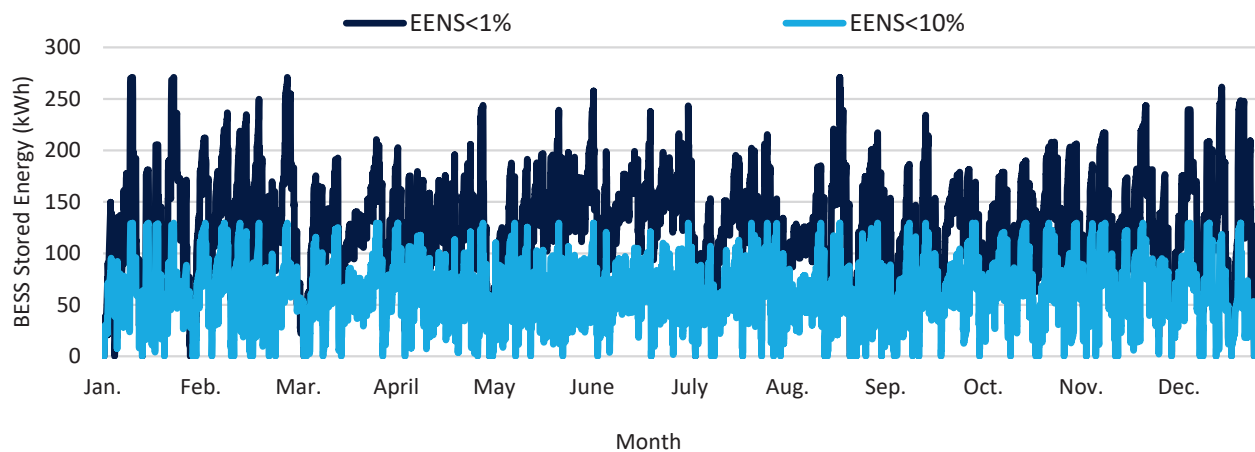


Figure 7. BESS stored energy for two levels of reliability.

To model the higher maintenance cost at the last years of operation, a case study is fulfilled which considers a 10% increase in the OPEX cost for each year and for all components of the system. The results of this case are indicated in Table 1. The results show an increase in the total planning cost due to the 10% yearly increase in the OPEX coefficients. However, the capacity results of each element are the same as when the OPEX coefficients remain constant. This study case and the results are added to the main manuscript.

Table 1. Capacity planning for the study case with variable OPEX.

$EENS_{max}(\%)$	Total Cost (GBP)	PV Capacity (kW)	Wind Capacity (kW)	BESS Capacity (kWh)	Converter Size (kW)
1	139,512	58	5.8	273	70
2	122,309	58	4.5	206	68
3	112,691	52	4.2	193	67
4	105,575	52	2.8	198	67
5	101,117	50	2.8	184	64
6	97,411	51	2.3	171	64
7	94,161	51	2.2	157	61
8	91,186	49	2.3	145	61
9	88,423	49	2.0	142	59
10	85,797	49	1.7	132	59

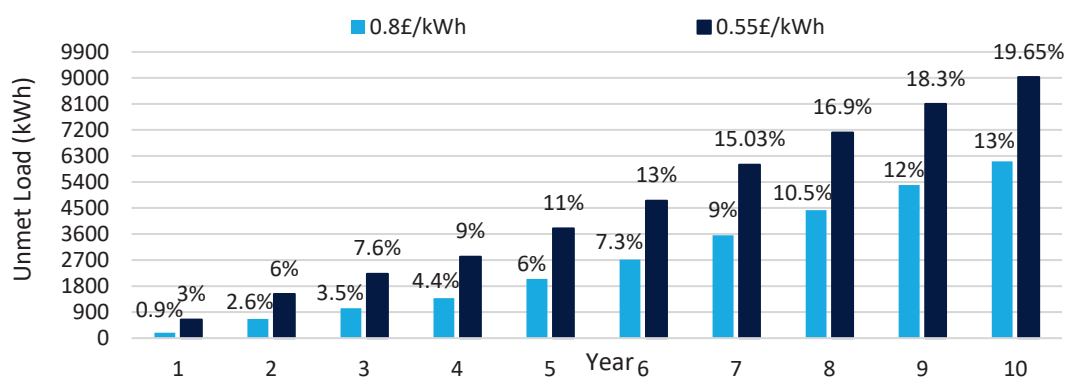
4.2. Results of the Cost–Benefit Optimisation Scenario without Reliability Constraints

In this section, the results are scrutinised when the profit acquired by charging EVs is taken into account. In order to find the optimal case, in this scenario, the EENS is not constrained. The results are presented for three discount rates of 0, 3%, 5%, and two charging prices including 0.55 GBP/kWh and 0.8 GBP/kWh. Table 2 shows the summary of the results for these case studies.

Table 2. Results of the cost benefit model for various discount rates.

	Charging Price (GBP/kWh)	Total Cost (GBP)	Total Income (GBP)	NPV (GBP)	PV Capacity (kW)	Wind Capacity (kW)	BESS Capacity (kWh)	Total Unmet Load (%)
Discount Rate = 0	0.55	60,556	167,250	71,694	44	0	100.5	13.1
	0.8	72,676	258,118	150,442	44	1.6	115.8	7.8
Discount Rate = 3%	0.55	55,760	136,308	45,548	40.5	0	90.2	15.8
	0.8	66,421	211,036	109,614	43.7	0	109.8	10.3
Discount Rate = 5%	0.55	52,368	119,087	31,718	38.2	0	83	18.1
	0.8	62,671	185,573	87,901	43.1	0	102.6	12

It is clear from this table that when the discount rate increases, not only does the NPV decrease, as expected, but also the proportion of unmet EV load increases. Conversely, when the charging price increases from 0.55 to 0.8 GBP/kWh, the NPV increases, and a higher proportion of the EV load is met. From the NPV values, GBP 35,000 has been subtracted and the figures in this table show the final NPV for each case (sum of the EV charger and CDM costs). Figure 8 shows the amount of unmet load for each year when the discount rate is equal to zero. The amount of unmet load also increases for the other cases during the final years of the project.

**Figure 8.** Amount of unmet load for each year for the discount rate of zero for the cost–benefit model and for two different EV charging prices.

4.3. Results of the IGDT Optimisation

This section illustrates the results of the IGDT approach for managing system uncertainties. The method is applied to the unmet load-constrained model. In this study, the results are shown for two strategies including the risk-averse and opportunity-seeking strategy, and for the variations in EV charging load and PV generation.

4.3.1. IGDT Results for the Risk-Averse Strategy

For this strategy, the decision maker is pessimistic about the EV charging load and PV generation. The results for this case are based on a planning cost of GBP 265,891 (risk-neutral), which is for the case with the maximum reliability. It is assumed that the planning budget can be increased to 20% in this case. Figure 9 depicts the variations in the uncertainty budget with the robustness radii of uncertainty for the EV charging load and PV generation, respectively. It is observed that by increasing the planning budget to GBP 319,609, the planning is robust for an increase in the EV charging load up to 20% and the decrease in PV generation of 21.3% for all the planning hours in the worst case. Or, the left figure shows that if the planning cost increases to GBP 308,000 (assuming a GBP 42,542 increase in the planning cost which will be the uncertainty budget), there can be an increase of 16% in the EV charging load or a decrease of 18% in PV generation assuring 100% reliability for the system. Figure 9 also shows the robustness radius for other uncertainty budgets for the EV charging load and the PV generation.

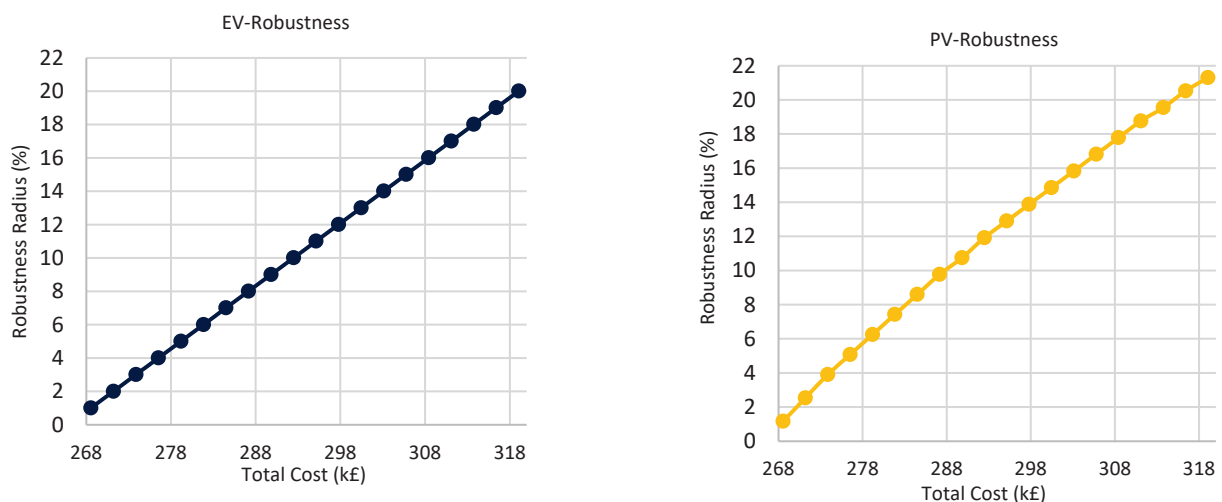


Figure 9. Variation in the robustness radius with the uncertainty budget for EV charging load uncertainty and PV generation uncertainty.

Figure 10 shows the size of the PV generation system and BESS capacity for each amount of uncertainty budget and the cases for EV charging load and PV generation robustness. In these figures, for the EV charging load robustness, the capacities of both the BESS and PV system increase to deal with the maximum increase in the EV charging load restricted by the uncertainty budget. In this case, the BESS and PV system capacities change in the intervals of 405–481 kWh and 236–280 kW, respectively. Furthermore, for the PV generation robustness, while the PV capacity variations are in the interval of 237–297 kW, the BESS capacity remains close to 400 kWh for different values of the uncertainty budget. It is worth mentioning that in these studies, the wind generation capacity is zero for all the cases.

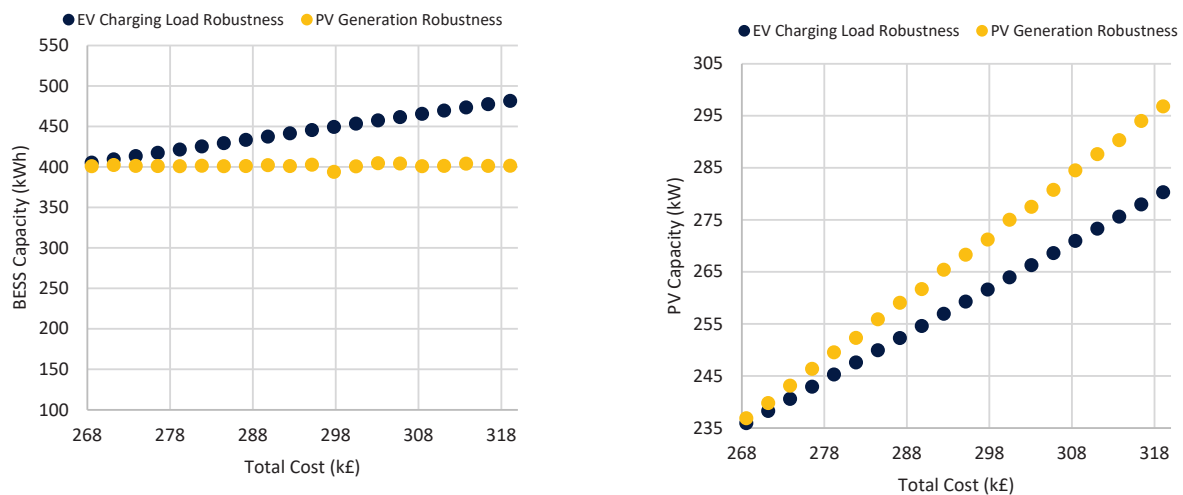


Figure 10. BESS and PV system capacity variations with the total cost for EV charging load and PV generation uncertainty for the risk-averse strategy.

4.3.2. IGDT Results for the Opportunity-Seeking Strategy

In this strategy, the decision maker is optimistic about the EV charging load and PV generation. Figure 11 shows the variation in the opportuneness radius when decreasing the planning cost according to the opportunistic factor for the EV charging load and PV generation. For the EV charging load, it can be seen that if the EV charging load decreases by 20% for the best case for all planning time intervals, the total planning cost of the system will also decrease by 20%. For the PV generation system, the opportuneness radius is about 37.5%. In other words, if the PV generation increases by 37.5% for all planning hours, the total planning cost will decrease by 20%. Or, if the decision maker intends to decrease the total planning cost from GBP 265,891 to GBP 242,000, the EV charging load has to decrease to near 10%, or the PV generation has to increase near to 15%. Like the risk-averse case, the variations for the BESS and PV system capacities are illustrated in Figure 12 for different amounts of total cost specified by the opportunistic factor. This figure shows that for the EV charging load reduction, the battery capacity changes in the range of 320 to 397 kWh and the PV capacity changes from 187 to 231 kW. Also, for the PV generation opportuneness strategy, while the PV capacity changes in the range of 170 to 230 kW, the BESS capacity remains close to 400 kWh for all the opportuneness factors. In other words, for both the risk-averse and opportunity-seeking strategies, only the PV capacity is affected by the robustness and opportuneness radii of uncertainty caused by PV generation.

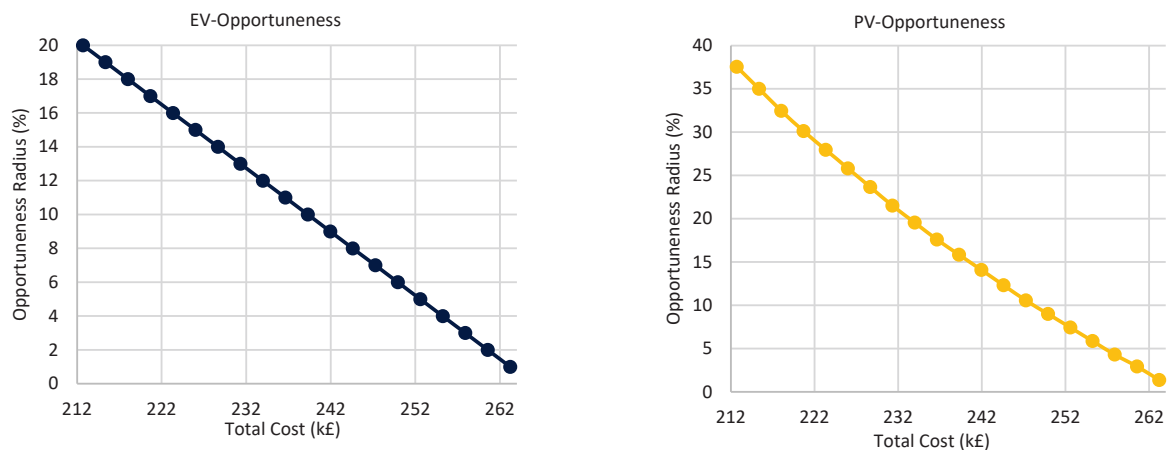


Figure 11. Variation in the opportuneness radius with the total cost for EV charging load and PV generation uncertainty.

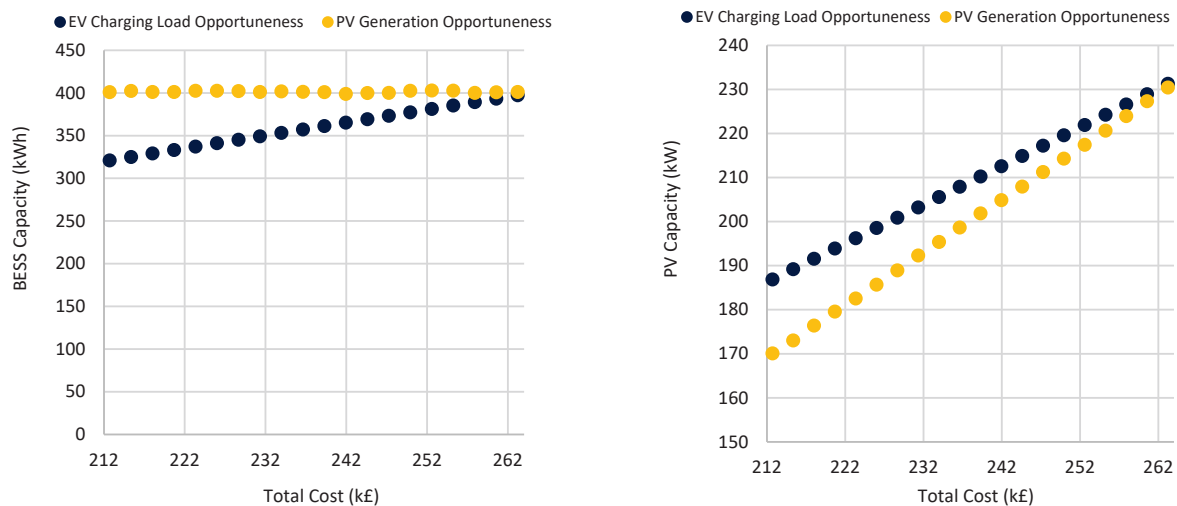


Figure 12. BESS and PV system capacity variations with the total cost for EV charging load and PV generation uncertainty for the opportunity-seeking strategy.

5. Conclusions

This paper presents an optimisation framework for sizing the various components of a stand-alone microgrid for supplying EV charging stations at a visitor attraction site near Southampton, UK, using different levels of reliability. Two different scenarios are studied. In the first one, the CAPEX and OPEX of the project are minimised considering a constraint of the maximum amount of unmet load for each year. In the second scenario, the objective function is based on the NPV of the project without limitation on the amount of unmet load. The results indicate that for the first scenario, the presented framework is able to obtain the optimal size of each component in terms of minimising the CAPEX and OPEX cost for the microgrid and for a certain amount of unmet charging of the EVs at the stations. While supplying 99% of the EVs' demand at the charging station results in a cost of GBP 131,428 for the system, this expenditure decreases to GBP 79,773 if meeting only 90% of the EVs' demand at the charging station is acceptable. For various levels of reliability, higher capacities of PV generation are preferred compared to wind turbines due to the lower investment cost and the nature of diurnal load profile. Moreover, the optimiser plans more BESS capacities when higher levels of reliability are desired instead of increasing the renewable generation capacity.

In the second scenario, the results show that when the amount of the discount rate increases, there are fewer variations in the size of PV systems and wind capacity, but the BESS capacity variations are considerable. The results also show that the amount of unmet load increases with the increase in the discount rate. The EV charging price is another important factor in this study; when it increases, not only does the NPV increase but also the amount of unmet load decreases, which is caused by increasing the size of the PV generation system and BESS capacities.

In the uncertainty studies, the information gap decision theory (IGDT) is used to manage the uncertainties according to risk-averse and opportunity-seeking strategies. For the risk-averse strategy, the results show that by increasing the uncertainty budget up to 20%, the system is able to handle a 20% increase in the EV charging load and a 21.3% in PV generation reduction. For the opportunity-seeking strategy, the results also indicate that the total planning cost can be decreased up to 20% for an EV charging load reduction of 20% or a PV generation increase of 37.5%. The results also show that for the case of PV generation variations, the battery capacity does not change, and the uncertainty is managed by changing the PV capacity.

The core findings of the paper can be summarised as follows:

- For the first scenario, the optimiser prefers to size PV panels and battery energy storage systems rather than wind turbines due to the diurnal EV charging load profile and the CAPEX of the components.
- When higher levels of reliability are desired for the system from 10 to 3%, the optimiser increases the size of the battery, and the PV generation size is almost constant. For reliability levels more than 3%, both the PV generation capacity and battery size increase.
- For the second scenario, when the discount rate increases, only the size of the BESS changes. Also, by increasing the charging price, in addition to the NPV, the sizes of the PV system and BESS increase, which results in decreasing the unmet load.
- For the IGDT studies, the results show that for the EV load charging variations, both the PV generation and BESS capacity change for both the RA and OS strategies. However, for the case of PV generation, the optimiser manages the uncertainty by only changing the capacity of the PV panels and keeping the BESS capacity constant.

Future work can be focused on the concurrent planning of EV charging stations supplied by microgrids and the cyber-security of these systems. Microgrids are becoming more digitised and more dependent on information and communication technology (ICT). Therefore, in order to assure the security of these systems against cyber vulnerabilities, automated control systems which are able to predict, detect, and protect microgrids against cyber-attacks will be needed.

Another possible future research can consider hybrid BESSs composed of different technologies to take advantage of their different features.

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Nomenclature

Sets and indices

t	Index for set of time
y	Index for set of year
N_T	Total time intervals for one year
N_Y	Total number of years
PV	Index for PV generation
W	Index for wind generation
BESS	Indices for battery
ch	Battery charge
dis	Battery Discharge
$Conv$	Index for converter
RA	Risk averse strategy
OS	Opportunity seeking strategy

Parameters

CAPEX	Capital cost of system (GBP/kW) or (GBP/kWh)
OPEX _F	Fixed operation and maintenance cost (GBP/y)
OPEX _V	Variable operation and maintenance cost (GBP/kWh/y)
Δt	Time interval (h)
Wind	Wind generation (kW) for 1 kW installed capacity
PV	PV generation (kW) for 1 kW installed capacity
C_{max}	Maximum capacity of each element (kW) or (kWh)
M	Large value
η	Efficiency
EV	Electric vehicle charger load (kW)
r	Discount rate
Pr_{EV}	EV charging cost (GBP/kWh)

Variables

C	Power of component (kW) or (kWh)
P	Power of component (kW)
UL	Unmet load (kWh)
RS	Renewable spillage (kWh)
u	Binary variable indicating operation mode of battery
E	Battery stored energy (kWh)
EENS	Expected energy not supplied

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Article

Optimal Fast-Charging Strategy for Cylindrical Li-Ion Cells at Different Temperatures

Joris Jaguemont *, Ali Darwiche and Fanny Bardé

SOLiTHOR, 3800 Sint-Truiden, Belgium; ali.darwiche@solithor.com (A.D.); fanny.barde@solithor.com (F.B.)

* Correspondence: joris.jaguemont@solithor.com

Abstract: Ensuring efficiency and safety is critical when developing charging strategies for lithium-ion batteries. This paper introduces a novel method to optimize fast charging for cylindrical Li-ion NMC 3Ah cells, enhancing both their charging efficiency and thermal safety. Using Model Predictive Control (MPC), this study presents a cost function that estimates the thermal safety boundary of Li-ion batteries, emphasizing the relationship between the temperature gradient and the state of charge (SoC) at different temperatures. The charging control framework combines an equivalent circuit model (ECM) with minimal electro-thermal equations to estimate battery state and temperature. Optimization results indicate that at ambient temperatures, the optimal charging allows the cell's temperature to self-regulate within a safe operating range, requiring only one additional minute to reach 80% SoC compared to a typical fast-charging protocol (high current profile). Validation through numerical simulations and real experimental data from an NMC 3Ah cylindrical cell demonstrates that the simple approach adheres to the battery's electrical and thermal limitations during the charging process.

