Article

Predictive Energy Management Strategy for Range-Extended Electric Vehicles Based on ITS Information and Start–Stop Optimization with Vehicle Velocity Forecast

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Abstract: Range-extended Electric Vehicles (REVs) have become popular due to their lack of emissions while driving in urban areas, and the elimination of range anxiety when traveling long distances with a combustion engine as the power source. The fuel consumption performance of REVs depends greatly on the energy management strategy (EMS). This article proposes a practical energy management solution for REVs based on an Adaptive Equivalent Fuel Consumption Minimization Strategy (A-ECMS), wherein the equivalent factor is dynamically optimized by the battery’s State of Charge (SoC) and traffic information provided by Intelligent Transportation Systems (ITS). Furthermore, a penalty function is incorporated with the A-ECMS strategy to achieve the quasi-optimal start–stop control of the range extender. The penalty function is designed based on more precise vehicle velocity forecasting through a nonlinear autoregressive network with exogeneous input (NARX). A model of the studied REV is established in the AVL Cruise environment and the proposed energy management strategy is set up in Matlab/Simulink. Lastly, the performance of the proposed strategy is evaluated over multiple Worldwide Light-duty Test Cycles (WLTC) and real-world driving cycles through model simulation. The simulation conditions are preset such that the range extender must be switched on to finish the planned route. Compared with the basic Charge-Depleting and Charge-Sustaining (CD-CS) strategy, the proposed A-ECMS strategy achieves a fuel-consumption benefit of up to 9%. With the implementation of range extender start–stop optimization, which is based on velocity forecasting, the fuel saving rate can be further improved by 6.7% to 18.2% compared to the base A-ECMS. The proposed strategy is energy efficient, with a simple structure, and it is intended to be implemented on the studied vehicle, which will be available on the market at the end of October 2022.

Keywords: range-extended vehicles; predictive energy management; adaptive-ECMS strategy; start–stop optimization; vehicle velocity forecast

1. Introduction

Pure Battery Electric Vehicles (BEVs) are now widely accepted in the market and have been adopted by Original Equipment Manufacturers (OEMs) owing to their simple power system structure, high mechanical efficiency, and lack of pollutant emissions when driving. However, even after many years of battery technology development [1], range anxiety is still the major concern for BEV drivers, and this anxiety is further increased by the long charging time and insufficient charging stations [2,3]. Compared with BEVs, REVs are regarded as a potential solution for range anxiety. A range extender is an auxiliary power unit (APU) that provides the vehicle with additional energy. The APU does not power the wheels directly, but is used to generate electricity. There are several different types of range extenders, including internal combustion engines (ICEs), fuel cells, free-piston linear
generators (FPLGs), and micro gas turbines (MGTs) [4]. Compared with other types of range extenders, ICE range-extended EVs are currently widely adopted by manufactures, such as in the Chevrolet Volt and the BMW i3. An REV is often equipped with a larger battery compared to Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs), which allows for a greater pure electrical range. As a result, REVs are able to produce zero emission while driving in urban areas, and travel long distances with the combustion engine as the power source. Similar to PHEVs, REVs reduce the consumption of fuel and energy originating from several energy sources compared with ICE vehicles, via their appropriate energy management strategy (EMS) [5,6].

The goal of energy management is to fulfill tractive power demand with the best possible fuel economy, and the battery state of charge (SoC) should be kept in the desired range under different driving conditions. To tackle these issues, numerous studies have been conducted into EMS for REVs as well as PHEVs. The EMS strategies are mainly placed into two categories: rule-based and online optimization-based [7–10]. For rule-based strategies, the energy-saving policies are determined by the operation conditions. In the meantime, battery SoC is managed according to the CD-CS method. Rule-based strategies are broadly used in the automotive industry for mass production. Their benefits in prolonging battery lifetime and reducing engine vibration have been well demonstrated [11]. However, although the rule-based strategies are efficient and robust when implemented in vehicles, it is very difficult to achieve optimal energy-saving levels in the real world. The rules are normally obtained under ideal operating conditions. Not surprisingly, this causes poor energy-saving performance under real-world driving conditions. Wang et al. [12] extracted the control rules from optimal algorithms, and the control parameters were optimized offline and corrected online. A better fuel economy performance was observed than under the original logic threshold rules. However, a more complex algorithm is required for the rule extraction and parameter optimization, which limits the application of this approach in massive production.

On the other hand, the optimization-based strategies are capable of adapting their control parameters to real-world conditions. Therefore, they have greater potential in terms of fuel-saving. Typical optimization-based strategies include the Equivalent Fuel Consumption Minimization Strategy (ECMS) and Dynamic Programming (DP). The ECMS is a semi-analytical algorithm for optimizing hybrid power systems based on the Pontryagin minimization principle [13]. Owing to its fast computation speed, the ECMS algorithm is able to be fully realized in real-time. Furthermore, it can not only be universally applied to hybrid power systems [14–16], but requires no knowledge of the global operating conditions. This makes it more practical compared to DP. Though the DP algorithm can provide a theoretically optimum solution, it requires an accurate knowledge of global operation conditions, which are very difficult to get.

The key to the ECMS design is to determine an equivalent factor between fuel and electrical energy based on the available vehicle information. Then, an Adaptive-ECMS (or A-ECMS in short) strategy is proposed. Attention has been paid to the relationship between the equivalent factor and battery SoC [17–19]. In many studies, this factor is optimized for a given typical driving cycle [20–22]. The results are promising for cycles close to the pre-given ones, whereas they are less positive for complex real driving cycles. This is because the driving conditions in real cycles are more complicated than typical cycles due to different driver behaviors and traffic conditions. Driver behavior refers to the acceleration, aerodynamic drag force, braking frequency, energy recuperation, and the frequency of periodic and aperiodic faults, which significantly influence the energy consumption [6,23]. Liu et al. [24] combined driver behavior recognition and Intelligent Transportation System (ITS) information to determine the optimum equivalent factor for the planned trip. Furthermore, the strategy was adjusted to deal with different levels of future ITS information. The result is satisfactory, but the problem is that the equivalent factor is fixed after the optimization, and it would not be dynamically adjusted during the rest of the trip. In order to achieve better optimization results, studies have recently
been focused on adjusting the equivalent factor dynamically, based on driver behavior and vehicle operation conditions in the planned route. Khayyer et al. [25] proposed a semi-empirical function to dynamically calculate the equivalent factor, based on the previous equivalent factor, the current SoC and the distance to the destination provided by ITS. A 9% fuel economy improvement can be achieved under the Urban Dynamometer Driving Schedule (UDDS) cycle. With velocity prediction up to 60 s available, the performance can be further improved. Although the results are promising, the parameters for calculating the equivalent factor rely on additional tuning, and the global optimization result has yet to be improved. A similar semi-empirical method has been adopted by Sun et al. [26] and Zhang et al. [27] to adjust the equivalent factor.

The above studies have shown the effectiveness of utilizing ITS information to determine the equivalent factor. However, semi-empirical methods are commonly used in most studies, and additional parameter tuning is inevitable. A better global dynamic optimization method for the equivalent factor is still yet to be developed. On the other hand, the strategy should be optimized and simplified for application in mass production vehicles.

In this paper, A-ECMS is applied as the solution to the REV energy management problem. According to the traffic information provided by ITS, a practical dynamic optimization method of the equivalent factor during the planned route is proposed. Furthermore, the real-time start–stop control of the range extender is optimized by velocity forecasting to achieve better fuel economy.

This paper is organized as follows. Section 2 deals with the system configuration and modeling of the studied REV. In Section 3, the research method and procedure are presented. Section 4 is focused on the energy management problem, in which the optimization of the equivalent factor based on ITS is demonstrated in detail. Section 5 presents the further improvement of the A-ECMS strategy, wherein the start–stop optimization of the range extender is optimized through velocity forecasting to achieve better power split performance. Finally, the summary and conclusions are given in Section 6.

2. REV System Modeling and Validation

2.1. Vehicle Specifications

The studied vehicle is a mass-production series-type REV, as shown in Figure 1. This vehicle will be available on the market from October 2022.
Table 1. Vehicle specifications.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle type</td>
<td>Series-type REV</td>
</tr>
<tr>
<td>Car curb weight (kg)</td>
<td>1980</td>
</tr>
<tr>
<td>Fuel</td>
<td>Gasoline</td>
</tr>
<tr>
<td>APU type</td>
<td>1.5 L 4-cylinder gasoline engine</td>
</tr>
<tr>
<td>Battery type</td>
<td>114 Ah ternary lithium battery</td>
</tr>
<tr>
<td>Motor type</td>
<td>Permanent magnet synchronous motor</td>
</tr>
<tr>
<td>Frontal area (m²)</td>
<td>2.45</td>
</tr>
<tr>
<td>Tire rolling radius (mm)</td>
<td>341</td>
</tr>
<tr>
<td>Drivetrain efficiency (%)</td>
<td>90</td>
</tr>
<tr>
<td>Main reduction ratio</td>
<td>11.591</td>
</tr>
</tbody>
</table>

The powertrain architecture of the studied vehicle is illustrated in Figure 2. It consists of a gasoline Internal Combustion Engine (ICE), an Integrated Starter–Generator (ISG), a power converter, a battery pack, and an electric motor. As this is a typical series-type scheme, the engine torque is not used to drive the wheels directly, but is used to generate electricity, and the vehicle is driven by an electric motor.

\[
F_t = F_f + F_w + F_i + F_j
\]

\[
\begin{align*}
F_f &= M_{nml} g \cos \theta f \\
F_w &= \frac{1}{2} C_d \rho A_f v^2 \\
F_i &= M_{nml} g \sin \theta \\
F_j &= \delta + 1M_{nml}a
\end{align*}
\]

where \(F_f, F_w, F_i\) and \(F_j\) are the rolling resistance, air drag, slope and inertia force, respectively; \(M_{nml}\) is the vehicle nominal mass; \(\theta\) is the road slope; \(f\) is the rolling resistance coefficient; \(C_d\) is the air drag coefficient; \(\rho\) is the standard air density; \(A_f\) is the vehicle frontal area; \(v\) is the vehicle’s speed; \(\delta\) is the vehicle’s rotating quality conversion coefficient; \(a\) is the vehicle’s acceleration. Derived from Equation (1), the demand power \(P_d\) of the vehicle can be calculated by

\[
P_d = (F_f + F_w + F_i + F_j) v
\]
and the demand electric machine torque $T_d$ is calculated as:

$$T_d = (F_f + F_w + F_i + F_j) \frac{R_{wh}}{i_0} \eta_e$$  \hspace{1cm} (4)$$

where $R_{wh}$ is the tire rolling radius; $i_0$ is the main reduction gear ratio, while $\eta_e$ is the effective efficiency of the transmission, which is further given by

$$\eta_e = \begin{cases} \frac{1}{\eta_{i_0}} & \text{motoring} \\ \eta_{i_0} & \text{breaking} \end{cases}$$

Here, $\eta_{i_0}$ is the transmission efficiency. The power flows from the traction motor to the wheels when motoring, and vice versa if braking.