Keywords: lithium; MPC; thermal control

1. Introduction

Lithium-ion batteries (LiBs) have become a cornerstone of modern technology, and are utilized in devices such as laptops, smartphones, and automobiles [1]. A significant challenge in the battery industry is achieving rapid charging while ensuring safety and minimizing degradation. Lengthy charging times are a major barrier to the widespread adoption of electric vehicles (EVs) [2], highlighting the need for fast charging stations [3]. These stations are essential for providing quick and reliable charging, thereby maximizing battery efficiency. However, charging at high c-rates involves a delicate balance, introducing trade-offs with battery thermal gradients and lifespan [4]. High c-rates accelerate ageing due to increased temperatures, faster growth of the solid–electrolyte interface (SEI) layer, elevated lithium plating, and greater mechanical stresses [5–7].

These adverse effects are aggravated when fast charging in extreme temperatures. For instance, at low temperatures, the internal resistance of the battery increases [8], leading to significant power loss [9,10]. Typically, a preconditioning thermal management strategy is integrated into the battery system to enable fast charging [11,12].

Various optimal control algorithms have been proposed to mitigate the negative effects of fast charging. These algorithms address real-time optimal charging problems using methods such as dynamic programming (DP) [13], Pontryagin's minimum principle (PMP) [14], and Model Predictive Control (MPC) strategies [15–17]. However, there is a relative scarcity of studies validating optimal fast-charging control with real-life batteries.

This paper introduces an MPC-based fast-charging controller developed with a straightforward yet high-fidelity electro-thermal model. The numerical solution accurately represents the cell's electrical and thermal characteristics using minimal equations while incorporating environmental temperature influence. The model underwent validation through fast-charging experiments conducted on an NMC 3Ah cylindrical cell and was subsequently utilized for optimization purposes for comparison.

The structure of this paper is as follows: Section 2 details the experimental setup used for the fast-charging test, while Section 3 outlines the fast-charging results. Section 4 covers the development of the electro-thermal and MPC models. Section 5 presents the optimization results. Finally, the conclusions are provided in Section 6.

2. Experimental Setup

2.1. Battery Feature

The tested batteries were cylindrical VTC6 3Ah 18650-type LiBs (Sony, Beijing, China) with the $\text{Li}(\text{NiMnCo})_{1/3}\text{O}_2$ cathode and graphite as anode, and the average mass was measured to be 46.6 g. The nominal capacity and voltage of the battery were 3 Ah and 3.7 V, respectively. Moreover, the c-rate noted C in this paper is defined as $1\text{C} = 3\text{ A}$.

The Neware CT-4008 (Neware, Shenzhen, China) (25 mV to 5 V—0.5 mA to 6 A) controlled by the computer was used to cycle the LiBs with the standard charging and discharging current of A, according to the battery specification [18]. A type-K thermocouple was attached to the cell and used to monitor the battery temperature. Figure 1 depicts the fast-charging experimental setup.

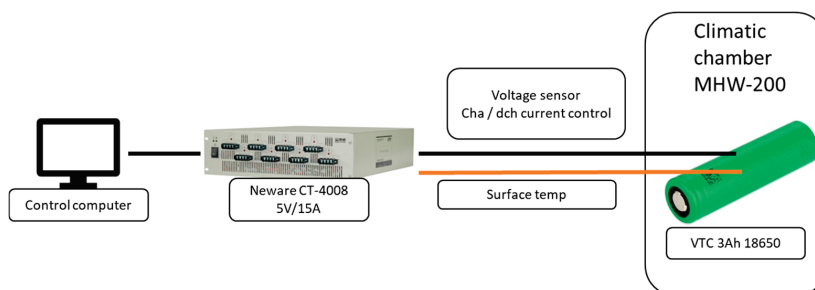


Figure 1. Schematic of the experimental setup used for testing the VTC6 NMC/G 3Ah.

2.2. Fast-Charging Profile

The fast-charging profile involves a high charging current of 4C (12 A) until the battery voltage reaches 4.2 V, which is the maximum recommended upper voltage limit [18]. This is followed by a constant voltage (CV) phase, which continues until the cut-off current reaches $\text{C}/20$ (0.15 A). The fast-charging mission profile is designed to emulate a real-world fast-charging scenario using high currents [19–21]. The testing procedure includes the following stages to provide a more comprehensive overview:

- Charging at $\text{C}/3$ from 0% to 10% state of charge (SoC).
- Charging at 4C from 10% SoC up to the upper cut-off voltage of 4.2 V.
- Maintaining a CV phase until the charge rate reaches $\text{C}/20$.

Figure 2 depicts the fast-charging profile.

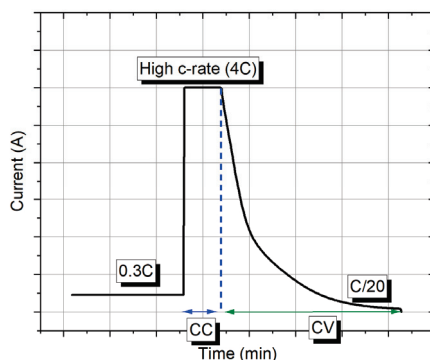


Figure 2. Fast-charging profile.

3. Fast-Charging Results

3.1. Ambient Temperature Testing

Figure 3 presents the fast-charging profile of a 3 Ah NMC cell at 25 °C, showing the current, SoC, and temperature over time. Initially, with a low current rate of C/3 (1 A), the SoC gradually reaches 10% in 18 min. When the current rate transitions to 4C (12 A), rapid charging occurs, and the SoC quickly rises to 80% in under 15 min. These results align with current commercial targets and highlight the impressive performance of these cells.

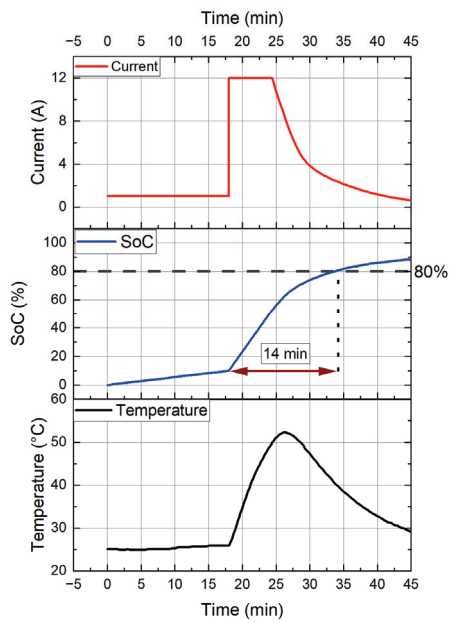


Figure 3. Fast-charging results of the NMC VTC6 3Ah cell.

Regarding temperature, the cell remains relatively stable during the 0% to 10% SoC range due to the low current rate. However, when the 4C (12 A) phase starts, the temperature increases to 54 °C. This temperature rise raises important concerns at the battery pack level, emphasizing the need for precise charging strategies to mitigate overheating risks and ensure the battery pack's safety and long-term operational integrity.

Ultimately, achieving safe fast charging for these cells requires balancing the desired SoC levels with effective temperature management strategies to avoid thermal runaway.

3.2. Extreme Temperature Testing

In Figure 4, the results of the fast-charging test at extreme temperatures (−10 °C, 10 °C, 45 °C, and 60 °C) are presented. The temperature results of the fast-charging test are shown in Figure 5, for which the variation in temperature, ΔT , is displayed in order to compare the tests. ΔT is a way of expressing temperature differences when conducting temperature tests and is calculated by subtracting the current battery temperature from the initial battery temperature. That is to say, it is a good way to compare different temperature tests for which the initial temperature is not the same.

For high-temperature tests, it is evident that 45 °C is the most favorable for fast charging, as the high-current phase lasts longer than at other elevated temperatures. When the temperature decreases to ambient (25 °C), the high-current phase shortens due to the higher resistance compared to that at 45 °C [22].

At 60 °C, the CC phase is shorter than at 45 °C. This may be attributed to increased resistance from accelerated ageing in this environment. The extreme testing conditions at 60 °C lead to a significant rise in resistance, which is linked to the growth of the solid-electrolyte interface (SEI) layer on the graphite negative electrode [23]. Elevated cycling temperatures cause increased lithium plating during cycling, with deposits de-

tected on the graphite electrodes [23]. Consequently, the fast-charging test at 60 °C may have triggered lithium deposition on the anode, increasing internal resistance.

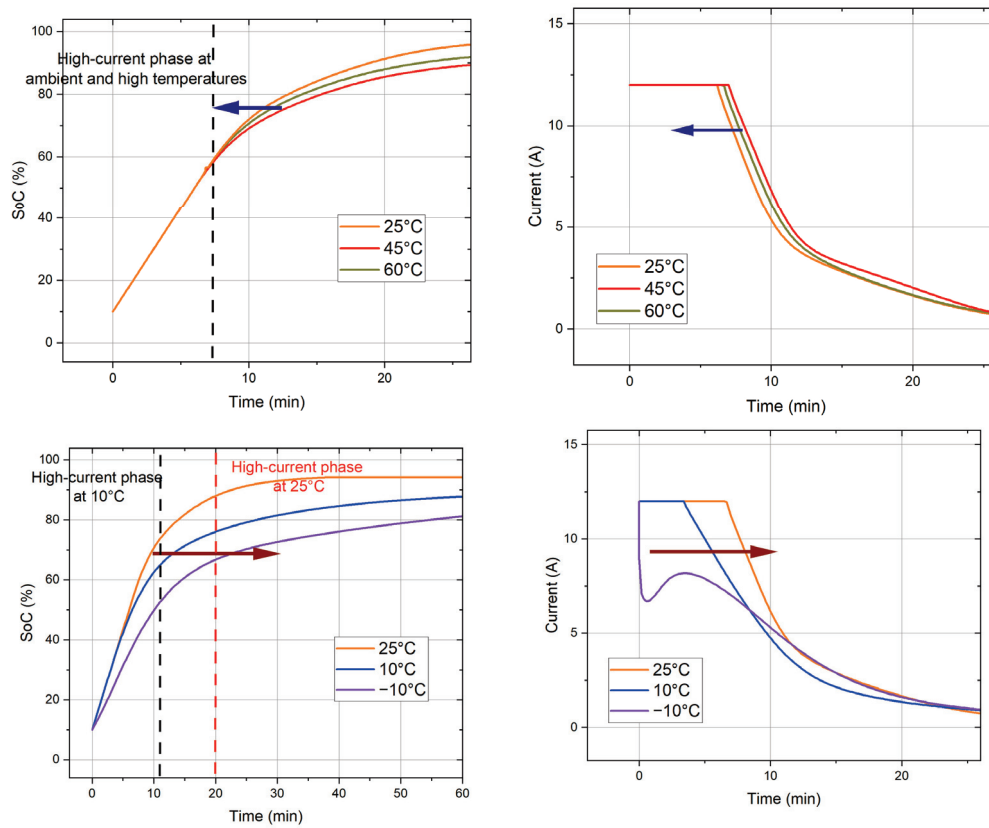


Figure 4. (Top): Fast-charging results of the NMC VTC6 3Ah cell at high temperatures (45 °C & 60 °C). (Bottom): Fast-charging results of the NMC VTC6 3Ah cell at low temperatures (−10 °C & 10 °C).

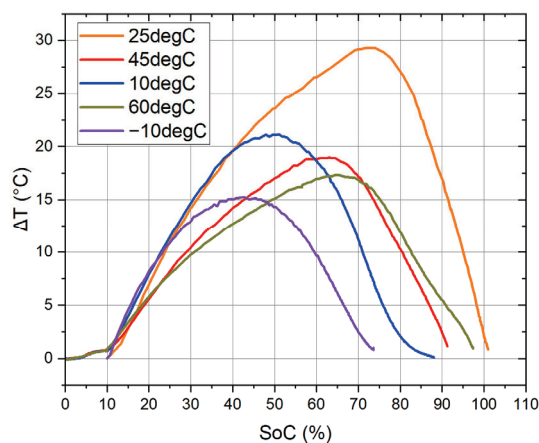


Figure 5. Temperature variation of the fast-charging test.

In low-temperature environments, the high current phase is notably impacted. At 10 °C and lower, the CC phase is shorter than at 25 °C due to a higher internal resistance [24]. Specifically, at −10 °C, the current profile initially drops but then shows a short increase as charging continues. This is due to the evolution of resistance: starting high at the beginning of the fast-charging test, it decreases as the cell's temperature rises, thus lowering resistance and causing the observed current profile [25,26].

Overall, low-temperature conditions are not conducive to fast charging, meaning that twice as much time is needed to charge to 80% in 10 °C conditions. Therefore, a preconditioning

tioning thermal management strategy should be developed to optimize fast charging in such environments [11,12].

4. Model Development

4.1. Model Methodology

This paper utilizes a 1D electro-thermal model based on a semi-empirical approach within a MATLAB/Simulink® 2023 interface. The model aims to replicate the cell's electrical and thermal performance through two primary components: the electrical and thermal modules. The electrical module calculates the SoC using electrical parameters, while the thermal module estimates the cell's temperature based on the heat generation equation.

The electrical model, depicted in Figure 6 and constructed using the R_{int} model [27], consists of a voltage source in series with a single resistance. According to the equivalent circuit model, the battery's output voltage for the Li-ion cell is determined by the voltage drop caused by the battery's open circuit voltage (OCV) and internal resistance (R_{int}). The cell's output voltage is calculated using the formula described in [27]:

$$V_{cell} = V_{oc} - R_{int} \cdot I_{batt} \quad (1)$$

where I_{batt} is the flowing current in the battery (A). Thereafter, the SoC is determined by the Coulomb-counting method and is defined in [26]:

$$SoC = SoC_0 - \frac{1}{C_{init}} \int I_{batt} dt \quad (2)$$

with SoC_0 as the initial SoC of the cell. C_{init} is defined as the initial capacity (Ah) and it is assumed to be temperature-dependent as well as being influenced by the current. In Equation (1), all the circuit parameters are derived from the manufacturer's datasheet, resulting in an internal resistance value of 28 mΩ at 25 °C and 44 mΩ/80 mΩ at 10 °C.

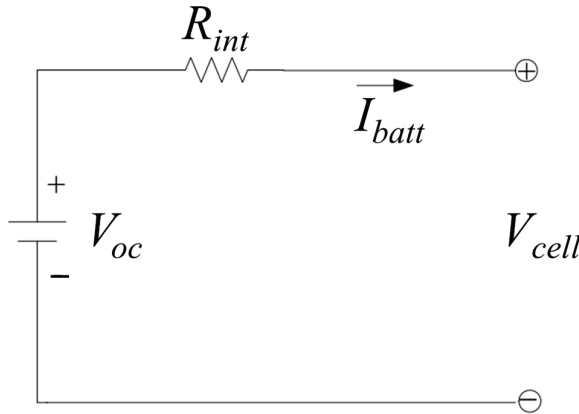


Figure 6. The R_{int} electrical model [27].

The thermal aspect of the model incorporates thermodynamic equations relevant to cylindrical cells. It considers a single temperature point, assuming heat generation at a specific location on the cell's surface, characterized by a defined heat capacity and mass. Heat is then transferred from the cell's surface to the surrounding environment. By applying a heat balance equation at this specific surface point, the following thermodynamic equations describe the heat transfer between the surface and the ambient environment [28]:

$$\left\{ \begin{array}{l} \frac{dU_{cell}}{dt} = Q_{gen}(t) - Q_{loss}(t) = m \cdot Cp \cdot \frac{dT}{dt} \\ Q_{gen} = R_{int} \cdot (I_{batt})^2 \\ Q_{loss} = Q_{conv} = h_{conv} \cdot S_{area} \cdot (T_{cell} - T_{amb}) \end{array} \right\}, \quad (3)$$

where U_{cell} , the internal energy, is the total energy contained by a thermodynamic system (J), Q_{gen} is the generating heating rate (W) in the corresponding element, and Q_{loss} is the heat losses of the corresponding element (W). C_p is the specific heat of the cell (kJ/kg·K) and m is the mass of the cell (kg). The thermal model operates under the following assumptions:

- The temperature of the cell's surface, denoted as T_{cell} , is considered to be uniformly distributed, and as such, it represents the overall temperature of the entire cell.
- This paper accounts for natural convective heat transfer, characterized by the following parameters: ambient temperature, T_{amb} , (°C), the heat exchange surface area, S_{area} (in m²), and the convective heat transfer coefficient, h_{conv} (W/m²·K).
- All thermal parameters utilized in this paper are sourced from the cell manufacturer's datasheet. Consequently, the model employs a specific heat capacity (C_p) of 1006 kJ/kg·K, a mass of 0.046 kg, and an area of 0.004327 m². Given the use of natural convection, an h_{conv} of 15 W/m²·K is applied [29].

4.2. Model Validation

Figure 7 presents the results of model validation at 25 °C and 10 °C, comparing the measured and estimated SoC and temperature for the cell during the fast-charging phase (4C or 12 A). The data show that the modeled SoC closely matches the SoC obtained from electrical experiments, further validating the electrical modeling and the accuracy of the electrical parameters at both ambient and low temperatures.

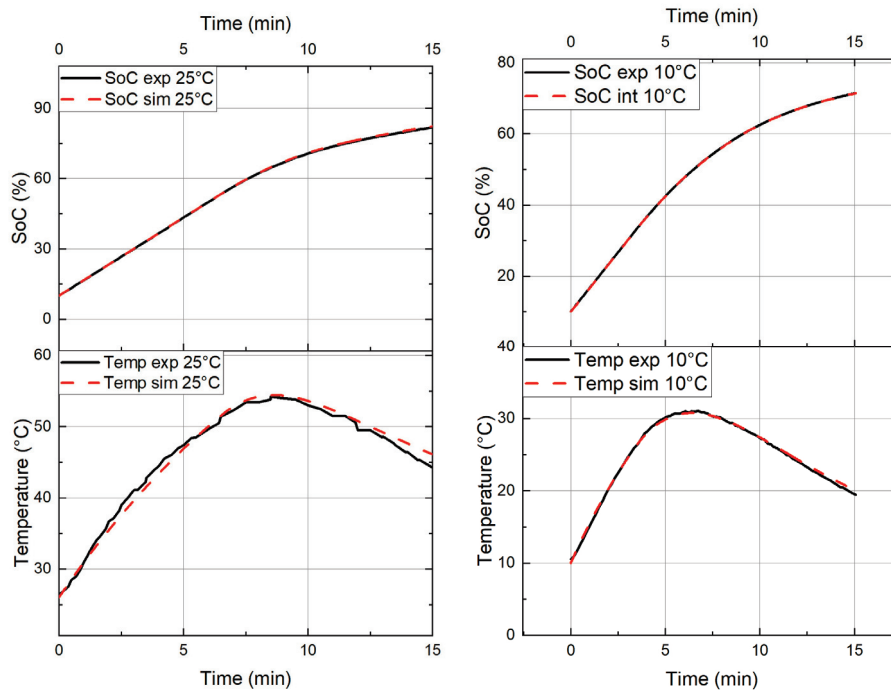


Figure 7. Validation of the electrical and thermal model at 25 °C (left-hand side) and 10 °C (right-hand side).

In terms of temperature evolution, the model demonstrates remarkable accuracy in predicting the cell's temperature at both 25 °C and 10 °C, even with the use of a single resistance. The strong correlation between the model's predictions and the experimental results for both electrical and thermal behaviors underscores the model's validity. Thus, the electro-thermal model is confirmed as a reliable tool for optimization processes.

4.3. Model Predictive Control

Model Predictive Control (MPC) is an advanced control strategy that is widely used in engineering, economics, and robotics [30,31]. MPC is a dynamic optimization technique

that leverages a mathematical model of a system to make informed control decisions. Unlike traditional control methods, MPC operates over a defined prediction horizon, which represents a future time window. During this horizon, the controller predicts the system's response to various control inputs.

MPC formulates an optimization problem that aims to optimize a cost or objective function over the prediction horizon. This function typically includes terms related to system performance, such as tracking a reference trajectory or minimizing costs, while adhering to constraints. At each time step, MPC solves the optimization problem based on the system's current state and the prediction horizon. It calculates the optimal control inputs for the horizon but only applies the first input to the system. After applying this control input, MPC advances to the next time step, updates the system state, and repeats the optimization process. This iterative procedure provides continuous feedback control as the system evolves. Figure 8 shows the flowchart of the MPC and the semi-empirical model.

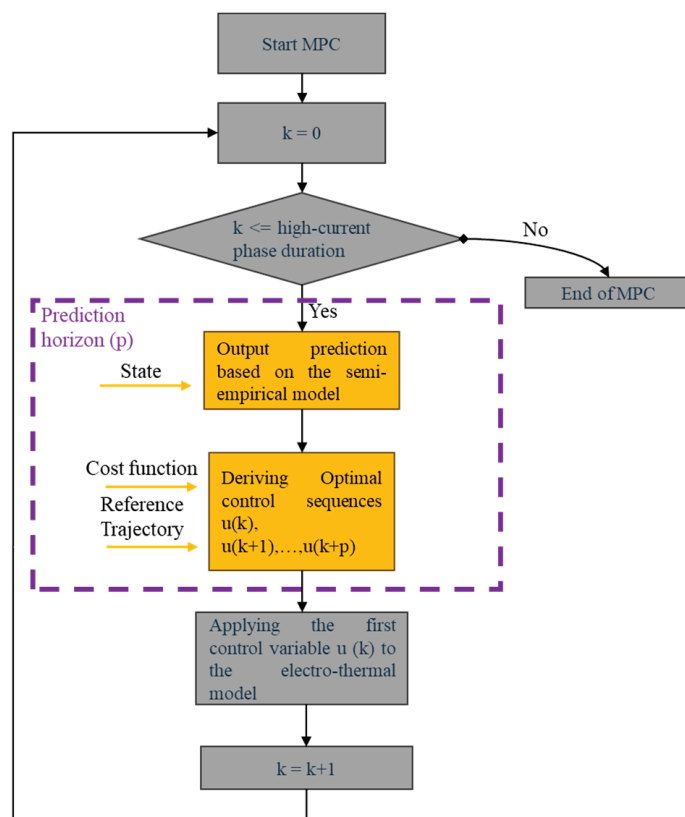


Figure 8. MPC flowchart.

The demand for safe and rapid charging strategies has become increasingly crucial, especially for fast charging [19,31–33]. MPC has emerged as a promising and versatile approach to meet this demand, utilizing predictive modeling and real-time optimization for precise control over the charging process.

In this paper, the primary objective of the controller is to minimize battery temperature while maximizing the SoC simultaneously. This is a complex challenge, involving a multi-state, constrained, and nonlinear dynamic optimal control problem. The key states considered are the battery temperature (T_{batt}) and SoC, with the charging current (I_{batt}) as the control variable.

To address fast charging, the MPC problem is formulated with strict constraints on both battery temperature and SoC. By utilizing the probability distribution of the estimated battery temperature and SoC levels, MPC strategically determines the optimal charging current rate. The goal is to maximize the SoC while effectively regulating the battery

temperature within set limits. This complex control challenge is encapsulated in the following cost function:

$$J = \left[\sum_{k=0}^{N_p-1} \alpha \cdot \frac{1}{\text{SoC}(N_p)} + \beta \cdot T_{\text{cell}}(N_p) \right], \quad (4)$$

where N_p , representing the prediction horizon, is set to 10 (equivalent to 10 s); SoC signifies the charge level at the k -th time step; and α and β represent the weighting factors. The first component of the cost function is dedicated to maximizing the SoC, aligning with our primary objective. The equality constraint of the MPC is stated as follows:

$$\begin{aligned} k &= k + 1 \\ x(k+1) &= f(x(k), u(k)), \end{aligned} \quad (5)$$

where $x(k)$ is the state and $u(k)$ is the control input. These are expressed as follows:

$$x(k) = \begin{bmatrix} T_{\text{cell}}(k) \\ \text{SoC}(k) \end{bmatrix}, u(k) = [I_{\text{batt}}(k)], \quad (6)$$

4.4. Problem Description

This section describes the case study for the optimization process. The study is centered on the fast-charging profile discussed in Section 2, specifically using the electro-thermal model designed for the VTC6 3Ah NMC battery.

The control algorithm utilized in this study employs a receding horizon mechanism. Within this framework, optimal control sequences are computed over a prediction horizon, and the initial control input is executed while adhering to predefined constraints. Throughout our study, these constraint values are set as follows:

$$\begin{pmatrix} T_{\text{cell},\min} \leq T_{\text{cell}}(k) \leq T_{\text{cell},\max} \\ \text{SoC}_{\min} \leq \text{SoC}(k) \leq \text{SoC}_{\max} \\ I_{\text{batt},\min} \leq I_{\text{batt}}(k) \leq I_{\text{batt},\max} \end{pmatrix} \quad (7)$$

where *min* and *max* refer to the minimum and maximum values, respectively.

The temperature and current values in use are in accordance with the cell manufacturer's recommendations. Regarding the initial SoC, given that during the initial 0% to 10% SoC range, the cell's temperature is relatively stable, the MPC will focus on optimizing the high-current phase, commencing at 10% SoC. Furthermore, the initial temperature is established at 25 °C, aligning with ambient environmental conditions.

5. Results and Discussion

5.1. Fast-Charging Optimization

Figure 9 depicts the outcomes of MPC application during the high-current phase (4C or 12 A). In this simulation, both weighting factors were assigned a value of one. The red line represents the optimal results, contrasting with the reference values shown by the black line.

The MPC-calculated current trajectory reveals a charging process divided into two phases. Initially, a peak current of 23 A is applied, gradually decreasing to a stable 6.5 A. Due to this variation in the current profile, it takes an additional minute to reach an 80% SoC compared to the reference profile.

Significantly, the optimal charging strategy effectively keeps the cell's temperature below 45 °C, aligning with the manufacturer's temperature limit without necessitating an external cooling system. This ability to regulate temperature via the optimal current profile suggests the feasibility of employing a smaller cooling system for this battery pack, potentially reducing weight, mass, and overall costs.

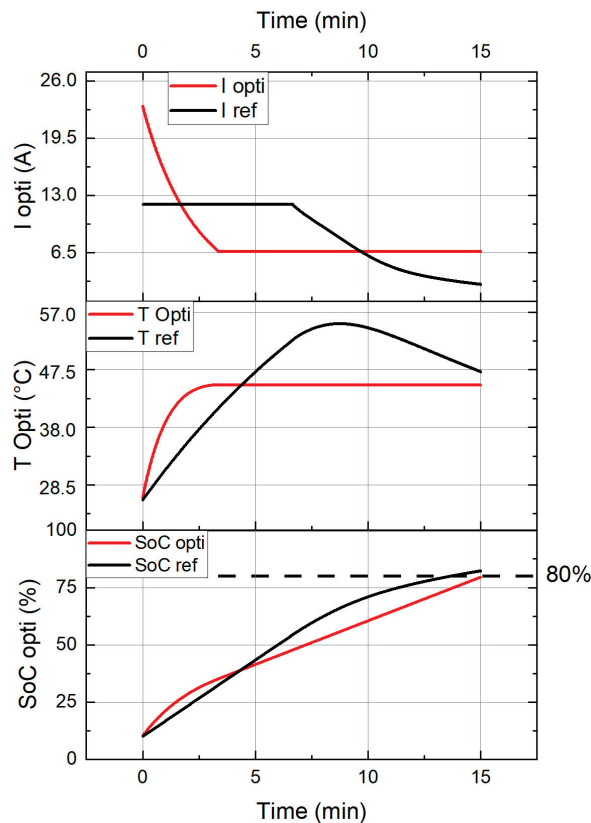


Figure 9. MPC results of the high-current phase.

5.2. Optimal Fast-Charging Profile Validation

In this subsection, validation of an optimal fast-charging profile was undertaken through a comprehensive analysis involving computational modeling and experimental testing. The charging profile, optimized using an algorithm, underwent evaluation by comparing the evolutions of SoC and temperature. The results of this validation test are illustrated in Figure 10, juxtaposing practical experiment data from a VTC6 3A NMC cell.

Figure 10 depicts a close alignment between the measured SoC and temperature evolution and the simulated values. This successful validation against real-world experimental data underlines that the profile is not merely a theoretical concept derived from a simplified battery model but highlights its practical potential for optimizing fast-charging strategies for LiBs.

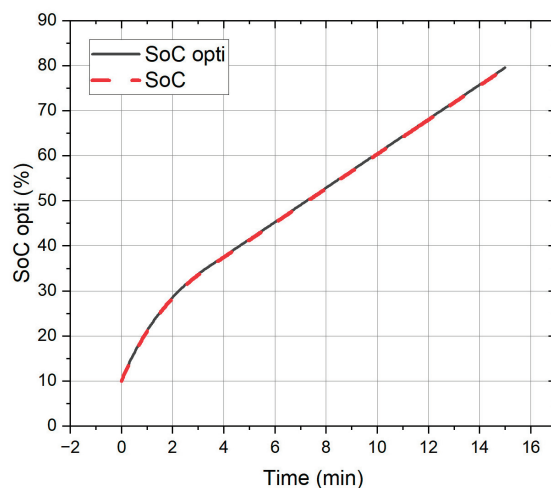


Figure 10. Cont.

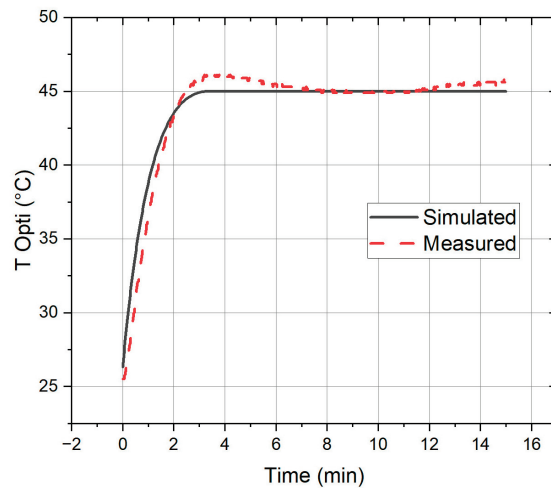


Figure 10. Optimal fast-charging profile validation.

5.3. Effect of the Current Limit

In the previous section, the MPC's maximum current limit was initially set to the manufacturer's recommended 10C, corresponding to 30 A. However, due to typical operational conditions within the battery pack application, which seldom exceed 4C, a new MPC simulation was conducted using a maximum current limit of 4C (12 A), maintaining consistent weighting factors.

Figure 11 presents the outcomes of the MPC simulation with the 4C current limit. The optimized charging profile exhibits a three-phase pattern. Initially, a 4C (12 A) charging rate is applied for 3 min, followed by a reduction to 6.5 A to ensure the cell's temperature remains below 45 °C. After 15 min, the current gradually decreases further. Despite extending the charging duration by more than 1 min and 30 s compared to the reference profile, this approach successfully maintains the cell's thermal gradient within a safe range.

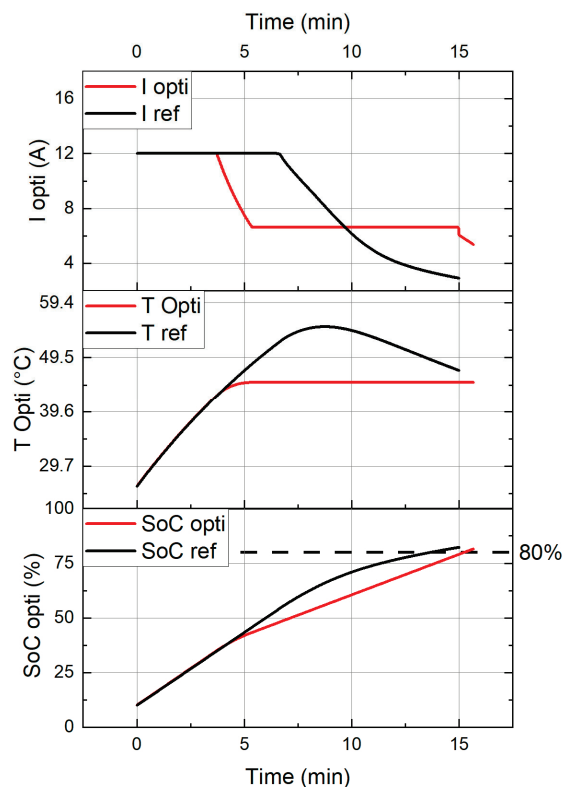


Figure 11. MPC results of the optimal high-current phase using a current limit of 12 A.

In the end, while the temperature remains below the critical 45 °C threshold, it is essential to conduct a comprehensive lifetime study to assess the long-term viability of this optimized charging strategy.

5.4. Effect of the Low-Temperature Environment

In the previous section, the MPC algorithm was configured for an ambient temperature of 25 °C. This section simulates the algorithm under cold temperature conditions, with both the initial cell temperature and ambient temperature set to 10 °C. The maximum allowable battery temperature is capped at 30 °C to ensure optimal battery performance, and the current limit is set to 12 A, reflecting the power limitations of battery systems operating in low-temperature environments [34]. Given the energy constraints imposed by cold temperatures, the algorithm prioritizes achieving the highest possible SoC while maintaining a safe temperature range.

Figure 12 illustrates the results obtained under low-temperature conditions. The optimized charging profile displays a three-phase charging pattern. Initially, a 4C (12 A) charging rate is applied for 4–5 min, followed by current oscillations between 5 A and 10 A to maintain the cell temperature at 30 °C. This section of the optimal current profile identified by the MPC alternates every second with an amplitude of 5 A. This high-frequency current switching is intended to maintain the cell's temperature within a safe range while maximizing the SoC. However, this profile must be tested on a single cell to evaluate its feasibility.

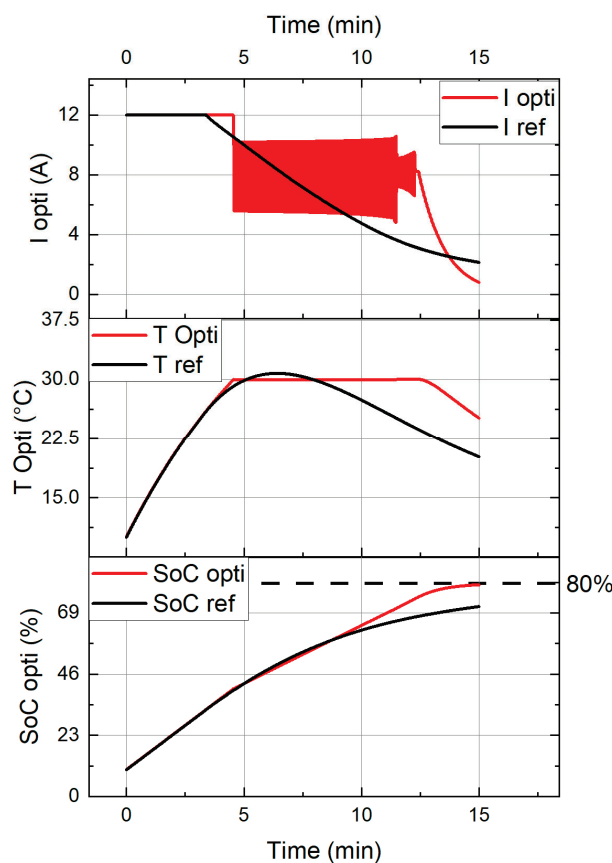


Figure 12. MPC results of the optimal high-current phase at 10 °C.

Charging at a high frequency at low temperatures is a promising preconditioning method that helps to manage the thermal gradient more effectively, with a faster temperature rise, and ensures a more uniform temperature distribution within the cell [35–37]. This can enhance the overall performance and longevity of the battery by counting on the internal resistance of the cell to provoke self-heat generation [12]. Moreover, rapid switching

can help mitigate lithium plating, which is more likely to occur at low temperatures and high current rates, thereby improving the safety and durability of the battery [38].

After 12 min, the current gradually decreases. This approach maintains the cell within an optimal temperature range while achieving an almost 80% SoC after 15 min, which was not feasible with the reference profile. By prioritizing maximum SoC, the MPC algorithm proposes a profile where the cell's temperature is optimized at 30 °C, maximizing its capacity under these conditions.

6. Conclusions

This paper represents a significant advancement in optimizing fast-charging strategies for Li-ion batteries (LiBs) using MPC, emphasizing the delicate balance between SoC management and thermal safety. Initially, an NMC battery model was developed and rigorously validated using a single-resistance framework, demonstrating the efficacy of this simplified modeling approach.

Building from this model, a customized MPC system tailored for fast-charging applications was conceptualized and implemented. The results illustrate an optimized charging profile that enhances thermal performance with minimal compromise—extending the charging duration by just one minute compared to typical fast-charging profiles.

Crucially, the study shows that this optimized profile not only enables rapid charging but also maintains the cell temperature within the recommended 45 °C threshold. Moreover, in cold environments, the algorithm identified a current profile that kept the cell within an optimal temperature range, achieving nearly 80% SoC in 15 min, whereas the reference profile only reached 70% within the same timeframe.

This advancement has the potential to reduce the need for elaborate cooling/heating systems, offering significant savings in costs, weight, and volume in battery pack design. Future research will focus on the ageing aspect of the cells. Extensive lifetime studies will be conducted to assess the long-term impact of fast-charging strategies on cell durability and the impact on the optimal fast-charging profile. Moreover, efforts will be dedicated to studying the discharging effect and comparing the effectiveness of the methodology.

Further enhancements in battery modeling methodologies, potentially incorporating additional electrical parameters such as an RC loop, are also planned. Extreme temperature simulations of the model and MPC are also intended to expand the model's capability. Ultimately, the goal is to scale up these findings to broader battery modules, aligning the research with practical applications in real-world scenarios.

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Article

Teleoperated Driving with Virtual Twin Technology: A Simulator-Based Approach

Keonil Kim ¹ and Seok-Cheol Kee ^{1,2,*}

¹ R&D, AVGenius, Cheongju-si 28116, Republic of Korea; kikim@avgenius.kr

² Department of Intelligent Systems and Robotics, Chungbuk National University, Cheongju-si 28644, Republic of Korea

* Correspondence: sckee@chungbuk.ac.kr

Abstract: This study introduces an innovative Teleoperated Driving (ToD) system integrated with virtual twin technology using the MORAI simulator. The system minimizes the need for extensive video data transmission by utilizing text-based vehicle information, significantly reducing the communication load. Key technical advancements include the use of high-precision GNSS devices for accurate vehicle location tracking, robust data communication via the MQTT protocol, and the implementation of the Ego Ghost mode in the MORAI simulator for precise vehicle simulation. The integration of these technologies enables efficient data transmission and enhanced system reliability, effectively mitigating issues such as communication blackouts and delays. Our findings demonstrate that this approach ensures stable and efficient operation, optimizing communication resource management and enhancing operational stability, which is crucial for scenarios requiring high video quality and real-time response. This research represents a significant advancement in ToD technology, establishing a precedent for integrating virtual twin systems to create more resource-efficient and reliable autonomous driving backup solutions. The virtual twin-based ToD system provides a robust platform for remote vehicle operation, ensuring safety and reliability in various driving conditions.

Keywords: teleoperated driving; ToD; remote driving; autonomous driving; virtual twin; digital twin

1. Introduction

As the interest in autonomous driving features has markedly increased, technological advancements in this field have rapidly accelerated [1,2]. Recent research on Autonomous Vehicles (AVs) employs a combination of sensors, cameras, radar, and artificial intelligence to perceive their environment and make driving decisions based on HD precision maps [3–5]. Furthermore, the addition of various learning methods related to artificial intelligence has further fueled research in autonomous driving [6,7]. AVs are classified into levels from 0 to 5 by the Society of Automotive Engineers (SAE), with Level 0 representing no automation and Level 5 representing full automation without any need for human intervention. In higher levels of autonomous driving, especially in systems at Level 4 and above, the driver is completely disengaged from vehicle operation [8,9]. This disengagement necessitates reliable backup systems to ensure safety and continuity in vehicle operation. In these contexts, the importance and demand for Teleoperated Driving (ToD) as a backup system for driverless autonomous vehicles have risen significantly in response to potential system failures [10–12]. ToD plays a crucial role in the autonomous driving system as a solution for transitioning to a Minimal Risk Condition (MRC) during system failures or in traffic situations that the system cannot handle independently [13–15]. With the application of V2N (Vehicle to Network) in C-V2X (Cellular Vehicle to Everything Communication) and with 5G communication, the reliability and speed of communication have greatly improved, enabling faster and more stable teleoperated driving [12,16]. Furthermore, there has been a significant amount of recent research related to 5G technology [17–19]. 5G technology

provides high data transfer speeds and low latency, enabling real-time response during remote driving and ensuring smooth data communication between the vehicle and the remote operation center. Additionally, the security enhancements of 5G networks play a crucial role in protecting the system from Denial of Service (DoS) attacks and other cyber threats [20,21]. These security enhancements increase the reliability of teleoperated driving systems, ensuring that autonomous vehicles can operate safely in various driving conditions.

Meanwhile, virtual twin technology, replicating real roads in the digital world, has become integral to autonomous driving technology [22,23]. It is primarily used for simulating and evaluating complex, potentially hazardous traffic scenarios that are impractical to replicate in reality. This technology not only allows for detailed testing and refinement of driving algorithms but also enhances the safety and adaptability of autonomous systems by mirroring diverse real-world conditions and integrating continuous feedback for improvement [24–26].

As a solution to the challenges faced by traditional ToD systems, this study proposes the integration of ToD with a virtual twin system. By using a virtual twin system in ToD, instead of transmitting video, vehicle information like coordinates, direction, and steering angle can be sent in a message format, significantly reducing the data communication load. This approach effectively addresses issues such as communication interruptions, latency in real-time monitoring, and remote assistance, along with high costs and telecommunication hardware challenges [27]. This research aims to enhance the effectiveness of the ToD system by applying digital twin technology. Through these developments, we seek to improve operational efficiency, reduce latency, and ensure seamless remote control of autonomous vehicles in various driving conditions.

The rest of this paper is organized as follows: Section 2 describes the methods and system architecture used in developing the virtual twin ToD system. Section 3 presents the results and discusses the performance and effectiveness of the proposed system. Section 4 concludes the paper with a summary of findings and suggestions for future research directions.

2. Methods

2.1. Teleoperated Driving (ToD)

In this research, we built upon a previously developed ToD system to construct the virtual twin ToD system [28]. While adhering to the basic vehicle operation mechanisms of the original ToD system, we utilized advanced simulators for visualizing vehicle information and camera footage. At the Remote Operation Center (ROC), a high-performance PC based on Linux [Ubuntu 20.04] was installed for stable and fast processing, along with a Logitech G29 driving device. The remote control mechanism was divided into two primary axes: longitudinal control using a PID (Proportional–Integral–Differential) controller based on the input values of brake and throttle; and lateral control adjusting the steering angle values transmitted in real-time through a PI (Proportional–Integral) controller [29]. This control approach allowed for real-time reflection of the remote driver's steering input, enabling synchronous operation with the vehicle.

In terms of vehicle system configuration, we equipped the vehicle with a PC [NVIDIA, Jetson Xavier AGX], image capture card [CANLAB, CLMU-200N], and Sekonix camera. Additionally, a high-precision GNSS [Novatel, Pwrpak7D-E2] device was installed for accurate vehicle location tracking, enhancing the precision of our positioning system. The experimental vehicle selected was the Hyundai Kona Hybrid, equipped with a 5G/LTE router [HUCOM wireless, HE-900] to facilitate high-speed data transmission. At the remote control station, we established a stable communication environment through a 100 Mbps Ethernet connection, focusing on enhancing the reliability of remote control operations.

2.2. Virtual Twin ToD System

We developed a virtual twin ToD system by integrating a ToD vehicle, Kona, with the MORAI simulator, and demonstrated it at the C-track, located in Cheongju City. C-track

is an autonomous driving test space equipped with various test roads, including circular, urban, and application roads [4,30]. An aerial illustration of C-track is shown in Figure 1. Due to legal restrictions related to ToD demonstrations in Korea, the virtual twin ToD system was implemented and demonstrated within C-track, not on public roads.

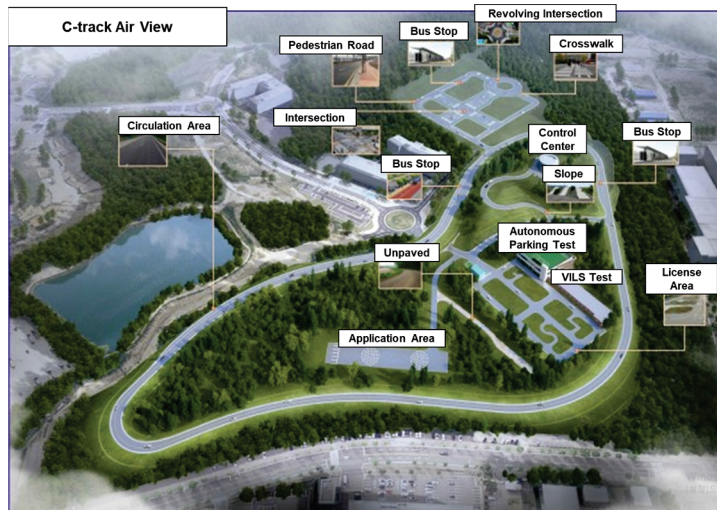


Figure 1. Aerial illustration of C-track. C-track is an autonomous driving test space equipped with various test roads, including an express way, urban area, and application roads.