2.2.2. Electrical Motor Modeling

The parameters of the electrical motor in this study are displayed in Table 2. The peak power is 170 kW, and the nominal power is 65 kW. The maximum speed is 16,500 rpm, and the peak torque is 310 Nm. The speed–torque–power characteristics of the motor are illustrated in Figure 3.

Table 2. Parameters of the electrical motor in this study.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor type</td>
<td>Permanent Magnet Synchronous Motor</td>
</tr>
<tr>
<td>Motor Peak Power (kw)</td>
<td>170</td>
</tr>
<tr>
<td>Motor Nominal Power (kw)</td>
<td>65</td>
</tr>
<tr>
<td>Maximum Speed (r/min)</td>
<td>16,500</td>
</tr>
<tr>
<td>Peak Torque (N·m)</td>
<td>310</td>
</tr>
</tbody>
</table>

Figure 3. The speed–torque–power curve of the electrical motor.

2.2.3. High-Voltage Battery Modeling

The general parameters of the high-voltage battery pack (the battery type is a ternary lithium battery) used in this study are demonstrated in Table 3. The battery SoC is estimated by ampere-hour integration (in the discrete format):

$$SoC(k) = SoC(k-1) - \frac{\int_0^{T_s} I_L dt}{3600 Q_{cap}}$$  \hspace{1cm} (5)$$
where \( \text{SoC}(k) \) is the current step battery SoC in percentage (%); \( \text{SoC}(k - 1) \) is the last step SoC in percentage (%); \( Q_{\text{cap}} \) is the battery capacity in Ah. \( I_L \) is the charging/discharging current. The Open Circuit Voltage (OCV) profile w.r.t SoC is illustrated in Figure 4.

**Table 3. General parameters of the high-voltage battery pack.**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery Type</td>
<td>Ternary Lithium Battery</td>
</tr>
<tr>
<td>Battery Capacity (Ah)</td>
<td>114</td>
</tr>
<tr>
<td>Battery Power (Kwh)</td>
<td>43.5</td>
</tr>
<tr>
<td>Nominal Voltage (V)</td>
<td>387</td>
</tr>
<tr>
<td>Maximum Voltage (V)</td>
<td>452.4</td>
</tr>
<tr>
<td>Number of Single Cells (-)</td>
<td>104</td>
</tr>
</tbody>
</table>

**Figure 4.** SoC–OCV curve of the studied battery.

### 2.2.4. Range Extender Modeling

The parameters of the range extender (gasoline engine) are given in Table 4. The Brake Specific Fuel Consumption (BSFC) map (in g/kwh) is a function of the engine speed and the engine torque, as shown in Figure 5, and the selected operation points are highlighted in the figure as blue dots. The contour lines of engine power are indicated in Figure 5 as white curves.

**Table 4. Parameters of the range extender.**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cylinder number (-)</td>
<td>4</td>
</tr>
<tr>
<td>Engine displacement (cm(^3))</td>
<td>1500</td>
</tr>
<tr>
<td>Maximum speed (r/min)</td>
<td>5000</td>
</tr>
<tr>
<td>Peak power (kw)</td>
<td>72</td>
</tr>
<tr>
<td>Peak torque (Nm)</td>
<td>142</td>
</tr>
</tbody>
</table>
Figure 5. Fuel consumption rate map of the range extender (fuel consumption in red and engine power in black).

2.3. Model Simulation and Validation

The vehicle model with the key components is established in AVL Cruise, which is a 1D vehicle dynamics simulation tool. The overall architecture of the model is shown in Figure 6.

Figure 6. Vehicle model, constructed with AVL Cruise.
The control strategy is modeled in Simulink, and is then compiled in the Dynamic Link Library (DLL) before being integrated with the vehicle model in Cruise. The base EMS strategy is rule-based, and the CD-CS strategy for battery SoC management is also applied. The base EMS strategy in this study is as follows:

1. If the battery SoC is above a given target ($SoC_{ev}$), the vehicle is operated in the pure EV mode. The vehicle is powered by the high-voltage battery only.

$$P_{batt} = P_m \text{ if } SoC > SoC_{ev}$$

where $P_m$ is the power demand of the driver, and $P_{batt}$ is the battery charging and discharging power.

2. If the battery SoC is below a target $SoC_{rev}$, the vehicle is operated in the range-extended mode. The range extender starts to drive the motor and charge the battery when needed. The power demand of the range extender is determined by the vehicle’s power demand and the battery SoC.

$$P_{batt} = f(SoC, P_m) \text{ if } SoC < SoC_{rev}$$

$$P_{ICE} = P_m - P_{batt}$$

in which $P_{ICE}$ is the range extender power demand. Note the battery power request is a function of battery SoC and vehicle power demand. This function can be calibrated online. As a special case of the range-extended mode,

$$P_{batt} = 0; P_{ICE} = P_m$$

This is the so-called power-follow approach. This is when the battery’s SoC is within a predefined range such that the charge and discharge power demands are set to zero. Therefore, the demanded driver power is provided by the range extender only.