Figure 2 presents a detailed diagram of the virtual twin ToD system. ROC sends control inputs such as steering, gear shifting, and acceleration for vehicle operation to the ToD vehicle through the MQTT network. The ToD vehicle transmits its position and rotation data to the simulator PC at the ROC. The simulator PC integrates this location information with the steering and velocity data received directly through the ROS network from the controller, then sends it to MORAI through the ROS bridge. The MORAI simulator processes these data, producing a precise and clear visual representation. Additionally, as an option to prepare for and prevent unexpected accidents or problems, a low-bandwidth AVM (Advanced View Monitor) video feed can be transmitted from the ToD vehicle to the operator [28].

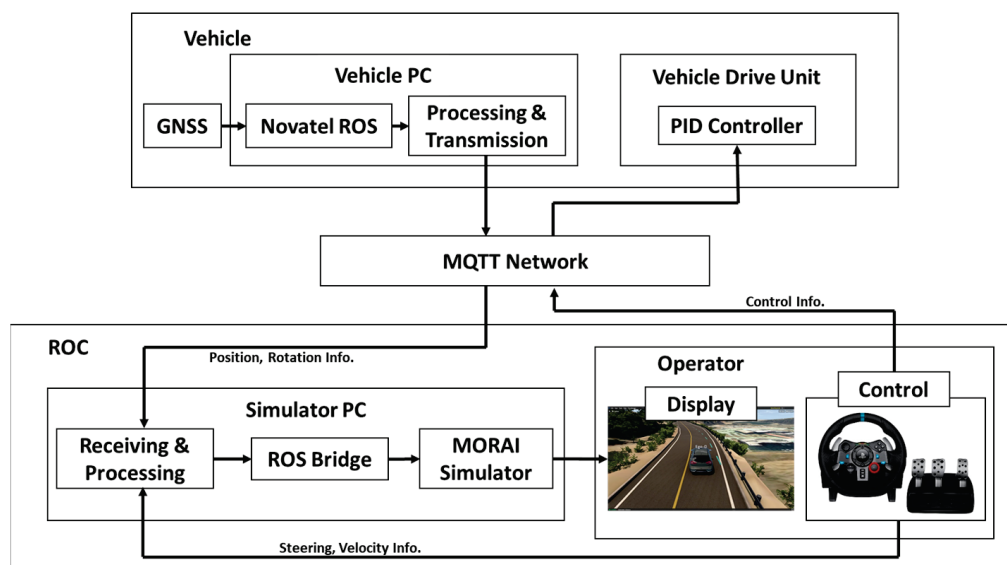


Figure 2. Detailed diagram of the virtual twin ToD systems. This diagram illustrates the virtual twin ToD system's data flow.

2.3. Virtual Twin Implementation

Figure 3 illustrates the fundamental concepts and differences between the traditional ToD and virtual twin ToD systems. In the traditional approach, the ROC communicates directly with the vehicle, where the substantial communication load required for video streaming presents one of the biggest challenges. Even though video data are compressed through encoding before transmission, the inherently large size of video data inevitably leads to significant load. In contrast, the virtual twin ToD system incorporates a simulator for visualization, which substantially reduces and distributes data transmission size, thereby implying a relatively lower communication load and overall burden.

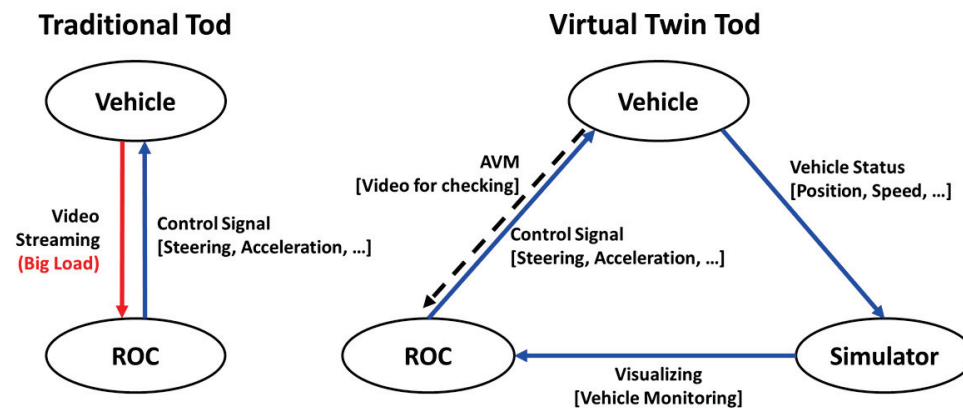


Figure 3. Conceptual diagram comparing the communication between traditional ToD and virtual twin ToD systems.

We utilized the latest version of MORAI's simulator, MORAI 23.R.1.0, for the virtual twin. This simulator was operated on the ToD ROC PC. The MORAI simulator operates in an ROS environment, so we installed and used the ROS Noetic version suitable for the Ubuntu 20.04 environment. The advanced option of the simulator, the Ego Ghost mode, which replicates real vehicles in the simulation world, was primarily used [31]. This mode receives vehicle information (position, rotation, velocity, and steering angle) in message format. The message format for the Ego Ghost mode is standardized in the egoGhost.msg format included in MORAI's ROS package, allowing for direct utilization. The position and rotation information is gathered from the high-precision GNSS device installed in the test vehicle, KONA, and transmitted from the vehicle to the ROC using the TCP/IP-based MQTT protocol.

The velocity and steering angle data are directly monitored and captured through the ROC operator equipment. Utilizing the same PC for both simulation and ToD operations enables efficient data transfer, achieved through ROS's internal communication system. Through ROS topics, a robust message exchange between nodes occurs, allowing for real-time, accurate updates of vehicle dynamics in the simulation.

To convert the received position and rotation data into the MORAI simulator's internal coordinate system and vehicle heading values, the GNSS coordinates were first transformed into UTM (Universal Transverse Mercator) coordinates using the Python UTM library. We then subtracted the easting and northing offset values from these transformed UTM coordinates to complete the conversion. These offset values are map-specific, provided for each distinct virtual environment available in the MORAI simulator when using its GPS sensor. Each map in the MORAI suite represents a different geographical area, with unique easting and northing coordinates. The rotation, consisting of x, y, and z axes, used only the z-axis value as the yaw value. Received in degrees, these rotation values were adjusted by subtracting a specific offset to obtain the Heading value. During the fine-tuning process of the easting, northing, and rotation offsets, we conducted hands-on driving tests on a designated test track (C-track) with the vehicle; thus precisely setting the vehicle's position and heading to reflect real-world conditions. Through this process, the egoGhost.msg is

completed and input into the MORAI simulator via the ROS bridge. To verify the accurate implementation of the ToD vehicle in the simulation, a GPS sensor was also mounted in the simulation at the same location as the GNSS on the actual vehicle. When driving on the track, sensors from both the real world and the simulation were read to analyze the differences between them.

In measuring latency, we precisely calculated the delay in the MQTT communication process using the message ID and its corresponding timestamp. Additionally, we assessed the time it took for the vehicle's data to appear on the simulator screen by tracking when the egoGhost.msg was processed and the output of ROS topic data. Combining these two aspects, we determined the total delay for the simulation's visualization. For the traditional ToD system, we measured the complete latency from the vehicle's camera to the ROC monitor's display, including the time needed for video encoding and decoding. In contrast, with the virtual twin system, we measured the delay from the moment the vehicle's GNSS device transmitted data until the vehicle was rendered on the simulator screen. Figure 4 visually represents these latency differences.

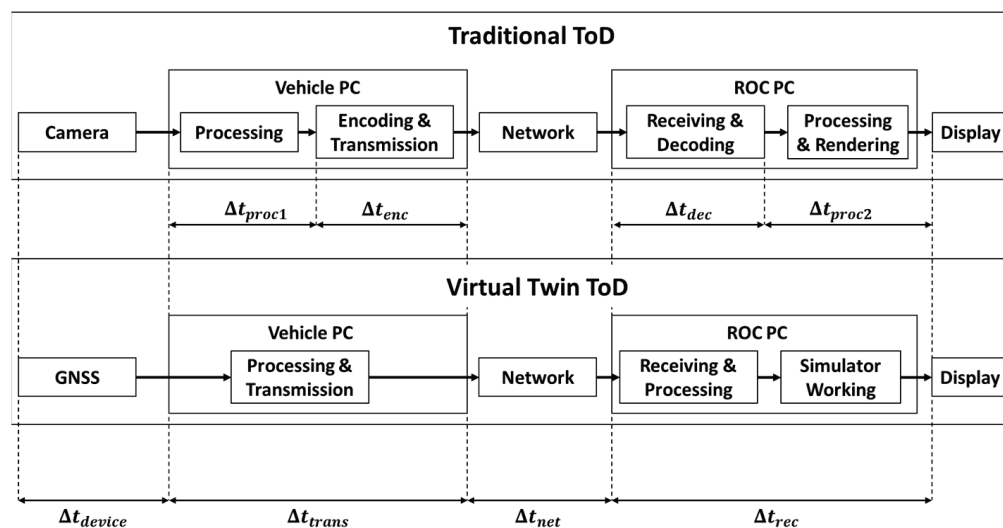


Figure 4. Comparative diagram of latency analysis showing data transmission and processing pathways in traditional ToD and virtual twin ToD systems, showing that the virtual twin ToD system significantly reduces latency by simplifying data processing and transmission, thereby enhancing the responsiveness and safety of remote driving.

3. Results and Discussion

Figure 5 presents a demonstration environment and example of the virtual twin ToD. The ToD operator drives while observing the simulation environment and, if necessary, can optionally check the AVM (Advanced View Monitor) video (Figure 5a). Figure 5b,c show the views that the operator would see in traditional and virtual twin ToD systems, respectively. In Figure 5b, the view is fixed to the camera's position, whereas in Figure 5c, the simulation view can be adjusted according to the user's preference, including angle of view, direction, and distance.

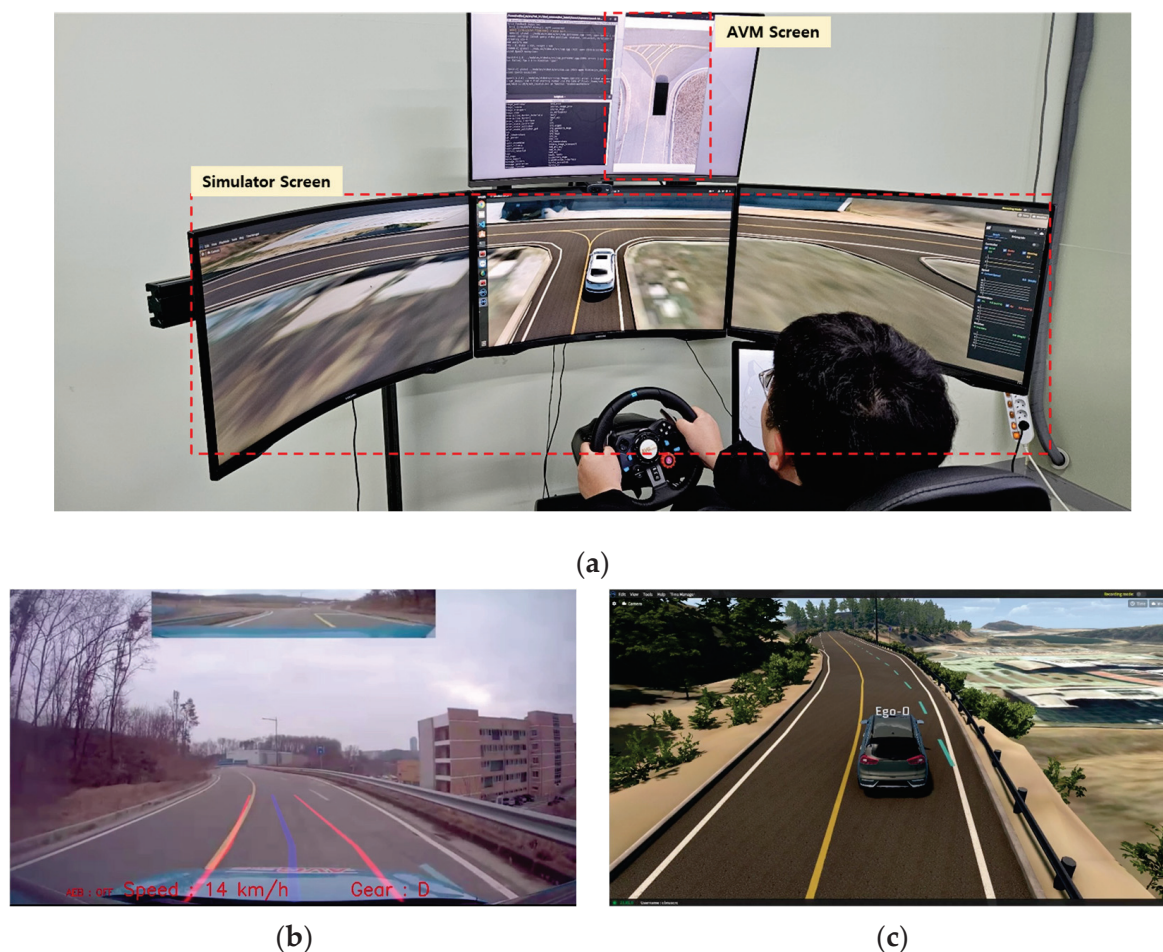


Figure 5. Demonstration of virtual twin ToD. (a) Operating scene of virtual twin ToD system. (b) The SD quality video screen of traditional ToD. (c) The simulator screen of virtual twin ToD, which can be adjusted according to the user's preference.

3.1. Driving Test

The driving tests involved comparing GPS data from a real vehicle (KONA) and a simulated vehicle using the virtual twin ToD system. Tests were conducted in both expressway and urban areas. In urban areas, specific situations such as roundabouts, U-turns, and left turns were targeted for measurement. GPS data were acquired at a frequency of 50Hz from both sources, and the distance differences between the two sets of coordinates were calculated and recorded simultaneously.

Table 1 and Figures 6 and 7 display the results of operating a vehicle using the virtual twin ToD system. In Table 1, which presents the results of coordinate differences for each driving course, the average distance difference across all test routes was less than 0.08 m. This indicates a negligible difference between the real and simulation datasets, with the distance discrepancy being only a few centimeters. Figure 6 overlays the actual GPS data of the KONA vehicle (red line) on the satellite image of the C-track, along with the GPS data obtained from the simulator (blue line) for the expressway. The two paths (KONA GPS and simulator GPS) perfectly coincide in the image.

Table 1. The coordinate differences of the virtual twin ToD and the real vehicle.

Coordinate Difference [m]	Average	Median	Standard Deviation
Expressway	0.05650	0.02742	0.08014
Roundabout	0.07420	0.06251	0.03379
U-Turn	0.05654	0.04742	0.02454
Left Turn	0.07361	0.06450	0.03066

**Figure 6.** The result of the virtual twin ToD driving test on the expressway. The image represents the actual GPS data of the KONA vehicle (red line) and the GPS data obtained from the simulator (blue line) overlain on the satellite imagery of the C-track.

To facilitate further analysis, the line graph and histogram depicting the difference in GPS data obtained are displayed in Figure 7. The line graph on the top part of Figure 7 presents a direct comparison of distance discrepancies between real-world and simulated GPS readings. On this graph, coordinate differences are traced in blue and then smoothed with a moving average, represented by the red line. The orange and green lines mark the mean and standard deviation, respectively. The histogram on the bottom, using a logarithmic y-axis, reveals that the data points predominantly fall within a 0.2 m range, indicating negligible variance in the GPS readings.

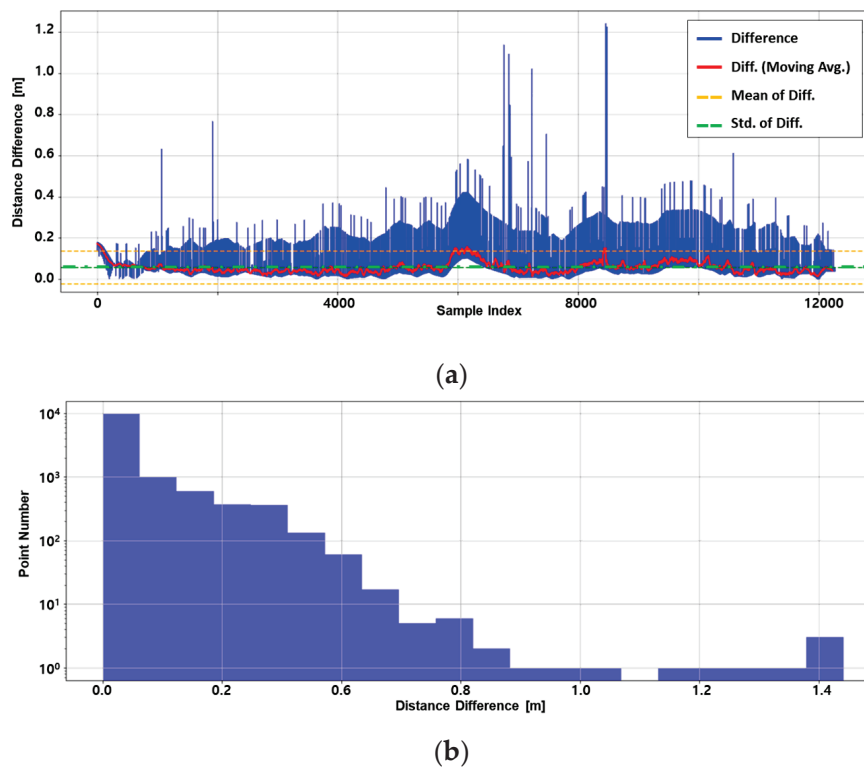


Figure 7. GPS Data discrepancy analysis. (a) The line graph details distance variance between actual and simulated GPS, with a moving average depicted in red. (b) The histogram, scaled logarithmically, confirms most data points lie within 0.2 m, evidencing the simulation’s precision.

The results from urban areas in Figure 8 were found to be nearly identical to those from the expressway. In Figure 8a–c, it was observed that the paths for roundabouts, U-turns, and left turns all align well, indicating accurate coordinate matching. Furthermore, in Figure 8d, it can be seen that for all three scenarios, the noise-mitigated red line remains below 0.1 m. Noise can be visually identified in each line graph above. The smoothed graph, obtained using the moving average method, compensates for this noise and stays below the 0.1 m range, aligning closely with the mean value. These results validate that the vehicle represented in the virtual twin and the actual vehicle move along nearly identical paths, proving the accuracy of the simulation.

In the graphs from Figures 7 and 8, the noise shows unique characteristics that differ from typical sensor noise. Unlike common white noise with random magnitudes, the noise here includes specific error values, resulting in a band-like appearance. Additionally, there are no values below a certain level. To analyze this noise, we performed additional experiments for a similar graph while the vehicle was stationary, shown in Figure 9. Figure 9a’s blue line depicts the stationary state with the same y-axis scale as before, revealing almost no visible noise due to its small scale, aligning closely with the smoothed red line. For a detailed view, the y-axis is magnified in Figure 9b, and the data are also presented as a histogram in Figure 9c. The magnified graph in Figure 9b,c exhibits typical white noise, which also shows a Gaussian distribution shape in the histogram.

This random white noise is characteristic of GNSS hardware and sensor noise. While the simulator’s GPS values remain perfectly fixed when stationary, the real vehicle’s GPS signal fluctuates due to noise. The difference between the fixed values and this fluctuation appears as white noise in Figure 9, with very slight values. The fluctuation is relatively large initially and decreases over time, stabilizing after about the 4000th point, likely due to the system settling down after being powered on. This indicates that the noise observed in Figures 7 and 8 is not typical white noise but rather originates from a different source or issue.

One such issue is the error from data sampling inconsistencies. Both the simulator and the real vehicle's GNSS equipment are set to a 50 Hz sampling rate. Although both the simulator and the real vehicle's GNSS equipment are set to same sampling rate, the simulator consistently maintains this rate, while the real equipment may fail to receive all signals at 50 Hz, especially during motion, potentially missing some data points. In the previous experiments (expressway and urban area), the vehicle moved at approximately 10 km/h (2.78 m/s), and, with a 50 Hz sampling period (0.02 s), the distance between sampling points should be about 5.56 cm. Figure 10 illustrates a segment of Figure 8d, highlighting quantized noise signals with specific magnitudes (red box). These peaks are approximately 16.8 cm, 11.2 cm, and 5.6 cm, corresponding to 3, 2, and 1 times the distance between sampling points, respectively. When plotted on a line graph, these consistent error values connect with the preceding and subsequent points, forming vertical lines and ultimately creating the band-like graph. Adjusting the simulator's GPS timing to match the real vehicle's data input timing could improve this discrepancy, as the real vehicle's precise sampling timing is challenging to handle due to hardware issues.

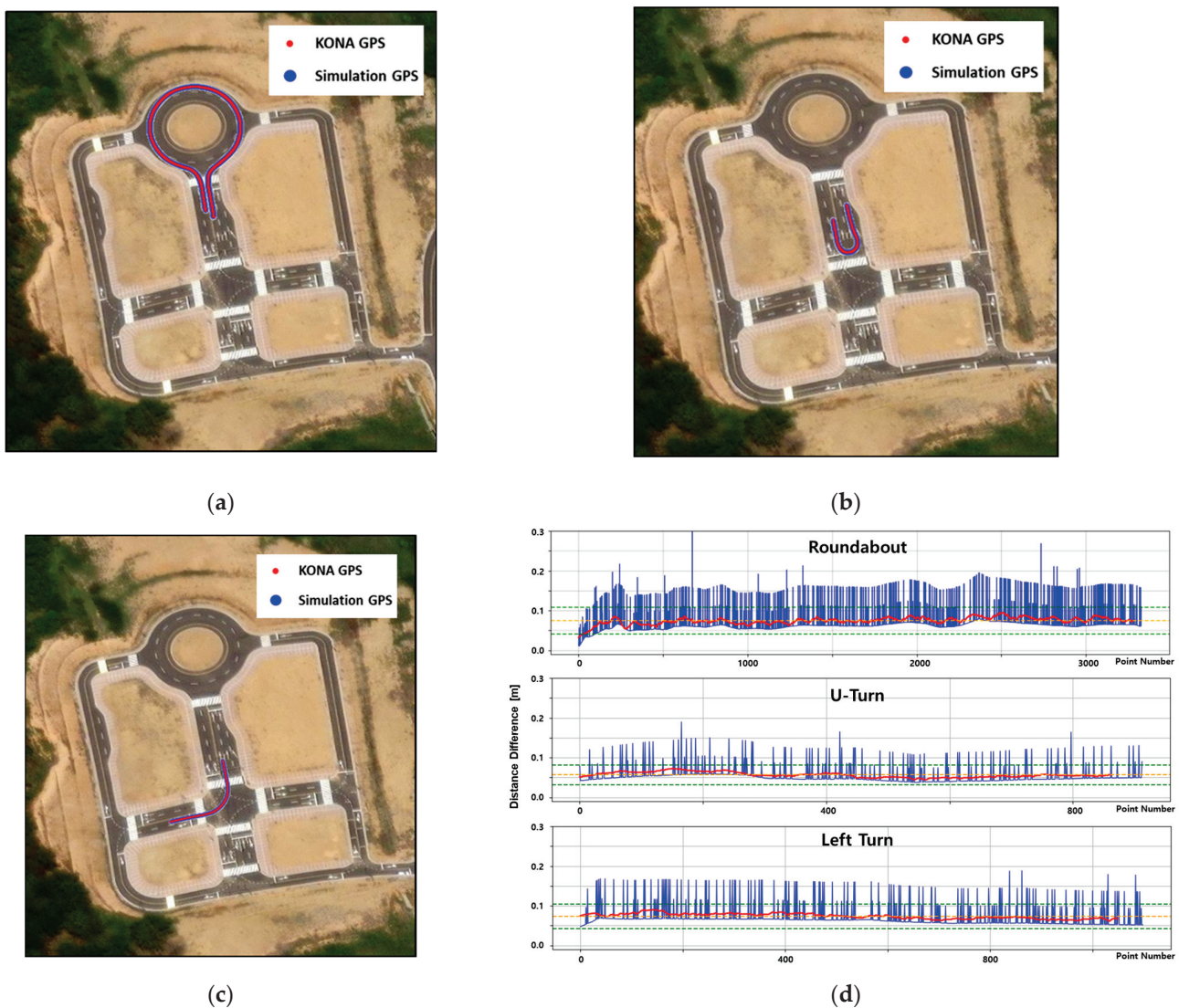


Figure 8. The result of virtual twin ToD driving test in the urban area for (a) roundabout, (b) U-turn, and (c) left turn. (d) The line graph displays the distance variance between the actual GPS data and the simulated GPS data for urban driving scenarios, demonstrating the high accuracy of the virtual twin ToD system in replicating real-world vehicle movements and ensuring minimal discrepancies.

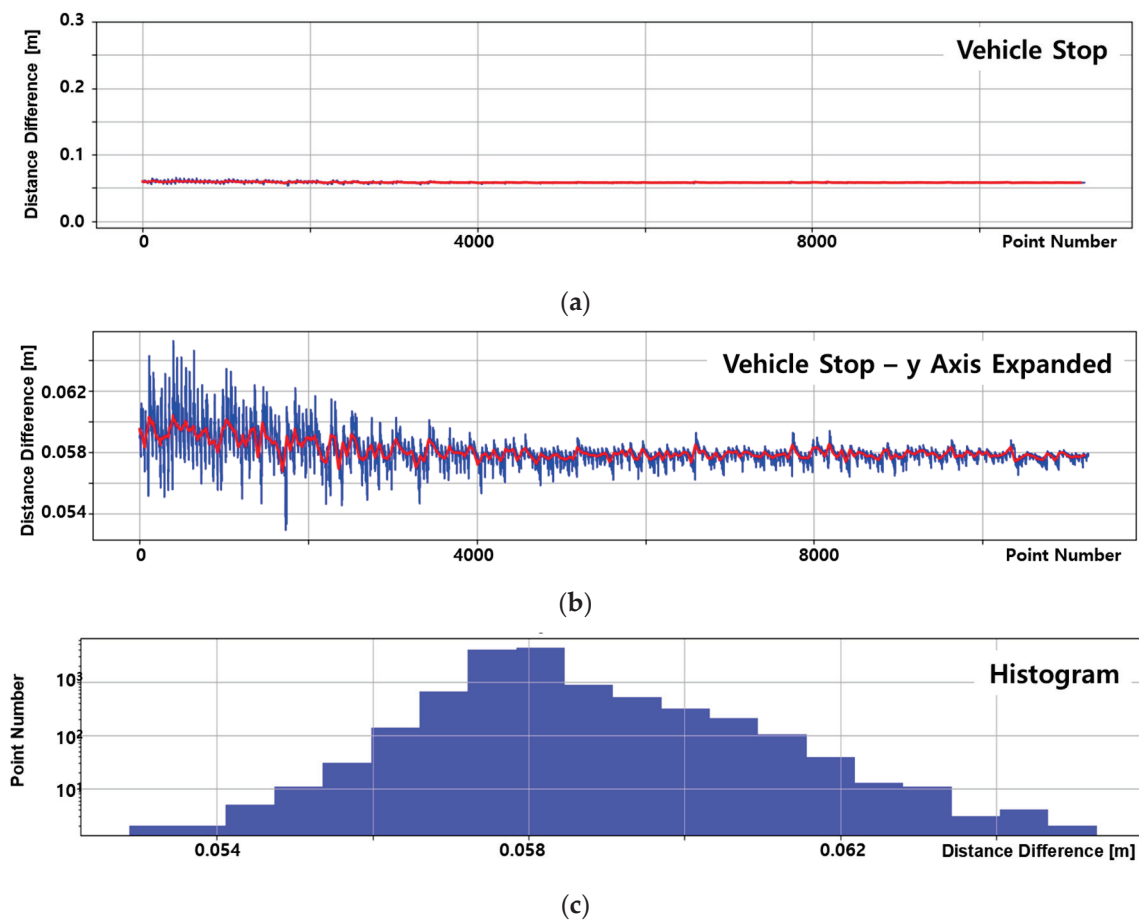


Figure 9. GPS data discrepancy analysis in the stationary state. (a) Same scaled line graph with the above results (Figure 8). (b) Magnified y-axis graph for a detailed view. (c) Histogram.

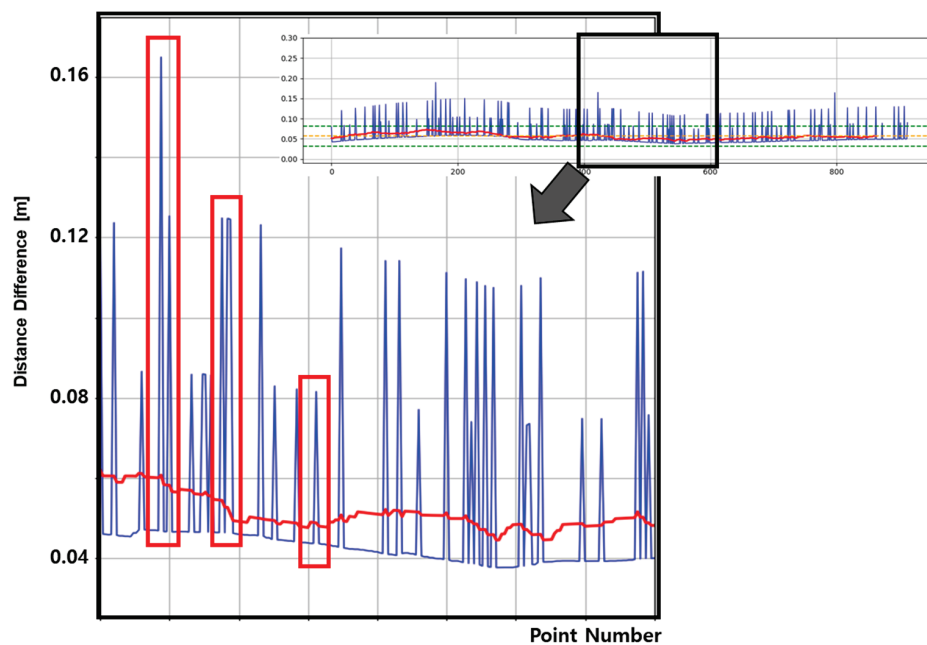


Figure 10. Segment of U-turn test graph (Figure 8d) highlighting quantized noise signals within the red box. The noise peaks, approximately 16.8 cm, 11.2 cm, and 5.6 cm, correspond to 3, 2, and 1 times the distance between sampling points (5.6 cm).

3.2. Data Transmission

The traditional ToD system relied on driving through real-time video streaming from the camera (Figure 5b). The acquired images in this system were encoded using the standard video compression technology, H.264/AVC, and transmitted through UDP communication using the real-time end-to-end transmission protocol, RTP. This method operates at a resolution of 640×480 pixels (SD quality) and 30 FPS, with a data transmission rate of approximately 1 Mbps.

In contrast, the virtual twin ToD system primarily relies on data transmission in the form of ROS messages, mainly containing coordinate information. The total size of the data packet, including the transmitted message, is about 63 bytes, sent at a frequency of 50 Hz. Consequently, the data transmission rate is measured to be approximately 25 Kbps.

Table 2 shows a comparison between the traditional and virtual twin ToD systems. The most significant difference in network communication lies in the medium of transmission, specifically image versus message, leading to a substantial difference in data size and communication load. Although a direct comparison of data packet sizes is challenging due to the use of video compression technology in the traditional ToD system, a comparison of transmission rates is possible. The transmission rate of 25 Kbps for the virtual twin ToD and 1 Mbps for the traditional ToD shows a difference of about 40 times.

Table 2. The results of both traditional and virtual twin ToD measurements.

	Transmission Medium	Data Packet [Byte]	Transmission Rate [bps]	Control Latency [s]	Video/ Visualizing Latency [ms]	Frame Rate [FPS]
Traditional ToD	Video Streaming	Variable	1 M	0.0312	32.5	30.38
Virtual Twin ToD	Message	63	25 K	0.0312	4.5	50

This substantial disparity in transmission rates can lead to significant challenges in network resource allocation, as higher data rates may require more bandwidth and potentially cause network congestion. In scenarios with limited network capacity, the high data throughput of traditional ToD could result in slower transmission speeds or even data loss, having an impact on the reliability of remote vehicle operation. Furthermore, such a large difference in transmission rates might necessitate the implementation of a more robust and costly network infrastructure to ensure consistent and reliable data flow, particularly for traditional ToD systems operating in dense urban areas or over extended distances.

Furthermore, traditional ToD uses UDP communication, while virtual twin ToD employs TCP/IP-based MQTT communication [32]. Unlike UDP, MQTT ensures reliability and integrity in the data transmission process. While MQTT may be slower than UDP in terms of speed, the measured delay time was only a few milliseconds. MQTT, suitable for transmitting small-sized messages, maintains stable communication even in network delays or congestion. These characteristics contribute to the stable operation of the virtual twin ToD system in even unstable network environments.

3.3. Latency

In remote vehicle control, latency is extremely important. Reducing latency allows the remote driver to control the vehicle more naturally and quickly recognize obstacles and surrounding conditions. Latency can be divided into control-related latency from the ROC to the vehicle and visualization latency from the vehicle to the ROC for images or simulation. The control-related latency at the ROC is the same as in the traditional ToD system, averaging 0.0312 s. However, there is a difference in visualization latency. Table 2 presents these results. The latency measurements indicated an average latency of 32.5 ms for the traditional ToD and 4.5 ms for the virtual twin ToD.

The reasons behind these latency differences can be found in the data transmission diagram illustrated in Figure 4. The most notable distinction between traditional ToD and virtual twin ToD is the presence or absence of video processing. With video streaming, the

process of encoding for large video transmission is essential, and, subsequently, the video must be decoded into a playable format, adding additional processing time (Δt_{enc} , Δt_{dec}) and computational load, thereby extending the total latency (Δt_{proc1} , Δt_{proc2}) [33,34].

In contrast, the virtual twin ToD simplifies the data processing and transmission (Δt_{trans}) and streamlines the data delivery to the simulator (Δt_{rec}), shortening the latency through these differences. Though the visualization latency of the virtual twin ToD may vary with simulator operation and the use of additional PC resources, the current findings show an approximate 86% reduction in latency, significantly enhancing the remote driver's reaction time and perception of safe driving.

Such a reduction in latency enhances the accuracy and responsiveness of remote control, particularly beneficial in complex road environments or urgent situations. Furthermore, lower latency provides the remote driver with more accurate, real-time information about the vehicle and its surroundings, thus increasing the overall safety and efficiency of remote driving.

4. Conclusions

In this study, we introduced an innovative virtual twin ToD approach by integrating traditional ToD systems with virtual twin technology to enhance the efficiency and safety of remote vehicle control. The system significantly improved the speed and precision of remote driving. Path analysis comparing the virtual twin ToD system with an actual vehicle showed an average trajectory error of within 8 cm, demonstrating high accuracy and reliability. Additionally, the virtual twin system's message-based data transmission approach increased efficiency, optimized network resource usage, and enhanced communication stability, significantly reducing latency and improving the reaction time and safety perception of the remote driver. These results underscore the virtual twin ToD system's capacity to replicate real driving conditions closely and provides a robust platform for informed decision-making during remote operation.

To conclude, while our virtual twin ToD system reduces communication load and enhances efficiency, further study is needed to fully realize its potential in real-world applications. The current system has been validated only with the driving vehicle, highlighting its limitations in public road scenarios. Future research should focus on integrating the virtual twin system with real driving conditions, visualizing external object data through the simulator, and incorporating LiDAR sensor data to identify potential hazards around the vehicle. These enhancements will ensure a more accurate and robust virtual twin system, leading to safer and more efficient teleoperated driving. Overall, this study provides a solid foundation for developing advanced virtual twin ToD systems and sets the stage for future research to build on these findings, broadening the potential for applications in remote control technologies and various other fields.

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Conflicts of Interest: Keonil Kim is an employee of R&D, AVGenius. The remaining authors declare no conflict of interest. The paper reflects the views of the scientists, and not the company.

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Defects and Mechanical Properties of Silicon Nitride Ball Bearings for Electric Vehicle Reducers

Jinhyeok Jang ^{1,*}, Youngmin Lee ¹, Hoonhee Cheong ¹ and Jeongho Yang ²

¹ Electrification Material Team, Hyundai-Transys, 95 Hyundaiakia-ro, Hwaseong-si 18280, Republic of Korea

² Transmission System Engineering Design Team, Hyundai-Transys, 95 Hyundaiakia-ro, Hwaseong-si 18280, Republic of Korea

* Correspondence: jinhyeokjang@hyundai-transys.com

Abstract: In this study, two types of Si_3N_4 ball bearings for integrated-type EV reducers developed via different manufacturing processes were analyzed to study the microstructure of the balls and the defects that may occur during the manufacturing process. Three types of defects were confirmed that can reduce the fatigue life of Si_3N_4 ball bearings in operating environments. The microstructure was analyzed to identify the main additive components of each bearing, and pore defects with a size of less than $1\text{ }\mu\text{m}$, and the types (particle defects or surface defects) and sizes of defects, were analyzed using LSCM, OM, and SEM. Hardness and fracture toughness, which are representative mechanical properties of ceramic materials, were evaluated. The results, evaluated using a Vickers indentation crack-based method, were statistically analyzed to confirm differences in hardness and fracture toughness between the two samples.

Keywords: silicon nitride ball; EV reducers; hardness; fracture toughness

1. Introduction

Silicon nitride (Si_3N_4) is a ceramic material with characteristics such as low density, high strength, heat resistance, and corrosion resistance [1–4]. It has recently been widely used in various industries such as aerospace, railway, and national defense, as well as for machine tools [5,6]. Si_3N_4 balls are used in bearings and high-speed operating environments; they offer advantages over existing metal balls.

Bearings used in electric vehicles (EVs), in particular, possess structural characteristics that can facilitate better electrical conduction compared to traditional engine vehicles. The current flowing from the motor to the input shaft of the reducer causes the micro-welding of metal balls to the metal raceway, resulting in current erosion that damages the balls and raceway. Ceramic hybrid bearings composed of the metal raceways and the ceramic balls prevent current erosion by impeding the current flow due to the higher electrical resistance of ceramic materials compared to air. The EV reducer used in this study contains a “hybrid bearing” comprising Si_3N_4 ceramic balls and a metal raceway, known as a silicon nitride hybrid bearing (SNHB). Si_3N_4 ceramics theoretically possess very high strength.

However, due to the brittleness of ceramic materials, surface defects are generated during processing (grinding and lapping) and inner defects are generated during sintering. Therefore, their actual strength is lower than the theoretically predicted value. Small defects, presumed to be sintering voids with a diameter of less than $2\text{ }\mu\text{m}$, can be a potential cause of failure and are considered inherent defects in the material rather than manufacturing defects [7]. Surface defects in Si_3N_4 balls and their propagation in rolling contact fatigue (RCF) are concerning, as they cause spalling, delamination, and rolling contact wear [8]. The spalling of Si_3N_4 balls may involve the propagation of the original ring crack and secondary surface cracks being induced as the crack grows. Fatigue life cannot be simply determined in terms of the propagation life of the surface crack; subsequent surface damage also plays

an important role in predicting the life of Si_3N_4 balls [8]. Potential defects, including inner and surface defects, can cause fatal damage to the bearing operating environment. Therefore, research has been conducted on non-destructive inspection methods, vibration analysis methods, and defect improvement methods to ensure the quality of Si_3N_4 balls and bearing life [9].

In this study, two types of Si_3N_4 ball bearings for integrated-type EV reducers developed via different manufacturing processes were analyzed to study the microstructure of the balls and the defects that may occur during the manufacturing process. The two types of Si_3N_4 ball bearings differ in their main additive components and whether they underwent the hot isostatic process (HIP) after sintering. In the case of specimen A, the density was increased through the HIP after sintering, while specimen B did not include HIP in its manufacturing process. The Si_3N_4 balls prepared using the HIP mainly consisted of β -grain, which can increase the toughness [10]. Additionally, the representative mechanical properties of ceramic materials, such as hardness and fracture toughness, were evaluated, and their correlation with microstructure was analyzed. Figure 1 shows the structures of the gear system, input shaft, and ball bearings located on both sides of the input shaft, which are the subjects of this study.

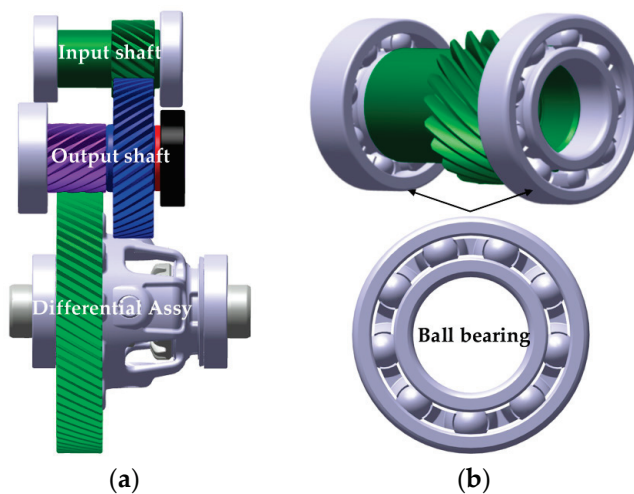


Figure 1. (a) Gear system of integrated-type EV reducers. (b) Input shaft and ball bearings.

Figure 2a shows the actual image of the SNHB and Si_3N_4 ball. Figure 2b shows the low-magnification scanning electron microscopy (SEM) image of the undamaged state of the Si_3N_4 ball, and Figure 2c shows the low-magnification SEM image of the Si_3N_4 ball, where spalling has occurred during driving. Figure 2d shows the enlarged SEM images of the spalling area in Figure 2c. Figure 2d shows the highly magnified SEM images of the fracture-initiated region A and the secondary propagated spalling region B.

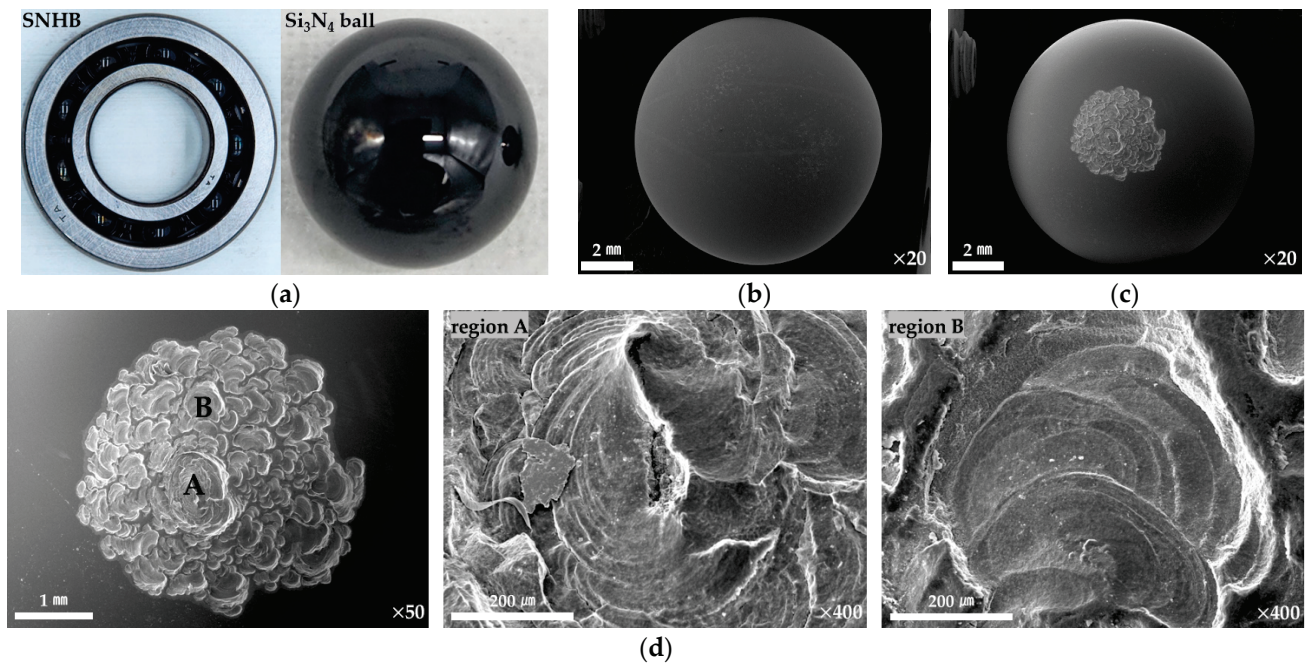


Figure 2. (a) SNHB and Si₃N₄ ball for EV reducers. (b) SEM image of the undamaged Si₃N₄ ball. (c) SEM image of Si₃N₄ ball with spalling. (d) Highly magnified SEM images of the spalling area.