3. If the vehicle is decelerating, energy recuperation will occur. The electrical motor is then driven by the inertia of the vehicle, and the generated power is transmitted to the battery through the converter.

$$P_{batt} = \min(f(SoC, P_m), P_m) \text{ if braking}$$

$$P_{ICE} = P_m - P_{batt}$$

In order to validate the model and the performance of the base control strategy, a comparison between a vehicle test-rig test and the simulation is conducted. The boundary and environment conditions of the test and simulation are kept the same. The results are given in Figure 7. For comparison purposes, the simulation uses the same driving cycle as that of the test-rig test, which is the WLTC cycle. The initial SoC is 20.6% and the target SoC is 20%. It can be observed that the SoC and engine torque trajectories match well in the simulation and experimental results, and that the base EMS strategy can maintain the SoC around the target. Good consistency is also observed in the engine start–stop time and engine operation points.
the battery through the converter.

\[
P_{\text{batt}} = \min (f(SoC, P_m), P_m) \quad \text{if braking (10)}
\]

\[
P_{\text{ICE}} = P_m - P_{\text{batt}} \quad \text{(11)}
\]

In order to validate the model and the performance of the base control strategy, a comparison between a vehicle test-rig test and the simulation is conducted. The boundary and environment conditions of the test and simulation are kept the same. The results are given in Figure 7. For comparison purposes, the simulation uses the same driving cycle as that of the test-rig test, which is the WLTC cycle. The initial SoC is 20.6% and the target SoC is 20%. It can be observed that the SoC and engine torque trajectories match well in the simulation and experimental results, and that the base EMS strategy can maintain the SoC around the target.

Good consistency is also observed in the engine start–stop time and engine operation points.

Figure 7. Comparison between simulation and experimental results for base EMS. (a) SoC and engine torque trajectory; (b) range extender operation points.

3. Research Method and Procedure

3.1. Energy Management Problem Formulation in REV

The goal of energy management in REV is to minimize the total fuel consumption over a given driving cycle. The base strategy used in this study is ECMS. The ECMS strategy was first proposed by Paganelli et al. [28], and it is commonly used in hybrid vehicles [29]. The simplified cost function of hybrid vehicles (including REVs) can be described as:

\[
J = m_{\text{fuel}} + k \frac{dSoC}{dt} \quad \text{(12)}
\]

where \(m_{\text{fuel}}\) is the fuel consumption rate and \(k\) is the equivalent ratio. The ECMS strategy aims to minimize \(J\) at a given \(k\). Thus, \(k\) plays an important role in fuel consumption
optimization. In general, $k$ is not necessarily a constant, but could vary with time, and is written as $k(k(t))$.

The ECMS strategy minimizes the energy consumption by seeking optimal control in each time-step. In this study, the range extender power ($P_{ICE}$) is regarded as the control variable, and the battery SoC as the state variable. Then, the Hamiltonian expression of the Pontryagin type of cost function becomes:

$$H(\text{SoC}(t), P_{ICE}(t), t) = m_{fuel}(P_{ICE}(t), t) + k(t) \frac{d\text{SoC}}{dt}(\text{SoC}(t), P_{ICE}(t), t)$$

This is essentially another version of Equation (12), and the ECMS strategy aims to find the minimum $J(J_{min})$ under the constraints given below:

$$\begin{align*}
    P_{batt}(t) &= P_m(t) - P_{ICE}(t) \\
    \text{SoC}_{low} &\leq \text{SoC}(t) \leq \text{SoC}_{high} \\
    P_{min}(t) &\leq P_m(t) \leq P_{max}(t) \\
    0 &\leq P_{ICE}(t) \leq P_{max_{ICE}}(t)
\end{align*}$$

where $P_m(t)$ is the power demand of the driver. For the powertrain architecture used in this paper, it is also the power of the electrical motor. $P_{batt}(t)$ is the battery power. The solution $P_{ICE}^*$ of ECMS is denoted as:

$$J = J_{min} \text{ when } P_{ICE} = P_{ICE}^*$$

3.2. Research Procedure and Hypothesis

Based on the above analysis, it is clear that energy management in an REV relies on two aspects of optimization with different time scales:

Firstly, the global (or long-term) and dynamic optimization of equivalent factor $k(t)$ over the given driving cycle.

Secondly, the instantaneous (or short-term) optimization of $P_{ICE}$ based on current $k(t)$ and $P_m(t)$.

The optimization of $k(t)$ depends largely on historical and future power demands and vehicle states (battery SoC is a key vehicle state). The power demand is, in turn, determined mainly by the road and traffic conditions of the planned route. These conditions are made available by the ITS, and include road slope, speed limits, and traffic flow speed. Detailed descriptions of the global optimization of $k(t)$ will be presented in Section 4.