2. Experimental Methods

Si₃N₄ balls were polished with emery paper (#100–#1000 Grit) and diamond suspension (9, 3, and 1 μm) to examine their microstructure. Their microstructure and additive components were analyzed using field emission scanning electron microscopy (FE–SEM, Quanta FEG 250, FEI Company, Hillsboro, OR, USA). To measure the surface defects, the balls were cleaned via sonication for 30 min in acetone, and a cotton swab dipped in acetone was rubbed on their surface. The entire surface of the balls was rubbed with ethanol using a latex glove and was then dried for 10 min. Surface defects were analyzed using an optical microscope (OM, Imager.M2m, ZEISS, Munich, Germany) and a laser scanning confocal microscope (LSCM, VK-X100, KEYENCE, Osaka, Japan). The chemical composition of the cluster-shaped particles on the surface were analyzed using scanning electron microscopy–energy dispersive spectrometry (SEM–EDS, VEGA3 XMU, TESCAN, Brno, Czech Republic). After the Si₃N₄ balls were polished with emery paper and diamond suspension, their hardness and fracture toughness were tested using a Vickers hardness diamond indenter (Q10A, ATM Qness GmbH, Mammelzen, Germany) under an indentation load of 10 kgf. In the global market, Si₃N₄ ball bearings are classified into grades based on fracture toughness characteristics [11]. The evaluation of fracture toughness of small and tough specimens such as Si₃N₄ balls bearings is difficult to characterize. In such cases, the indentation fracture resistance (IFR) method might be considered as the most suitable method because it requires a small specimen size and simple experimental procedures, and it has been adopted as the evaluation method for fracture toughness in the American standard specification for Si₃N₄ balls bearings [12,13]. The fracture toughness was measured using the IFR method proposed by Niihara, and the crack length of the indentation surface was observed using the OM and SEM. The hardness and fracture toughness were calculated using Equations (1) and (2), respectively, and are shown in Figure 3.

$$HV = 1,854,400 P / (2a)^2 \quad (1)$$

$$IFR = 10.4 (E^{0.4})(P^{0.6}) \left(\frac{a^{0.8}}{c^{1.5}} \right) \quad (2)$$

E is Young's modulus, with a value of 270 GPa (minimum value of typical mechanical properties, ASTM F2094/F2094M-18a); P is the applied load of 10 kgf; a is the half diagonal value in microns (μm); and c is the half tip-to-tip crack length in microns (μm).

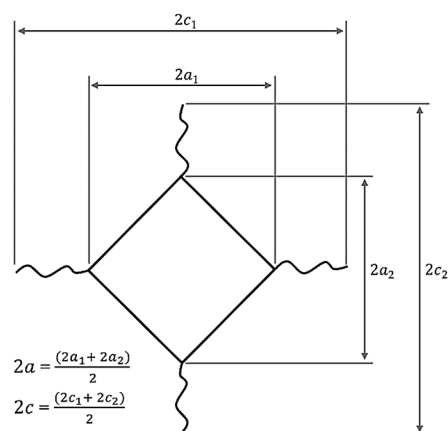


Figure 3. Hardness and toughness calculations.

3. Results

3.1. Microstructure

The microstructure is one of the major factors influencing the mechanical properties of Si₃N₄ [14,15]. Figure 4 shows the SEM–EDS analysis results of the inner defects (Figure 4a,d) and additive components (Figure 4b,c,e,f). The inner defect (micro-pores) sizes of specimens A and B are less than 1 μm, but the porosity of specimen A is relatively lower. The phase of the additive can be distinguished using the back-scattered electron (BSE) mode. EDS was used for the elemental analysis of additives, which revealed Ti and W to be the main elements in the additives of specimens A and B, respectively.

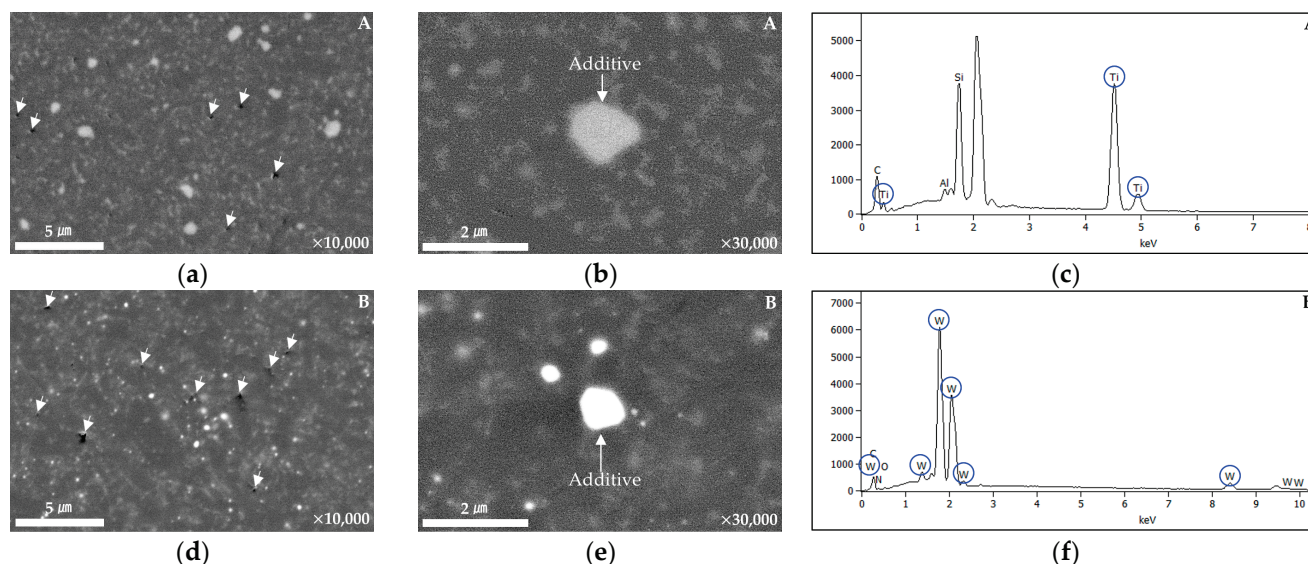


Figure 4. SEM (BSE) images of microstructure and EDS spectrums of additives: (a–c) specimen A; (d–f) specimen B.

3.2. Defects

The defect types of Si_3N_4 balls are broadly divided into two types (particle defect and surface defect). Figures 5 and 6 show the analysis results of particle defects. Cluster-shaped particles protruding from the surface were identified using the OM, and their length and height were measured using the OM and an LSCM. Finally, the components of particles

and clean surfaces were analyzed using SEM–EDS. The length and height of the particles in the two specimens were approximately 14–15 μm and 2.2–2.5 μm , respectively. Elemental analysis revealed that the surface contained Si, Al, and N as the main components, similar to Si_3N_4 balls, and the intensities of C and O were relatively higher than that of the clean surface. Based on the shape, size, and elemental components, the protruding particles are presumed to be Si_3N_4 grains that protruded from the surface before processing and were attached to the surface after being damaged during processes such as grinding and lapping. These protruding particles can become a source of stress concentration when in contact with a counterpart such as a raceway, which can cause cracks on the surface and can ultimately cause surface damage.

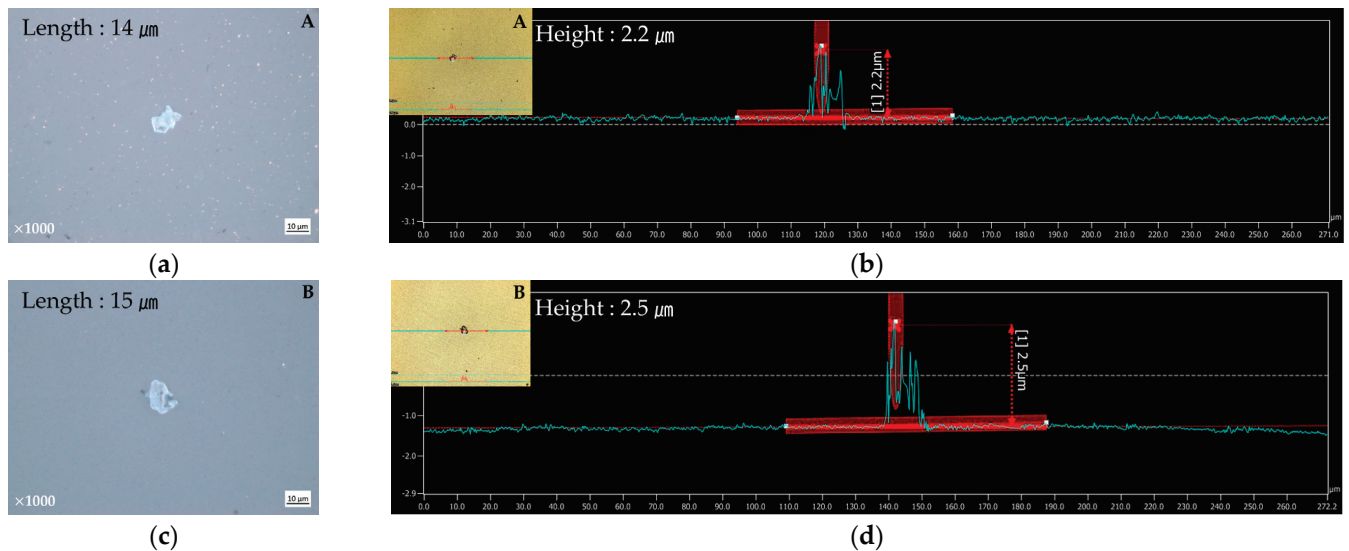


Figure 5. OM images and LSCM profile graphs of particle defects: (a,b) specimen A; (c,d) specimen B.

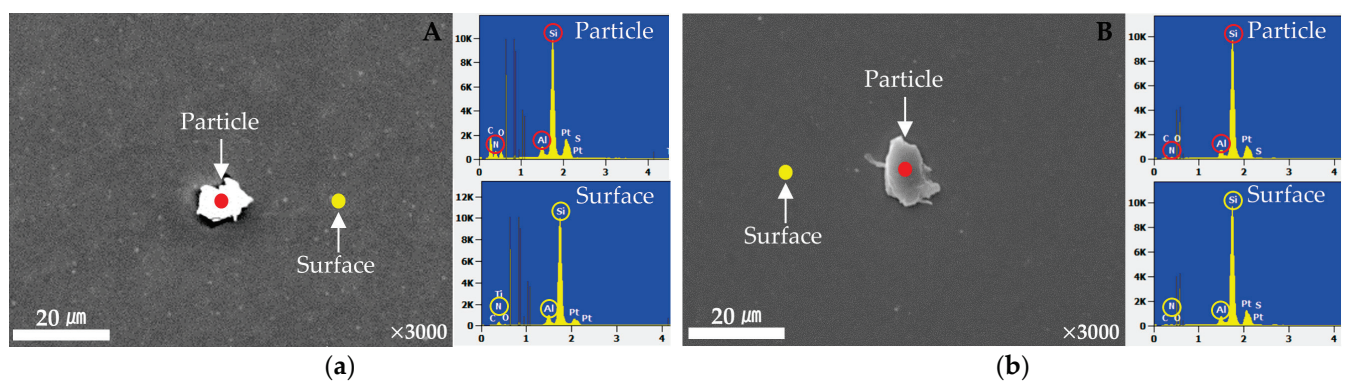


Figure 6. SEM images and EDS spectra of particles on surface: (a) specimen A; (b) specimen B.

Figure 7 shows the analysis results of surface defects (scratches, cracks, and pores). The shapes and lengths of the surface defects were measured using the OM, and their depths were measured using an LSCM. As shown in Figure 7a,d, the length was measured to be over 100 μm . An LSCM confirmed that the defect was not deep, implying that it was a scratch. Figure 7b,c,e,f show that the length was relatively small at 9–32 μm ; however, an LSCM confirmed the depth to be approximately 3.9–4.4 μm . Thus, this defect was deemed as a crack or pore defect. Damage defects may have different causes depending on their length, depth, and shape, but they can occur during any manufacturing process of Si_3N_4 balls. Scratch damage may occur if the processing pressure is abnormal or if the quality of the abrasive particles is low during processes such as grinding or lapping. In

the case of a crack or pore defect, determining their cause is difficult. However, it could be an inner defect that occurred during sintering, a defect exposed due to surface polishing, or a defect that occurred due to abnormal processing. Damage defects affect fracture toughness, flexural resistance, and impact resistance [16]. As Si_3N_4 balls are spherical, manual observation of these defects is difficult. Thus, identifying and classifying these surface defects are complicated, making it difficult to effectively detect each defect type [17].

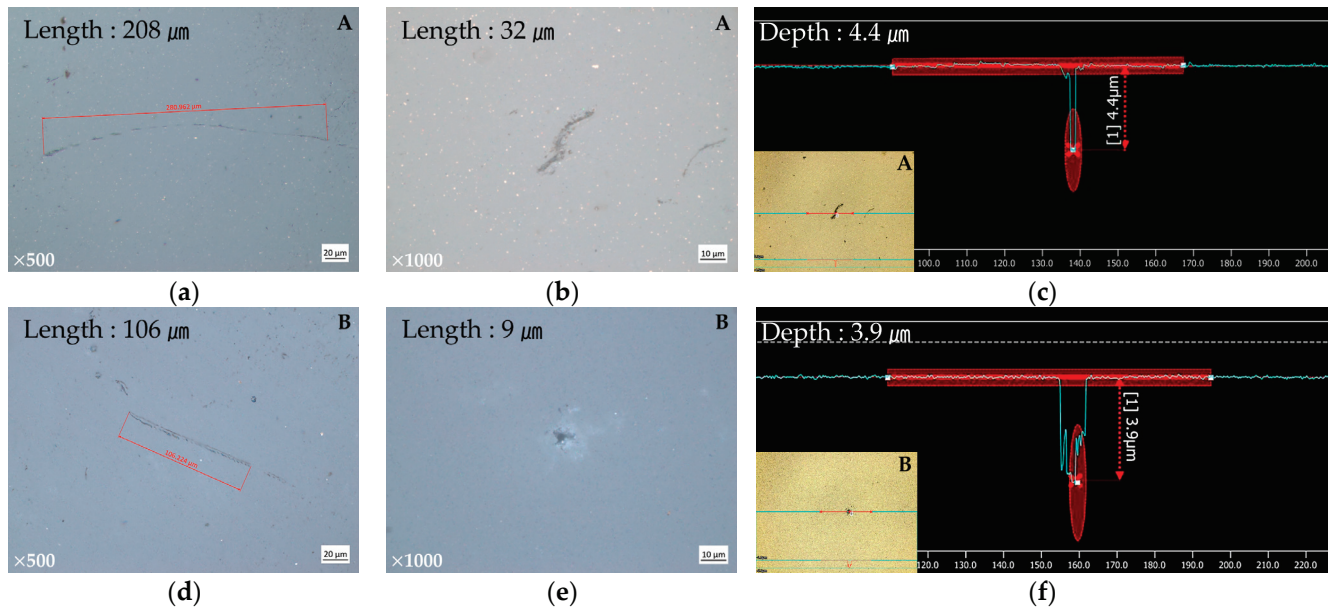


Figure 7. OM images and LSCM profile graphs of types of surface defects: (a–c) specimen A; (b–f) specimen B.

3.3. Hardness and Fracture Toughness

The fatigue life of the ball bearing depends on the basic dynamic load rating, and the rating factor and coefficient of the basic dynamic load rating is influenced by the material and manufacturing quality. The hardness and fracture toughness are commonly highlighted strength characteristics of engineering ceramic materials. A Vickers indentation crack-based method has been proposed to evaluate the fracture toughness of brittle materials [18]. Under the same indentation loading conditions, hardness and fracture toughness were determined based on the numerical results in terms of the morphology of the indented zone (including cracks and plastic zone) [19]. Figure 8 shows the OM and SEM results of a plastic zone and crack formed due to an indentation.

Table 1 shows the hardness and fracture toughness of each of the five specimens.

Table 1. Hardness and fracture toughness values.

Mechanical Properties	A	B
Hardness [HV]	1561	1482
	1567	1461
	1561	1482
	1573	1482
	1537	1477
	Avg. 1560	Avg. 1476
Fracture toughness [MPa·m ^{1/2}]	10.7	8.8
	10.8	8.5
	10.7	8.8
	10.8	8.8
	10.1	8.7
	Avg. 10.6	Avg. 8.7

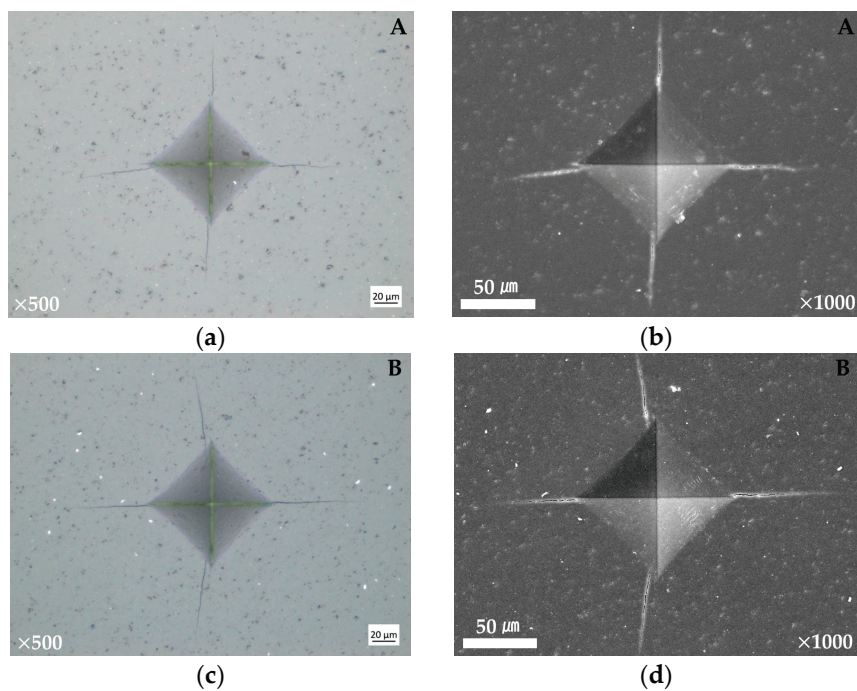


Figure 8. OM images and SEM images of the indented zone: (a,b) specimen A; (c,d) specimen B.

The hardness of specimen A was approximately 5.3% higher than that of specimen B, and the fracture toughness of specimen A is about 18.7% higher than that of specimen B, indicating that specimen A has a higher dynamic load rating than specimen B. Specimen A, with a lower porosity, has a relatively larger hardness, which proves the correlation between relative density and hardness. In the condition of Si_3N_4 balls of the same chemical composition, the grain size (diameter of β -grain) is proportional to fracture toughness, and inversely proportional to strength [20,21]. Based on these several investigations, it can be assumed that the grain size (diameter of β -grain) of specimen A is larger than that of specimen B, and that their different sintering and heat treatment conditions affect their grain sizes [22]. Specimen A surpassed the minimum hardness and fracture toughness of Si_3N_4 balls specified for ASTM material class I. Figure 9 shows the confidence interval graphs and the p -values through t -tests for each result group. For the results in which the intervals do not overlap and the p -values are less than the significant level of 0.05, it proves that the difference in means is statistically significant, and that the mechanical properties are different.

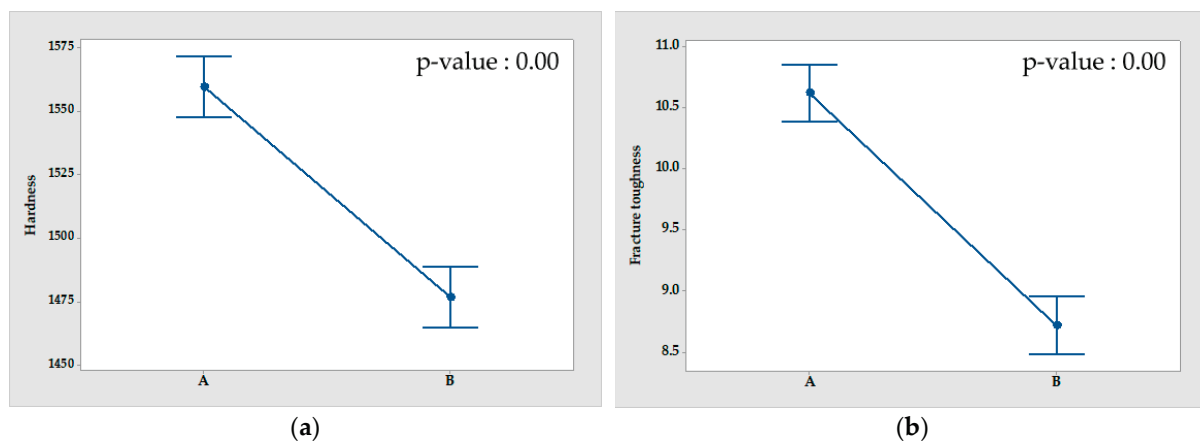


Figure 9. Confidence interval graphs and p -values for each result group: (a) hardness, (b) fracture toughness.

4. Conclusions

The microstructure (pores and additives), defects, and mechanical properties of Si₃N₄ ball bearings for EV reducers were analyzed. The defects of the two specimens with different manufacturing processes were largely classified into pore defects (inner), particle defects, and surface defects, all of which are potential defects that can occur during the manufacturing process. These defects can cause damage due to crack growth driven by rolling contact fatigue and can reduce the fatigue life of bearings in the operating environment. Further studies are needed to determine how the types and sizes of the defects identified in this study affect the lifespan of Si₃N₄ ball bearings. The evaluation of mechanical properties revealed that specimen A showed a relatively higher hardness and fracture toughness than specimen B. This result proves that the mechanical properties of Si₃N₄ ball bearings with a high relative density and a dominant β -grain are high, and there may be differences in their fatigue life in actual driving environments. The application of the SNHB is the best approach for preventing current erosion in EV reducers. For the successful operation and long-term performance of SNHBs in driving environments, the exploration of various manufacturing techniques to minimize defects, and materials research to improve mechanical properties are essential.

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Article

Global Patent Analysis of Battery Recycling Technologies: A Comparative Study of Korea, China, and the United States

Chae-Hoon Lee

Technology Commercialization Department, Korea Electronics Technology Institute (KETI), Seongnam-si 13509, Republic of Korea; ljh20@keti.re.kr

Abstract: This study provides a comprehensive analysis of global patent trends in battery recycling, focusing on secondary batteries and related technologies across Korea, China, and the United States. The methodology involved collecting data from various patent databases, followed by quantitative analysis to identify technology trends and guide future development. The research employed statistical tools to analyze patent activities, including the frequency and scope of patent filings, and comparative analysis to highlight differences between countries. This study reveals distinct emphases on technologies such as lithium-ion and waste battery recycling, highlighting notable differences in patent activities among key companies and countries. China's large number of patents in battery manufacturing processes contrasts with the USA's focus on electrochemical cell construction and storage systems, while Korea shows significant activity in waste battery technology. The novelty of this paper lies in its detailed comparative analysis of patent trends across these three major economies, providing insights into the technological focuses and priorities of each country. The study also identifies key challenges, such as the need for consistent innovation and broader geographic coverage in Korea, enhancing patent influence and international presence in China, and ensuring high patent quality and fostering innovation in lagging sectors in the United States. Addressing these challenges through enhanced collaboration, increased R&D investments, and supportive policies is crucial for strengthening the global position and driving further innovation in the battery recycling sector.

Keywords: battery recycling; electric vehicle (EV); secondary batteries; patent analysis

1. Introduction

Electric vehicle sales are increasing rapidly, starting with COVID-19 in 2020 accelerating the spread in the market. According to the International Energy Agency, global electric vehicle sales in 2022 reached over 26 million units, more than eleven times the 2.2 million in 2013 [1]. In 1997, Toyota Motor Corp. launched the world's first hybrid passenger car, the Prius. Since then, companies solely dedicated to producing electric vehicles, like Tesla and Lucid, have emerged. Additionally, traditional automobile OEMs (Original Equipment Manufacturers) are striving to gain a foothold in the rapidly expanding electric vehicle market by introducing diverse electric vehicle models. Notably, in China, the world's largest electric vehicle market, numerous electric vehicle startups such as Xiaopeng, Li Xiang, and Nio have arisen, competing with international electric vehicle brands like Tesla.

The battery, the core of electric vehicles, is one of the most important areas for national economy and technological competitiveness as it is included in the government's national affairs as a future strategic industry [2]. In particular, recent rapid changes in the international political and economic landscape, such as the U.S.-China trade dispute, have heightened concerns about the potential instability of the global value chain (GVC). As a result, there is a clear reshoring movement in major countries such as the United States and the EU to foster and strengthen national strategic industries such as semiconductors and batteries by themselves. In this situation, it is time for Korea to consider policies on how to foster the battery industry.

In particular, demand for battery raw materials has also increased due to inflation and increased supply of electric vehicles after COVID-19, leading to a sharp rise in prices of lithium and nickel [3]. According to a White House report, the demand for lithium and graphite is expected to increase by 4000% by 2040, with China controlling 55% of the world's rare minerals as of 2020 and 85% of the rare mineral renewable sector, therefore China's influence will continue in the future [4]. Korea also needs several strategies for stable supply and demand for electric vehicle battery production in the future, and in this regard, recycling of waste batteries is attracting new attention.

The global demand for lithium-ion batteries is expected to increase up to 4500 gigawatt hours (GWh) by 2030, and the demand for lithium-ion batteries is expected to grow more than 32% annually from 2015 to 2030. In addition, the demand for batteries used for mobility is overwhelmingly high compared to the demand for batteries used in power storage and home appliances [5].

Interest in recycling waste batteries after production of electric vehicle batteries is also increasing. Vehicle batteries can be made into new battery packs after mass production of cells and used in electric vehicles, and old battery packs can be discarded or sent to recycling companies to recycle at a limited capacity or used to produce new batteries after extracting and reprocessing raw materials from waste batteries [6].

Despite the increasing interest in battery recycling, the current literature shows limitations in comprehensively analyzing global patent trends specific to battery recycling technologies. Existing studies often focus on the material technology or overall system and process of battery recycling but lack a detailed comparative analysis of patent trends across different countries. This paper aims to fill this gap by providing an extended analysis of patent trends in Korea, China, and the United States, highlighting the technological focuses and priorities of each country.

The structure of this paper is as follows: Section 2 reviews the relevant literature and highlights key technologies in battery recycling. Section 3 presents the patent analysis methodology and the data sources used. Section 4 discusses the results of the patent trend analysis, comparing the activities in Korea, China, and the United States. Finally, Section 5 concludes with the implications of the findings, the identified challenges, and potential future directions for research and policy.

2. Literature Review

2.1. Key Technologies in Battery Recycling

Key technologies in recycling waste batteries are secondary battery collection and dismantling technology, lithium salt selective extraction technology, metal salt selective extraction technology, battery condition monitoring, recycling material purification technology, and mixing technology between recycled materials and existing materials. If this is extended to the reuse of waste batteries in electric vehicles, related core technologies include secondary battery diagnostic technologies and equipment, reusable waste battery pack separation methods, optimal operation technologies of reusable batteries, and secondary battery pack manufacturing technologies.

2.2. Approaches to Battery Recycling Processes

The papers on battery recycling can be summarized into three main topics: the process of battery recycling (dry, wet, etc.) and recycling materials (lithium-ion metal extraction) and the economic effects of battery recycling and new techniques.

First, the papers on the approach to the battery recycling process are as follows. Focusing on the recycling process of Li-ion batteries, there is a study that comprehensively organizes cutting-edge technologies for lithium-ion battery recycling, focusing on pre-treatment, water supply recycling, and direct regeneration of anode materials [7]. Next, it is analyzed from the perspective of battery life cycle and integration into the recycling process [8], and by analyzing the recycling process using a systematic literature review

method, it is emphasized that there is a lack of research on lithium-ion battery recycling in the existing literature [9].

Second, papers on battery recycled materials are as follows. In the application of mineral treatment for battery recycling, mineral treatment processes such as grinding, sieving, and self-separation are important to recycle lithium-ion batteries, but these processes should pay attention to the loss and high cost of valuable battery parts [10]. Metal extraction and pretreatment for recycling metal from spent lithium-ion batteries are a key part of the recycling process of lithium-ion batteries, and although these methods face challenges such as environmental impact and cost, recycling can be carried out using pyrometallurgy and hydrometallurgy technologies [11].

Third, from the viewpoint of evaluating the life cycle of battery recycling, recycling different cell chemicals in lithium-ion batteries can significantly reduce environmental impact, and the biggest advantage can be seen in recycling lithium nickel manganese cobalt oxide type batteries due to the recovery of cobalt and nickel [12]. And there is a life-cycle analysis for lithium-ion battery production and recycling, underscoring the potential for resource savings [13].

2.3. Economic Effects and New Techniques in Battery Recycling

Economic and environmental aspects of battery recycling have also been extensively studied. For economic advantages, with the recent development of battery recycling technology, recycling of spent batteries, including lead-acid and lithium-ion types, focuses on pro-metallic and hydrometal processes, and the future issues are high cost and secondary pollution [14]. The economic viability of lithium-ion battery recycling in India was studied, emphasizing cost savings and environmental benefits [15]. Recycling of lithium-ion batteries has significant economic and environmental advantages, such as reducing chemical pollution and improving the safety of storage facilities [16].

For innovative techniques, new techniques in battery recycling include bio-leaching using bio-hydrometallurgy, which offers an eco-friendly and cost-effective alternative for recovering metals from spent lithium-ion batteries [17]. These bio-technical approaches have the potential to reduce secondary pollution.

2.4. Patent Analysis in Battery Recycling

The literature review on battery recycling patent analysis reveals a focus on innovative recycling devices and methods, addressing the challenges in recycling various types of batteries. Key insights include advancements in electrolysis methods for recycling, devices for efficient processing of storage batteries, and trends in recycling technologies identified through patent and paper analysis. Previous studies have focused on analyzing patent trends in battery recycling, offering insights into technological innovations and market dynamics.

Previously, in Korea, patent analysis was conducted to analyze patent trends in waste battery recycling. Keywords were battery, electronic cell, patent, and recycling, and 2490 cases were selected from 1971 to 2000 for H01M-006/52 and H01M-010/54 among International Patent Classifications (IPCs), and 871 of them were analyzed through filtering [18].

There has also been multi-country analysis of used battery recycling [19]. This paper analyzes patents and published papers on recycling technologies for used batteries, focusing on the years, countries, companies, and technologies involved. The paper analyzed patents and published papers on recycling technologies for used batteries from 1972 to 2011, focusing on the open patents of the USA (US), European Union (EU), Japan (JP), Korea (KR), and SCI journal articles. The trends of the patents and journal articles were analyzed based on the years, countries, companies, and technologies involved. However, in this paper, there is no analysis for Chinese patents and papers of battery recycling. The 2012 to 2023 period is also missing for battery recycling patent analysis due to when it was published.

For global trends, there is a study that analyzed 90,000 battery patents from 2000 to 2019 [20]. In addition, there is a study that analyzed technologies and trends for recycling

lithium-ion batteries [21]. There is also a patent analysis study that reviews patent applications filed by major Japanese battery manufacturers, providing insights into technology development in the Japanese battery industry, which could be relevant for understanding the trends in patenting in the battery recycling sector [22].

Even though there are many academic articles about battery recycling, it is hard to find articles that are about battery recycling patent analysis because most articles focused on material technology [23–25] or the overall system and process of battery recycling [26,27].

Based on the information available, the battery technology patent race is intensifying among South Korea, China, and the USA, with significant developments and strategic moves observed in each country [28]. South Korea and China are particularly competitive in the arena of battery patents, with South Korean companies like LG Energy Solution and Samsung SDI leading in terms of both quantity and quality of patents, especially in areas such as electrode materials, cell processes, and packaging. China, while having the largest market share through companies like CATL, focuses more on lithium–phosphate–iron (LFP) cathode materials and silicon anode materials.

The current trends in battery recycling in the United States are marked by significant developments and investments, driven by the growing demand for electric vehicles (EVs) and the associated need for efficient battery recycling. The US currently employs mainly two methods for battery recycling—hydrometallurgical and pyrometallurgical [29,30]. The hydrometallurgical process involves using an acid-rich solution to extract battery materials, while the pyrometallurgical method uses simpler pretreatments like crushing or shredding. Companies like Redwood Materials and Li-Cycle are scaling up their operations, focusing on innovative recycling processes that recover crucial metals like cobalt, nickel, and lithium from used batteries and manufacturing scrap.

As such, the market and technology for battery recycling in Korea, China, and the United States are fully expanding. However, it is not easy to find a paper that analyzes in-depth battery recycling patents in Korea, China, and the United States. Therefore, through this paper, we will analyze battery recycling patents in the three countries, how to increase battery cycle efficiency through battery recycling, and the differences between the countries through patent trends.

2.5. Gaps and Limitations in Existing Knowledge

Despite extensive research, three gaps and limitations remain. First, for comparative analysis, existing studies often lack a detailed comparative analysis of patent trends across different countries. This paper aims to fill this gap by providing an extended analysis of patent trends in Korea, China, and the United States, highlighting the technological focuses and priorities of each country.

Second, for patent quality and impact, there is a need for more in-depth analysis of patent quality and impact, particularly regarding citations per patent and patent family size. Understanding these metrics can provide insights into the influence and geographic reach of patents.

Third, for emerging technologies, while numerous studies focus on existing technologies, there is limited research on emerging technologies in battery recycling. Future studies should explore innovations in smart technologies and data management systems in recycling operations.

The literature review reveals a robust body of research on battery recycling technologies, processes, and economic impacts. However, gaps in comparative patent analysis and emerging technologies highlight the need for further investigation. This paper aims to address these gaps by providing a comprehensive analysis of patent trends in Korea, China, and the United States, offering insights into technological innovations and strategic directions for future research.

3. Patent Analysis

3.1. Methodology

In relation to secondary batteries, we collect data on patents from Korea, China, and the United States for batteries, secondary batteries, electrorods, lithium-ion, anodes, cathodes, waste, cycle, etc. and analyze patent trends.

Through quantitative analysis, multiple technology trends were analyzed based on the effective population searched in the waste battery technology field, setting future technology development directions and future development areas and patent portfolio analysis of major players and market analysis were performed. In quantitative analysis, it is possible to grasp the recent market status of the technology field from various angles through the analysis of the following items, and detailed technology classification is also performed for more detailed technology classification. Through this, we intended to extract major patents and explore the direction of discovering promising technologies in the future.

A patent analysis was conducted based on patent applications for battery recycling in three countries: Korea, China, and the United States. Patents were selected based solely on application and registration criteria. These data were searched with Wintelips (wintelips.com) and Energy Patent House (energypatenthouse.com) that gather patent data.

In this study, the analysis of patents was limited to companies. This is because the purpose of the study was to measure how companies in each country innovate battery recycling technology through the tool of patents. Therefore, the patents of individual researchers were not analyzed in this study. For reference, the proportion of individual patents for battery recycling in South Korea, China, and the United States was not significant. In South Korea, there were 16 out of a total of 65 patents (24.6%), in China, there were 748 out of 3496 patents (21.3%), and in the United States, there were 247 out of 548 patents (45.0%).

Table 1 shows a topic analysis of patent abstracts for each country to identify the top three types of patents for battery recycling in Korea, China, and the United States.

Table 1. Topic Analysis of Battery Recycling Patents.

Country	Topic 1	Topic 2	Topic 3
Korea	Device and method for recycling materials	Separation methods for battery materials	Recycling system for electric vehicle batteries
China	High-nickel ternary cathode materials	Lithium recovery processes	Nickel cobalt manganese recovery methods
US	Battery crushing and recycling plants	Safety mechanisms for recycling processes	Recovery of valuable metals from batteries

In Korea, the primary focus is on devices and methods for recycling materials from used batteries, separation methods for battery components, and systems specifically designed for recycling electric vehicle batteries. Examples include patents on devices and methods for recycling battery materials and systems for separating battery cell components.

In China, patents emphasize the creation and recycling of high-nickel cathode materials, lithium recovery processes, and methods for recovering nickel, cobalt, and manganese from used batteries. This focus reflects China's commitment to developing advanced battery materials to maintain a competitive edge in battery technology.

In the United States, the focus is on patents detailing battery crushing and recycling plants, safety mechanisms for the recycling process, and methods for recovering valuable metals from batteries. The emphasis on safety mechanisms highlights the importance of preventing hazards during the recycling process.

This result provides a concise overview of the top three patent types for each country, highlighting the different technological focuses and priorities in battery recycling patents across Korea, China, and the United States.

3.2. Patent Filing Trend

Figure 1 shows the annual status of battery recycling patent applications in Korea (KR), China (CN), and the United States (US) from 2007 to 2024. Data for the year 2024 were only been found up to March; therefore, they have not been displayed in Figure 1. Korea showed modest and consistent patent activity with a notable increase in 2022. China demonstrated a significant and consistent rise in patent filings over the years, peaking in 2023. The US showed a steady increase in patent filings, peaking in 2022, followed by a decline in subsequent years.

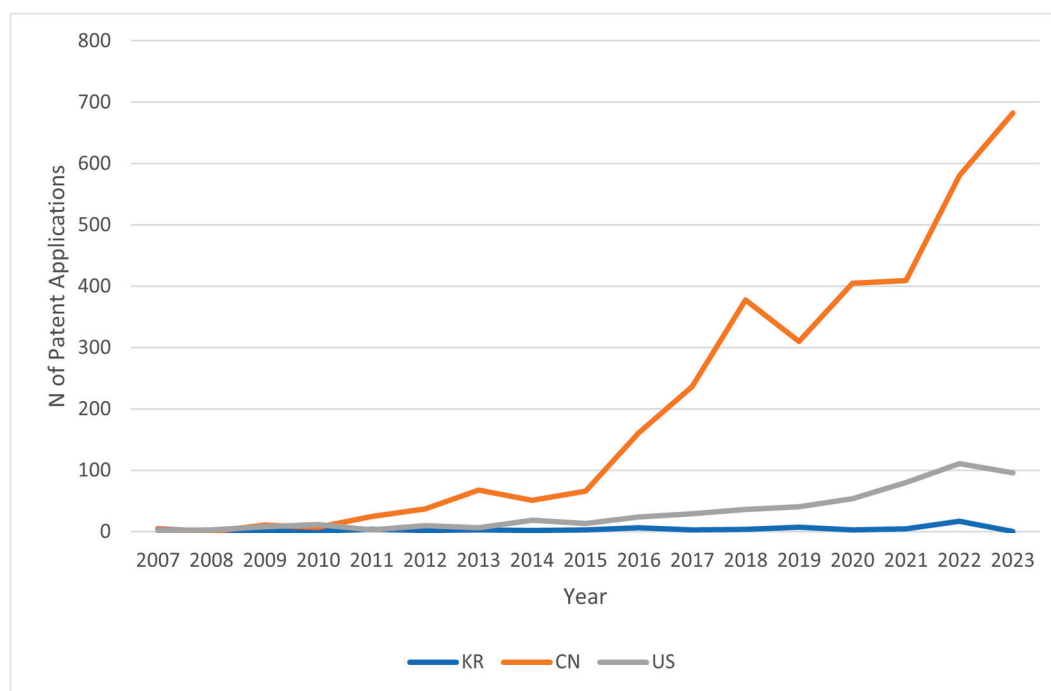


Figure 1. Battery Recycling Patent Volume by year (KR, CN, and US).

Figure 2 presents the data on battery recycling patent filings from 2008 to 2023 across Germany (DE), the European Patent Office (EP), Japan (JP), and the United Kingdom (UK), revealing distinct trends (there were no patents in 2007). The UK shows the most consistent filing activity, with notable filings in 2008, 2014, 2015, and 2018. In contrast, Germany and Japan exhibit minimal and sporadic filings, with Germany having filings only in 2016 and 2023 and Japan showing activity primarily in 2015 and 2020. The EP demonstrates a steady increase in filings, peaking in 2020 with four patents.

Overall, the UK maintains steady activity, while the EP shows a notable upward trend, indicating increased research and development efforts or regulatory changes in recent years. Germany and Japan's low activity suggests less emphasis on battery recycling innovation. These data highlight regional differences in prioritizing battery recycling technology through patent filings.

Based on Figures 1 and 2, the following two points are the results of comparison of patent filing trends in battery recycling technology. The first point is the analysis of patent filings in the UK, EP, Japan, and Germany. The analysis of patent filings in the UK, EP, Japan, and Germany shows distinct trends in the development of battery recycling technology. In the UK, the number of patent filings is minimal, with a few filings each year. The European Patent Office (EP) displays a slightly higher activity level, yet it still remains modest compared to other regions. Japan and Germany also show low but consistent patent filings over the years, reflecting a steady but limited focus on battery recycling technology in these regions. The data indicate that while these countries are involved in

battery recycling innovation, the volume of patent filings is not as substantial as in other major players.

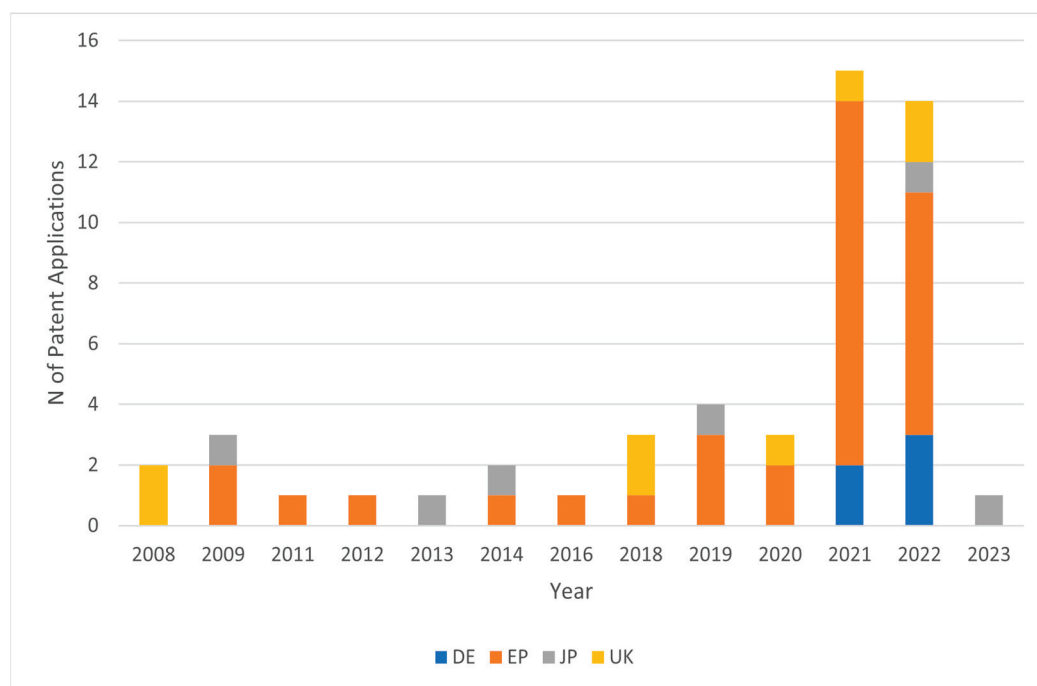


Figure 2. Battery Recycling Patent Volume by year (DE, EP, JP, and UK).

The second point is the comparison with Korea, China, and the USA. When comparing Korea, China, and the USA, the trends show significant differences. China leads in the number of patent filings, with a sharp increase from 2007 onwards, peaking in recent years. This surge indicates China's robust focus and investment in battery recycling technology. Korea, while showing some activity, has fewer filings, suggesting a more moderate approach. The USA exhibits a steady increase in patent filings, particularly from 2010 onwards, reflecting a growing interest and development in this sector. The substantial number of filings in China and the USA highlights a more aggressive stance towards innovation in battery recycling technology compared to the relatively modest numbers seen in the UK, EP, Japan, and Germany.

3.3. Comparative Analysis of Major Players and IP Comparativeness

Table 2 shows a comparison of different companies regarding their intellectual property (IP) holdings, specifically patents, in the context of battery recycling technology. This is a kind of snapshot of the patent landscape among key players in battery recycling technology, which is useful for understanding the competitive environment and innovation trends.

Table 2 presents data on patents related to battery recycling, specifically organized by country (Korea, China, and United States) and the IPC keywords associated with the patents. The analysis reveals a strong emphasis on battery recycling technologies (H01M-010) across various countries and companies, indicating a global trend towards improving battery recycling processes. Companies in Korea and China also show significant interest in metal extraction and material preparation processes, while those in the United States focus on intelligent control systems and data management in recycling. The details of the IPCs in Table 2 can be obtained from the World Intellectual Property Organization (WIPO) [31].

Table 2. Number of patent applications and IPC keywords in technology.

Country (N of Patents)	Player Name	N of Patents	Technology Keywords Based on IPC
Korea (N = 65)	Umicore	9	C22B-003, H01M-010
	Recycle Cooperation	10	H01M-010
	BASF SE	7	H01M-010, B01J-035
	RD Solution	5	H01M-010, B09B-003
	ED Engineering	3	B09B-003
China (N = 3496)	Anhui Nandu Huabo	34	H01M-010, B02C-004
	New Material Technology		
	Anhui Lvwo Recycling	16	H01M-010, B02C-003
	Energy Technology		
	Guizhou Zhongwei	17	H01M-010, C22B-007
	Resources Recycling		
	Industry Development		
	Guangdong	8	H01M-010, H01M-004
United States (N = 548)	Haozhi Technology		
	Changsha Research Institute of	19	C22B-007, B02C-018
	Mining and Metallurgy		
	Strong Force VCN	61	G06Q-010, G05D-001
	Grst International Limited	9	H01M-010
	Guangdong Brunp	29	H01M-010
	Recycling Technology		
	Hunan Brunp Recycling	27	C22B-007
	Technology		
	Worcester Polytechnic Institute	17	H01M-010

In the United States, the keyword H01M-010 shows consistent activity over the years, indicating ongoing research and patent filings in battery recycling technologies. Keywords C22B-003 and C22B-007 also exhibit significant activity, reflecting the importance of metal recovery in the recycling process. The keywords B01J-035, B02C-003, and B02C-004 display variability in trends, with some years showing higher activity related to chemical processes and material crushing. Additionally, G06Q-010 and G05D-001 have noticeable activity in recent years, highlighting the integration of smart technologies in recycling operations.

In Korea, H01M-010 shows a steady increase in activity, reflecting a growing focus on battery recycling technologies. Keywords C22B-003 and C22B-007 show some activity, indicating efforts in metal recovery from recycled materials. The keywords B01J-035 and B09B-003 exhibit variable trends, suggesting an interest in chemical processes and waste disposal technologies. B02C-003 and B02C-004 are less prominent but still present, indicating activities related to material crushing and preparation.