With a determined optimum $k(t)$, the instantaneous optimization concerns determining the power demand of the range extender, and appropriately switching the range extender on and off. This is the so-called start–stop strategy. The optimum start–stop control of a range extender requires more precise power demand estimation be developed in the near future. In this paper, a penalty function is designed in the A-ECMS strategy based on short-term vehicle velocity forecasting to realize the optimized start–stop control of the range extender for better fuel economics, which will be described in Section 5.

In this study, the following hypotheses have been proposed:

1. All of the research and results are obtained through the model described in Section 2. The simulation environment is AVL Cruise. Both the model and the base energy management strategy, which is a rule-based CD-CS strategy, have been validated by experimental results. Details can be found in Section 2.3;

2. The vehicle operation conditions in this study are determined by the rule that the vehicle is not able to finish its planned trip driven only by a battery. In other words, the range extender must be used. In this study, the initial battery SoC is set as 40% and the target SoC is 20%. The lengths of the studied trips are above 88 km, with a capacity of the battery of 114 Ah and the distance driven by battery alone of about 240 km in the WLTC cycle;
(3) The strategy proposed in this study requires complete traffic conditions provided by ITS, including the distance remaining to the destination, traffic flow speed, road slope and speed limit along the planned route. If the aforementioned ITS information is missing, the proposed strategy will not be operational. In this scenario, the equivalent factor can be adjusted through driving cycle recognition, which has been studied in other papers [24]. As a result, this study focuses only on a scenario with complete traffic conditions provided by ITS.

4. The Global Equivalent Factor Optimization Based on ITS Information

4.1. Adaptive ECMS Strategy Description and Formulation

In order to realize the mass implementation of the proposed strategy, a simplified logical structure of the A-ECMS strategy has been proposed. As illustrated in Figure 8, the desired power of the range extender ($P_{ICE}^*$) is determined by the power split result of the ECMS strategy based on the vehicle’s current states and the (quasi-)optimal equivalent factor $k_{opt}$. $k_{opt}$ is determined by ECMS iterative optimization in a predefined segment along the planned route.

![Figure 8. Logical structure diagram of the A-ECMS strategy.](image)

In this study, a segment with a fixed travel distance is selected as the study object. The segment is 19.2 km ($L_{seg} = 19.2$ km) along the planned route, starting from the current position of the vehicle, and the route is traversed via vehicle driving. We use 19.2 km because of the contradiction between the spatial resolution of the road profile and the signal transmitting rate between the ITS and the vehicle controller, as the strategy is designed for mass-produced vehicles. If the remaining distance to the destination is less than 19.2 km, then the segment length $L_{seg}$ is adjusted to the actual remaining distance. The road profile information ($\varphi_{rt}$) of the segment updates every 30 s and is then imported to the software to estimate the vehicle speed and power demand. The goal is to determine the optimum $k_{opt}$ over the segment every 30 s.

In order to evaluate the $k(t)$ performance, the target SoC at the end of the segment ($SoC_{\text{tgt}}^{\text{seg}}$) must be determined. In our current study, the planned SoC follows the linear-depleting principle. Consequently, the $SoC_{\text{tgt}}^{\text{seg}}$ can be calculated through the current vehicle SoC ($SoC_{ini}$) and the final SoC target at the end of the planned route ($SoC_{tgt}$), as described in Equation (15):

$$SoC_{\text{tgt}}^{\text{seg}} = SoC_{ini} + (SoC_{tgt} - SoC_{ini}) \frac{L_{seg}}{L_{rmin}}$$

where $L_{seg}$ is the length of the segment, and $L_{rmin}$ is the remaining distance to the destination.

$k_{opt}$ is calculated through the following steps:
(1) Based on the characteristics of the given range extender and the battery, a set of \( K \) is pre-determined
\[
K = \{k(i), \ i = 1 : M\};
\]

(2) For each \( k(i) \), there is a further \( N \) iteration (explained in the latter part of this section) to calculate the SoC at the end of the segment, denoted as \( SoC_{seg}^{end}(i) \).
ECMS optimization
\[
P_{ICE}^i(i, j) = f_{ICE}(P_m(j), k(i), SoC_{j-1}(i))
\]
State updated
\[
SoC_{seg}^{end}(i) = SoC_{N}(i)
\]
where \( i = 1 : M \) denotes the sequence of \( k \) in set \( K \) for the \( k_{opt} \) calculation, while \( j = 1 : N \) represents the fragment iteration for the \( SoC_{seg}^{end}(i) \) calculation;

(3) The two \( SoC_{seg}^{end} \)s that are closest to \( SoC_{seg}^{tgt} \), together with the corresponding \( k \), are selected. These are denoted as \( SoC_{seg}^{end}(m) \) and \( SoC_{seg}^{end}(n) \), \( k(m) \) and \( k(n) \), respectively, where \( SoC_{seg}^{end}(m) > SoC_{seg}^{tgt} > SoC_{seg}^{end}(n) \). The logic can be further explained by looking at Figure 9.

![Figure 9. Scheme of the logic used to determine \( k_{opt} \).](image)

The quasi-optimal \( k_{opt} \) is given by:
\[
k_{opt} = k(n) + (k(m) - k(n)) \frac{SoC_{seg}^{tgt} - SoC_{seg}^{end}(n)}{SoC_{seg}^{end}(m) - SoC_{seg}^{end}(n)}
\]

Figure 10 shows the SoC iteration process in each segment. Firstly, the segment is divided into \( N \) fragments based on the ITS information (100 fragments, for example). The fragment length (distance) and road slope information are provided by the ITS. Then, a mean estimated vehicle speed during the fragment is deduced through speed limits, traffic flow speed, and the vehicle’s acceleration/deceleration limit. Finally, the power requested of the electrical motor can be obtained through Equations (1)–(3).