In China, the keyword H01M-010 shows significant and increasing activity, demonstrating a strong focus on battery recycling. Keywords C22B-003 and C22B-007 show high activity, highlighting extensive efforts in metal recovery. The keywords B01J-035, B09B-003, B02C-003, and B02C-004 exhibit substantial activity, indicating a broad approach to recycling involving chemical processes and material crushing. Additionally, H01M-004 has a notable presence, suggesting innovations in primary cell technologies.

All three countries show strong and consistent activity in battery recycling (H01M-010), with China leading in the number of patents. Significant efforts in metal recovery (C22B-003, C22B-007) are observed in the US and China, with Korea also contributing. Chemical processes and material crushing show variable but present trends in all three countries, indicating ongoing research in optimizing recycling processes. Smart technologies (G06Q-010, G05D-001) have a more recent focus, particularly in the US, reflecting the integration of data processing and control systems in recycling.

Table 3 reveals varying levels of patent activity and impact across the three countries from 2007 to 2024. CPP stands for “citations per patent” and represents the average number

of times a patent is cited by other patents or publications. It is a metric used to assess the impact and influence of a company's or institution's patents on further research and technological development. CPP is calculated by dividing the total number of citations by the total number of patents.

Table 3. CPP, PII, TS, and PFS by players in Korea, China, and United States (2007–2024).

Country	Player Name	CPP	PII	TS	PFS
Korea	Umicore	0.7	0.34	6.0	2.22
	Recycle Cooperation	2.8	1.41	28.0	3.00
	BASF SE	0.7	0.36	5.0	2.14
	RD Solution	0.4	0.20	2.0	2.00
	ED Engineering	2.7	1.34	8.0	2.67
China	Anhui Nandu Huabo	0.4	0.22	15.0	1.32
	New Material Technology				
	Anhui Lvwo Recycling	0.4	0.22	7.0	1.56
	Energy Technology				
	Guizhou Zhongwei				
	Resources Recycling	0.3	0.18	6.0	1.29
	Industry Development				
United States	Guangdong	0.1	0.06	1.0	1.25
	Haozhi Technology				
	Changsha Research Institute of	4.5	2.25	85.0	3.16
	Mining and Metallurgy				
	Strong Force VCN	3.6	1.82	220.0	2.46
	Grst International Limited	0	0.00	0.0	1.00
	Guangdong Brunp	1.0	0.52	30.0	1.72
	Recycling Technology				
	Hunan Brunp Recycling	0.4	0.13	7.0	1.00
	Technology				
	Worcester Polytechnic Institute	6.9	3.50	118.0	3.53

- **CPP = Total Citation/Total Patents**

A high CPP indicates that the patents are frequently cited, suggesting that the technology is innovative and significantly contributes to the field. Conversely, a low CPP implies that the patents are less frequently cited, which could mean they are less influential, newer, or not yet widely recognized. For example, if a company has filed 10 patents and these patents have been cited 50 times, the CPP would be 5. Thus, CPP serves as a vital indicator of the qualitative impact of patents.

China leads in the number of patents, particularly in battery recycling and metal recovery, though the citation impact (CPP) varies significantly among players. Korea shows a growing focus on battery recycling, with some companies demonstrating high CPPs indicating influential patents. The United States exhibits strong activity in both the number and impact of patents, particularly in smart technologies and data processing related to recycling operations.

In Korea, Umicore has a moderate number of patents (9) with a relatively low citation count (6), resulting in a CPP of 0.7. Recycle Cooperation stands out with a higher CPP of 2.8 from 10 patents and 28 citations, indicating that their patents are well-regarded and frequently referenced. BASF SE shows similar characteristics to Umicore with seven patents and a CPP of 0.7. RD Solution, with five patents and a CPP of 0.4, shows lower impact, while ED Engineering, despite having only three patents, has a high CPP of 2.7, suggesting highly regarded contributions.

In China, Anhui Nandu Huabo New Material Technology leads with 34 patents but has a low CPP of 0.4 from 15 citations, indicating extensive patenting activity with limited citation impact. Anhui Lvwo Recycling Energy Technology and Guizhou Zhongwei Resources Recycling Industry Development have similar profiles, with moderate patent activity and low CPPs of 0.4 and 0.3, respectively. Guangdong Haozhi Technology has the lowest CPP of 0.1 with eight patents and one citation. However, Changsha Research Institute of Mining and Metallurgy stands out with a high CPP of 4.5 from 19 patents and 85 citations, indicating highly influential patents.

In the United States, Strong Force VCN shows substantial patent activity with 61 patents and a high CPP of 3.6 from 220 citations, indicating influential patents. Grst International

Limited has nine patents but no citations, resulting in a CPP of 0. Guangdong Brunp Recycling Technology has 29 patents and a balanced CPP of 1.0 from 30 citations. Hunan Brunp Recycling Technology has a moderate number of patents (27) with a low CPP of 0.4 from seven citations. Worcester Polytechnic Institute exhibits the highest CPP of 6.9 with 17 patents and 118 citations, highlighting their significant contributions to recycling technologies.

Furthermore, Table 3 provides PII, TS, and PFS information of players in Korea, China, and the United States. The patent impact index (PII) is a measure that compares the average number of citations per patent of a specific entity to the average number of citations per patent of all entities in a given dataset. It is calculated as follows:

- $PII = \text{CPP of the entity} / \text{average CPP of all entities}$

A higher PII indicates that an entity's patents are cited more frequently compared to the average, suggesting a greater impact or influence in the field.

Technology strength (TS) quantifies the overall impact of an entity's patent portfolio. It is calculated as the product of the number of patents and the average number of citations per patent (CPP):

- $TS = \text{total patents} \times \text{CPP}$

A higher TS indicates a stronger technological position, reflecting both the quantity and the quality (impact) of the patents.

Patent family size (PFS) indicates the average number of countries in which a patent is filed within the same patent family. It is calculated as follows:

- $PFS = \text{total number of family members} / \text{total patents}$

A larger PFS suggests that the patents have wider geographical coverage, which can imply broader market protection and greater potential for commercialization.

In Korea, Umicore has a moderate patent count with a low patent impact index (PII) of 0.34, reflecting less impact compared to the average, and a technology strength (TS) of 6.0, with an average patent family size (PFS) of 2.22. Recycle Cooperation, however, shows significant impact with a high PII of 1.41, a TS of 28.0, and a broad geographic coverage indicated by a PFS of 3.00. BASF SE has a low PII of 0.36 and a TS of 5.0, indicating moderate technology strength, with a PFS of 2.14. RD Solution has minimal impact with a PII of 0.20 and low technology strength (TS of 2.0), with a PFS of 2.00. ED Engineering shows strong impact with a high PII of 1.34, a TS of 8.0, and good geographic coverage (PFS of 2.67).

In China, Anhui Nandu Huabo New Material Technology and Anhui Lvwo Recycling Energy Technology both have a low PII of 0.22, indicating limited impact, with TS values of 15.0 and 7.0, and narrow geographic coverage with PFS values of 1.32 and 1.56, respectively. Guizhou Zhongwei Resources Recycling Industry Development also has a minimal impact with a PII of 0.18 and low TS of 6.0, with a PFS of 1.29. Guangdong Haozhi Technology has very limited impact with a PII of 0.06, minimal TS of 1.0, and narrow geographic coverage (PFS of 1.25). In contrast, Changsha Research Institute of Mining and Metallurgy has significant impact with a high PII of 2.25, strong TS of 85.0, and good geographic coverage indicated by a PFS of 3.16.

In the United States, Strong Force VCN shows significant impact with a high PII of 1.82, very strong technology strength (TS of 220.0), and broad geographic coverage (PFS of 2.46). Grst International Limited has no impact, as indicated by a PII of 0.00, no technology strength (TS of 0.0), and narrow geographic coverage (PFS of 1.00). Guangdong Brunp Recycling Technology shows moderate impact with a PII of 0.52, a TS of 30.0, and narrow geographic coverage (PFS of 1.72). Hunan Brunp Recycling Technology has limited impact with a low PII of 0.13, low technology strength (TS of 7.0), and narrow geographic coverage (PFS of 1.00). Worcester Polytechnic Institute, on the other hand, has significant impact with a high PII of 3.50, very strong technology strength (TS of 118.0), and broad geographic coverage (PFS of 3.53).

Figure 3 shows a scatter plot and this provides a clear picture of patent influence (CPP) and geographic coverage (PFS) across key players in Korea, China, and the United States. Players like Worcester Polytechnic Institute, Changsha Research Institute of Mining and Metallurgy, and Recycle Cooperation are leaders in terms of influential patents with wide geographic coverage. Conversely, some players in China and the US exhibit lower influence and narrower coverage, highlighting areas for potential improvement or strategic focus.

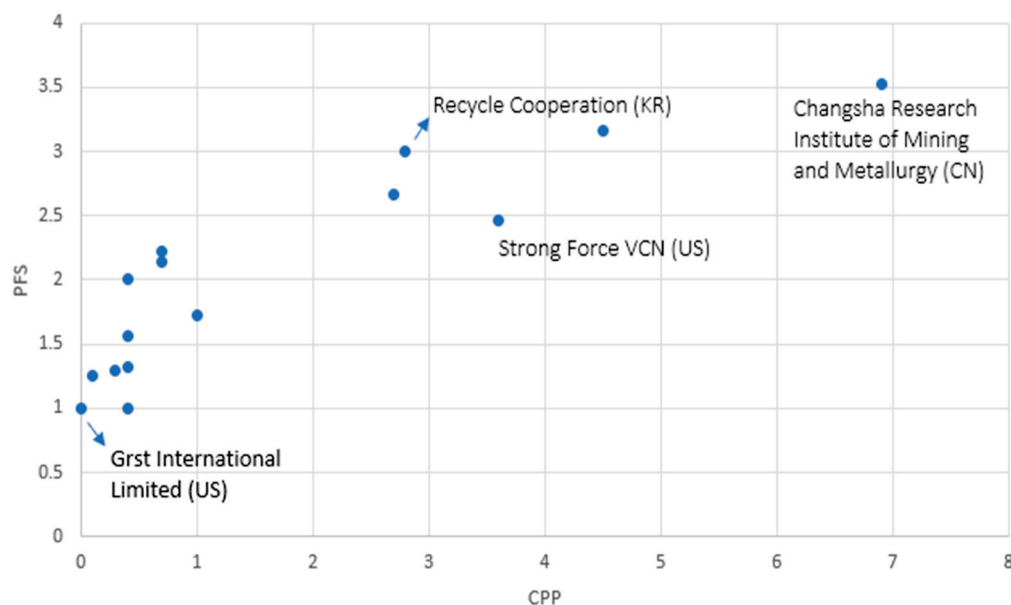


Figure 3. CPP and PFS Scatter Plot.

Korea exhibits a diverse range of patent influences across its key players, with a general trend towards moderate to high influence and decent geographic coverage. Notably, Recycle Cooperation and ED Engineering stand out for their exceptional citations per patent (CPP) and large patent family size (PFS). Recycle Cooperation, with a CPP of 2.8 and a PFS of 3, demonstrates substantial influence in the field, indicating that their patents are both highly impactful and widely recognized across different regions. Similarly, ED Engineering, with a CPP of 2.7 and a PFS of 2.67, shows a strong patent influence and good geographic reach, underscoring their significant contributions to battery recycling technologies. Other players like Umicore and BASF SE maintain a steady presence with moderate CPP values of 0.7, reflecting a consistent, if not outstanding, impact in the field. RD Solution, with a lower CPP of 0.4 and a PFS of 2, indicates less influential patents, suggesting room for growth in both impact and reach.

In China, the range of patent influences varies widely among the key players. The standout performer is Changsha Research Institute of Mining and Metallurgy, which boasts a remarkable CPP of 4.5 and a PFS of 3.16. This indicates that their patents are highly influential and enjoy extensive geographic coverage, making significant contributions to the industry. On the other end of the spectrum, companies like Guangdong Haozhi Technology exhibit a very low CPP of 0.1 and a narrow PFS of 1.25, reflecting minimal impact and limited geographic reach. Other Chinese players, such as Anhui Nandu Huabo New Material Technology and Anhui Lvwo Recycling Energy Technology, maintain low CPP values of 0.4 with varying geographic coverage, indicating that while they have a presence in the market, their patents are less influential. Guizhou Zhongwei Resources Recycling Industry Development, with the lowest CPP of 0.3, further underscores the disparity in influence among Chinese companies, highlighting a broad spectrum from highly influential to minimally impactful patents.

The United States features a wide range of patent influences, from very high to virtually nonexistent. Worcester Polytechnic Institute is the leader, with an impressive CPP of 6.9 and a PFS of 3.53, indicating exceptional influence and extensive geographic coverage. This demonstrates that their patents are not only highly impactful but also widely recognized and adopted across different regions. Strong Force VCN also shows a strong presence with a CPP of 3.6 and a PFS of 2.46, reflecting significant influence and good geographic reach. In contrast, Grst International Limited exhibits no patent citations, resulting in a CPP of 0 and a PFS of 1, indicating that their patents have no discernible impact or geographic reach. Guangdong Brunp Recycling Technology and Hunan Brunp Recycling Technology fall in the middle, with CPP values of 1.0 and 0.4, respectively, and varying PFS, showing moderate influence and geographic coverage. This wide range illustrates the diversity in patent influence among US players, from leading innovators to those with minimal impact.

Overall, Korea, China, and the United States each display distinct characteristics in their patent influences and geographic coverages. Korea's key players generally exhibit moderate to high influence with decent coverage, with standout performers like Recycle Cooperation and ED Engineering. China's landscape is more varied, with Changsha Research Institute of Mining and Metallurgy leading in influence, while other players lag significantly. The United States presents a broad spectrum, with Worcester Polytechnic Institute achieving exceptional influence and others like Grst International showing no impact, reflecting a diverse range of patent efficacy and reach.

3.4. Patent Transaction Analysis

Figure 4 shows that the trends in patent transactions in Korea (KR), China (CN), and the United States (US) from 2007 to 2024. China has shown a significant and consistent increase in patent transactions over the years, especially from 2014 onwards, with the number of transactions peaking in 2023. This suggests that China has been rapidly intensifying its patent activities, indicating a strong focus on intellectual property.

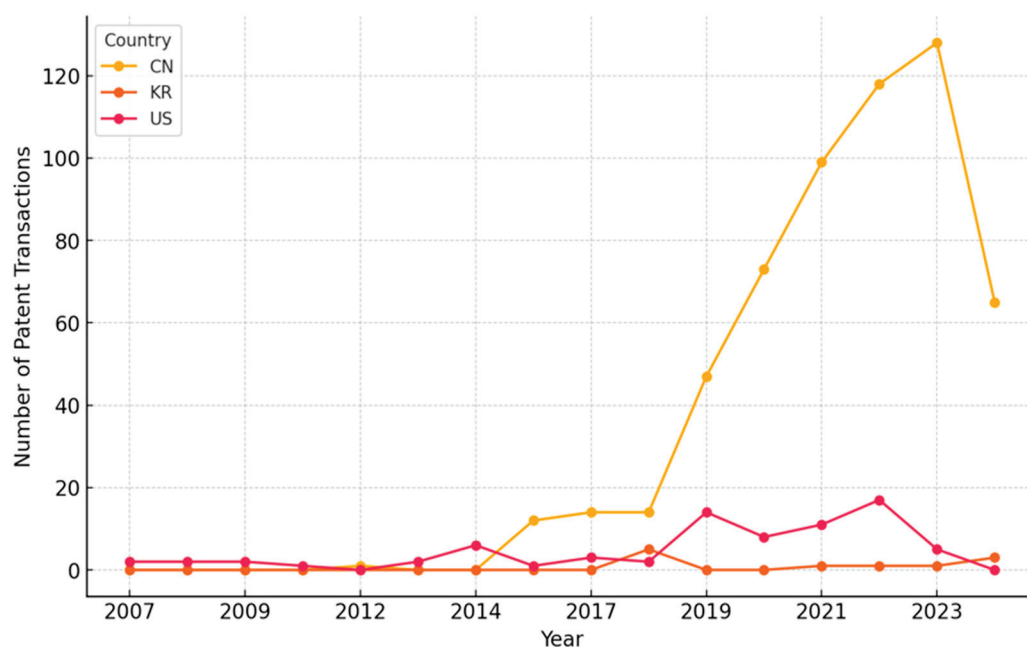


Figure 4. Transaction Volume of Battery Recycling Patent by year (KR, CN, and US).

Korea, in contrast, has had relatively fewer patent transactions compared to China and the US, with notable activity starting from 2018. The highest number of transactions in a single year was five in 2018, showing moderate activity with a slight increase in recent years. This indicates that while Korea is engaged in patent transactions, its activity level is more modest.

The United States displays a steady but less pronounced increase in patent transactions, with occasional peaks, the highest being 17 transactions in 2022. This steady level of activity reflects an ongoing but stable approach to patent transactions, indicating a consistent engagement in maintaining and managing intellectual property without significant fluctuations.

Based on the analysis of patent transactions, several key insights emerge regarding the most frequently traded patents. The patent titled “METHOD FOR COMPOSITE DELAMINATION” appears the most frequently, with seven transactions. This suggests a high market interest in technologies related to the delamination process, which is crucial in the recycling and recovery of composite materials from batteries.

Another highly traded patent is “Battery recycling system for electric vehicle,” which appears four times. This reflects the growing importance of developing efficient recycling systems specifically tailored for electric vehicle batteries. The transition to electric vehicles has heightened the need for effective recycling technologies to manage the increasing volume of used batteries.

Additionally, patents related to comprehensive battery management and recycling systems also appear, such as “Secondary battery module, battery information management device, battery information management system, secondary battery reuse system, secondary battery recovery and sales system, secondary battery reuse method, and secondary battery recovery and sales method,” which appears four times. This indicates significant interest in integrated systems that handle the entire lifecycle of secondary batteries, from usage to recycling and resale.

Furthermore, patents focusing on specific materials recycling, such as “RECYCLING OF LEAD- AND TIN-BASED MATERIALS,” show a focused interest in recovering valuable materials from batteries. Other frequently traded patents include those related to non-aqueous electrolyte secondary batteries and lithium battery recycling equipment, reflecting ongoing advancements in battery technology and safety mechanisms during the recycling process. Overall, the data highlight the market’s priority on innovations that enhance the efficiency, safety, and comprehensiveness of battery recycling systems, particularly for electric vehicle batteries.

Analysis of frequently sold patents reveals several key technology trends in the battery recycling sector. There is a significant focus on delamination processes, which are essential for efficiently separating and recovering materials from batteries. Additionally, specialized recycling systems for electric vehicles are highly sought after, reflecting the industry’s emphasis on developing sustainable solutions for the increasing number of electric vehicle batteries.

Comprehensive battery management and recycling systems are also prevalent, indicating a trend towards integrated solutions that cover the entire lifecycle of batteries, from use to recycling and resale. Material-specific recycling technologies, such as those for lead, tin, and lithium, highlight the market’s interest in efficient recovery of valuable materials. Safety mechanisms during the recycling process, particularly in handling non-aqueous electrolyte secondary batteries and protection during crushing, are crucial areas of innovation.

Overall, the analysis shows that the market prioritizes technologies that enhance the efficiency, sustainability, and safety of battery recycling processes. These trends align with broader industry goals of improving resource recovery and reducing environmental impact.

4. Discussion

These are the challenges and strategies for policy makers in order to promote battery recycling technology and related industry.

Korea faces the challenge of maintaining consistent innovation across all its players. While companies like Recycle Cooperation and ED Engineering exhibit high CPP, others like Umicore and RD Solution show moderate to low CPP, highlighting the need for more

impactful R&D efforts. To address this, fostering collaboration between industry and academia, increasing R&D investments, and implementing innovation-friendly policies are crucial. Additionally, expanding the geographic coverage of patents is essential, as companies like RD Solution have room for improvement in international patent family size. Encouraging global patent filings and partnerships with international entities can help Korean companies enhance their market influence.

China's primary challenge is increasing the patent influence of many of its companies. Firms like Guangdong Haozhi Technology and Guizhou Zhongwei Resources Recycling Industry Development have low CPP, indicating less impactful patents. Improving patent quality through better R&D practices and focusing on innovative technologies can help increase their influence. Moreover, there is a significant disparity in patent influence among Chinese companies, with Changsha Research Institute of Mining and Metallurgy leading significantly. Bridging this gap by supporting smaller or less advanced companies through subsidies, tax incentives, and access to advanced research facilities is essential. Enhancing international presence is also crucial, as some companies have limited international patent coverage. Facilitating international patent applications and collaborations can help strengthen their global presence.

The United States exhibits a wide range of patent influences, from highly impactful (Worcester Polytechnic Institute) to minimal or none (Grst International Limited). Ensuring high patent quality across all players by strengthening review processes and providing support for companies with lower CPP can help maintain high standards. Addressing variability in geographic coverage is also important, as some companies have limited reach. Encouraging broader geographic patent filings and international collaborations can help expand US companies' influence globally. Additionally, fostering innovation in lagging sectors through targeted support and incentives can stimulate innovation and increase overall patent influence.

To address these challenges, promoting enhanced collaboration between academia, industry, and government can lead to more innovative and impactful patents. Increasing R&D investments by both governments and private sectors is crucial to boost innovation. Encouraging companies to file patents internationally can enhance their global presence and market influence. Implementing supportive policies, such as tax incentives, subsidies for R&D, and easier access to patenting processes, can further help overcome these challenges. By addressing these key challenges, Korea, China, and the United States can strengthen their positions in the global patent landscape and drive further innovation in the battery recycling sector.

5. Conclusions

This study conducted a comprehensive global patent analysis on battery recycling technologies, focusing on secondary batteries across Korea, China, and the United States. The findings reveal significant differences in patent activities and technological focuses among these countries. Korea exhibits a mix of moderate to high patent influence with decent geographic coverage, with standout companies like Recycle Cooperation and ED Engineering. China shows a wide range of patent influences, with Changsha Research Institute of Mining and Metallurgy leading significantly, while other companies lag. The United States displays a broad spectrum of patent influences, from highly impactful patents by Worcester Polytechnic Institute to minimal influence from companies like Grst International Limited. Addressing the identified challenges—such as maintaining consistent innovation in Korea, increasing patent influence and reducing disparity among companies in China, and ensuring high patent quality in the United States—can significantly enhance the global competitiveness of these nations in battery recycling technologies.

Moreover, several additional analyses could further strengthen this study. Economic impact assessments of patent activities could reveal cost savings from recycling and the economic benefits of enhanced technologies. Environmental impact assessments could evaluate the reductions in resource extraction and waste generation. Developing a technological

roadmap could identify future trends and emerging technologies in battery recycling, guiding strategic planning and investment decisions. Conducting detailed case studies of leading companies would provide deeper insights into their strategies and contributions. Additionally, examining national policies and their impact on battery recycling technologies could offer recommendations for policy improvements. Finally, analyzing market trends and forecasting future demand for battery recycling technologies, considering the rapid growth of the electric vehicle market, would provide valuable insights into the industry's future directions.

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