![Figure 10. The diagram of ECMS iterative optimization.](image)
For each fragment, ECMS optimization is performed to update the SoC under the power split solution while minimizing the cost, as described as Equation (11), where $SoC_{j-1}$ is the output SoC of the previous fragment, $k(i)$ is the $i$th equivalent factor in the predefined set, and $P_{est}^{est}(j)$ is the estimated electrical motor power request of ($j$). Once the iteration is completed, the final output of $SoC_N$ will be $SoC_{seg}^{end}$ under the given $k(i)$.

$$SoC_j = f_{soc}(SoC_{j-1}, k(i), P_{est}^{est}(j))$$ (17)

Note that $f_{soc}$ is a combination of $f_{ice}$ and $f_{batt}$.

4.2. Results and Discussion of the A-ECMS Strategy

4.2.1. Performance over WLTC Driving Cycle

In this section, the performance of the A-ECMS strategy is compared with the base CD-CS strategy over four continuous WLTC driving cycles; the total driving distance is 93 km. The vehicle velocity is plotted in Figure 11. The initial SoC is 40% and the target SoC is 20%. Given the battery capacity in the studied vehicle (114Ah), the range extender must be switched on to achieve the target SoC at the route destination. In all the simulation cases, the ambient temperature was set to 20 °C. In order to demonstrate the fuel economy improvements of the proposed A-ECMS strategy, the base CD-CS strategy was employed in the simulation as a contrast. All the boundary conditions for the CD-CS and A-ECMS strategy simulations were kept the same. The only difference was the compiled energy management strategy. The traffic flow speed in the simulation was obtained by averaging the vehicle speed.

![Figure 11. Velocity profile of WLTC cycles.](image)

The vehicle performance results are illustrated in Figure 12 and summarized in Table 5. The power split trajectory of the A-ECMS strategy clearly differs from that of CD-CS. In the CD-CS strategy, the engine does not work until the target SoC is reached (20%), while with the A-ECMS strategy, the engine works in all four of the WLTC cycles, mostly in regions with higher vehicle power demand, resulting in a slower (and a more linear) battery SoC depletion.
mostly in regions with higher vehicle power demand, resulting in a power consumption of 40 kW. The use of the battery is penalized, implying the range extender is more preferable. The above results indicate that the proposed A-ECMS strategy is capable of dynamically updating the equivalent factor to adapt to the road and traffic conditions (if information on these is available). Nevertheless, more frequent range extender stopping and starting is expected.

Combining the above with Figure 13, it can be concluded that: (1) the A-ECMS strategy tends to start the engine at a higher power demand when a higher equivalent factor is presented; (2) the equivalent factor becomes slightly higher in the latter stage of the trip when the SoC gets closer to the target (20%). With a higher equivalent factor, the use of the battery is penalized, implying the range extender is more preferable. The above results indicate that the proposed A-ECMS strategy is capable of dynamically updating the equivalent factor to adapt to the road and traffic conditions (if information on these is available). Nevertheless, more frequent range extender stopping and starting is expected.

The total energy cost as defined in Equation (18):

\[
Q_{\text{total}} = \int_{t_0}^{t_n} (U_{\text{batt}} I_{\text{batt}} + \rho_{\text{fuel}} h_{\text{fuel}} v_{\text{fuel}}) dt
\]

(18)

where \(I_{\text{batt}}\) and \(U_{\text{batt}}\) are the current and voltage of the battery, \(v_{\text{fuel}}\) is the fuel flow rate (L/s), \(\rho_{\text{fuel}}\) is the density of the gasoline fuel (fixed at 745 g/L), and \(h_{\text{fuel}}\) is the lower heat capacity of gasoline (fixed at 44,000 J/g).

According to Table 5, it can be observed that the final SoC of the A-ECMS strategy is closer to the target (20%). The fuel saving here is 6.6% compared to the CD-CS strategy, and the total energy saving is 3.7%. The improvements in economy are on the same scale as those achieved with the other optimization-based strategies [25–27]. The A-ECMS strategy shows greater potential in reducing energy consumption, at least for the studied WLTC driving cycles. However, we must keep mind that the benefits can be achieved only when complete traffic information from ITS is available.

**Table 5. Summary of the vehicle performance comparison for WLTC cycles.**

<table>
<thead>
<tr>
<th>Control Strategy</th>
<th>Initial SoC (%)</th>
<th>Final SoC (%)</th>
<th>Cumulative Fuel Consumption (L)</th>
<th>Fuel Savings (%)</th>
<th>(Q_{\text{total}}) (J)</th>
<th>(Q_{\text{total}}) Savings (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD-CS</td>
<td>40</td>
<td>20.8</td>
<td>2.57</td>
<td>-</td>
<td>(1.148 \times 10^8)</td>
<td>-</td>
</tr>
<tr>
<td>A-ECMS</td>
<td>40</td>
<td>20.1</td>
<td>2.40</td>
<td>6.6</td>
<td>(1.106 \times 10^8)</td>
<td>3.7</td>
</tr>
</tbody>
</table>

Figure 12. Vehicle performance comparison for WLTC cycles.
4.2.2. Performance in Real-World Driving Cycles

The performance of the A-ECMS strategy is also studied with real-world driving cycles. Here, the distance of a single cycle was 14,713.5 m, and the duration was 1800 s. Real-world cycles pertain mostly under urban conditions, with greater vehicle idle operation compared to the WLTC cycle, and the last part of the real-world cycle is a highway condition, lasting for about 300 s. In order to evaluate the vehicle’s performance more effectively, the original cycle was repeated six times in the simulation (about 88.3 km in total). The initial SoC was 40%, and the target SoC was 20%, which is the same as that in the WLTC simulations; the range extender had to be switched on to achieve the target SoC at the route’s destination. The velocity profile is plotted in Figure 14. Compared to WLTC, the real-world driving cycle achieves: (1) lower mean speed; (2) more dynamical speed-change; (3) a rather narrow high-speed region at the end of the cycle. The simulations were performed for both the CD-CS strategy and the proposed A-ECMS strategy. The simulation boundary conditions were set to the same as those in the WLTC simulation in the previous sub-section.

Figure 13. Calculated the equivalent factor and motor power in the A-ECMS strategy.

Figure 14. Vehicle velocity within the real driving cycles in the study.
The simulation results are plotted in Figure 15. The overall performance is very similar to that achieved in the WLTC study. In the A-ECMS strategy, the range extender is activated at the end of each cycle to assist the battery when the power demand is high. Therefore, battery depletion is more linear. As summarized in Table 6, the fuel consumption and total energy cost of the A-ECMS strategy are decreased by 9% and 4.1%, respectively.

![Figure 15. Vehicle performance comparison for real-world cycles.](image)

**Table 6. Summary of vehicle performance comparison for real-world cycles.**

<table>
<thead>
<tr>
<th>Control Strategy</th>
<th>Initial SoC (%)</th>
<th>Final SoC (%)</th>
<th>Cumulative Fuel Consumption (L)</th>
<th>Fuel Savings (%)</th>
<th>( Q_{\text{total}} ) (J)</th>
<th>( Q_{\text{total}} ) Savings (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD-CS</td>
<td>40</td>
<td>21</td>
<td>1.88</td>
<td>-</td>
<td>( 9.174 \times 10^7 )</td>
<td>-</td>
</tr>
<tr>
<td>A-ECMS</td>
<td>40</td>
<td>19.9</td>
<td>1.71</td>
<td>9</td>
<td>( 8.798 \times 10^7 )</td>
<td>4.1</td>
</tr>
</tbody>
</table>

The A-ECMS strategy performs better than the WLTC for real-world driving cycles. A comparison is made in Figure 16. Figure 16a shows the motor power trajectory for one real-world and WLTC cycle. It can be observed that the power demand of the real-world driving cycle is more dynamic and concentrated in high-power demand regions. This is further indicated by the motor power demand distribution map in Figure 16b. With a narrower (or more concentrated) high motor power-demand region (in time), the A-ECMS strategy tends to keep the range extender working towards the higher efficiency region. Therefore, better fuel savings are expected. On the other hand, more range extender start–stop operation can be observed in the WLTC cycle, as illustrated in Figures 12 and 15, which further deteriorates the fuel economy. Based on the above analysis, it can be concluded that further improvements of the A-ECMS strategy could be achieved by avoiding unnecessary start–stops, especially in the low power-demand region. For this purpose, more precise power demand estimations in the near future are required.
real-world and WLTC cycle. It can be observed that the power demand of the real-world driving cycle is more dynamic and concentrated in high-power demand regions. This is further indicated by the motor power demand distribution map in Figure 16. With a narrower (or more concentrated) high motor power-demand region (in time), the A-ECMS strategy tends to keep the range extender working towards the higher efficiency region. Therefore, better fuel savings are expected. On the other hand, more range extender start–stop operation can be observed in the WLTC cycle, as illustrated in Figure 12 and 15, which further deteriorates the fuel economy. Based on the above analysis, it can be concluded that further improvement of the A-ECMS strategy could be achieved by avoiding unnecessary start–stop, especially in the low power-demand region. For this purpose, more precise power demand estimation in the near future are required.

Figure 16. Motor power comparison result between real-world and WLTC driving cycles. (a) Comparison of motor power trajectory in an individual cycle; (b) comparison of motor power distribution.

5. Optimized A-ECMS with Range Extender Start–Stop Management Based on Velocity Forecast

In order to optimize the start–stop management of the range extender, more precise power demand estimation in the near future is essential, which requires more accurate vehicle velocity forecasting. The power demand in the previous section was basically calculated through the traffic flow speed provided by ITS. The local traffic flow speed was the average speed of all the vehicles driving through the fragment of the route (the fragment length was defined by ITS). Consequently, the traffic flow speed cannot be used to represent a precise velocity profile for individual vehicles. In this section, the NARX network is designed to predict vehicle velocity in the near future (30 s) and facilitate more accurate power demand estimation. Then, a penalty function is developed to punish undesired range extender start–stops in the low power-demand region. The fuel economy performance is discussed last.
5.1. Vehicle Velocity Forecast Based on NARX Network

Typical speed prediction methods include State Vector Machine (SVM), Markov chain, and Artificial Intelligence (AI) methods, such as Genetic Algorithm (GA) and NN [30–35]. Korosh et al. [36] estimated future vehicle speeds up to 30 s by combining the traveling route with the driving behavior model. The estimation error, described as the Mean Absolute Error (MAE), was only 12%, and speed prediction accuracy was improved by 27% compared to other methodologies, such as Random Forest (RF) and Feed Forward Neural Networks (FFNN).

In this paper, a NARX neural network is applied for vehicle velocity forecasting. NARX is one of the simplest architectures of Recurrent Neural Networks (RNN), and it includes feedback channels between two different layers of nodes. Its prediction performance has been demonstrated by numerous researchers [36,37].

To predict vehicle velocity, we evaluate \( V_{i+1}^m = \{ v_i | k \leq k \leq m \} \), which are the predictions for \( m \) future seconds at time \( t \). \( m = 1 \) is used for single-step prediction, while \( m > 1 \) is used for multistep prediction. Then, the challenge is to estimate function \( f \) in the equation

\[
V_{i+1}^m = f\left(V_{i-1}^d, \tilde{v}_i^{-q}, \tilde{v}_i^{+p}\right)
\]  

(19)

where the following pertains:

- \( v_i \) is the current vehicle speed;
- \( \tilde{v}_i^{-q} \) is the mean speed from time \( t - q \) to time \( t \);
- \( \tilde{v}_i^{+p} \) is the mean speed from time \( t \) to time \( t + p \). It is an average of the ITS-fed speed;
- \( V_{i-1}^d = \{ v_{i-k} | 1 \leq k \leq d \} \) represents the speed vector in the previous \( d \) seconds (\( d \geq 1 \)).
- \( V_{i-1}^d \) is the actual feedback loop in NARX, as illustrated in Figure 17, which helps in capturing the behavior of a specific driver. The specific driver behavior is learned by training the NARX offline. As a result, the trained NARX has the ability to adapt to an individual driver’s behavior.

![NARX architecture](image)

**Figure 17.** NARX architecture used to predict future speed.

In this paper, the Matlab Neural Network tool-box is used to train the NARX network. The hidden layer has a size of 5, and the feedback delay (\( d \)) is 5. Meanwhile, the average past speed \( \tilde{v}_i^{-q} (q = 30) \) and the average future speed \( \tilde{v}_i^{+p} (p = 30) \) are also inputs into NARX. In the offline training phase, the NARX network is organized in an open-loop form, meaning that the real vehicle velocity derived from the training dataset is directly fed into
the model. However, when applied online, since real vehicle velocity in the future is not available, the NARX network is re-organized into a closed-loop structure. The predicted future speed is used for closing the loop. The diagrams of the open-loop and closed-loop NARX networks are illustrated in Figure 18.

The real driving dataset in this study is obtained from one driver; it has a duration of 1800 s and a distance of 14.7 km. This dataset has been randomly partitioned. Consequently, 70% of the data are applied for training, 15% for validation, and another 15% for testing. The Levenberg–Marquardt approach is selected for training the network, and the training process is demonstrated in Figure 19. The results show the fast converge speed of the trained network and good correlation between the predicted and real velocities.

Figure 20 shows the comparison of the real, predicted (closed-loop), and traffic flow velocities. It can be observed that the predicted velocity shows good consistency with the real one. The maximum forecast error is less than 3.5 m/s. Although the prediction errors become relatively higher at dynamic stages with lower vehicle velocity, the predicted results show similar patterns to the real ones. Thus, the predicted results are closer to the real velocity than the traffic flow velocity provided by the ITS.

Figure 18. The diagram of the Matlab Neural Network tool-box for the NARX network. (a) Open-loop structure; (b) closed-loop structure.
Figure 19. The training performance of the trained NARX network. (a) The MSE performance of the trained NARX network; (b) the regression performance of the trained NARX network.

Figure 20 shows the comparison of the real, predicted (closed-loop), and traffic flow velocities. It can be observed that the predicted velocity shows good consistency with the real one. The maximum forecast error is less than 3.5 m/s. Although the prediction errors become relatively higher at dynamic stages with lower vehicle velocity, the predicted
Results show similar patterns to the real ones. Thus, the predicted results are close to the real velocity than the traffic flow velocity provided by the ITS.

Figure 20. Comparison of the real velocity, NARX-predicted velocity and the traffic flow velocity. (a) Velocity comparison result; (b) velocity error comparison result.

5.2. Penalty Function Design of A-ECMS Strategy Based on the NARX Vehicle Velocity Forecast

As discussed in Section 4, more precise control of the range extender start–stop function could be beneficial in further improving the energy management performance. With the assistance of the NARX network, the estimation of the power demand in the near future can be greatly improved. These future power demands are in turn applied to A-ECMS to enhance the system performance. In this study, an extra penalty function $\Delta J$ is developed based on the estimation of the requested power.

$$J = \left( m_{fuel} + \Delta J \right) + k \frac{dSoC}{dt}$$  \hspace{1cm} (20)

The determination of the extra penalty is carried out as below. Based on the velocity $v_{est}$ forecasted by NARX, the demanded power is estimated as

$$P_{dmd}^{est}(t + \tau) = F_{i}^{est}(t + \tau)v_{est}^{est}(t + \tau), \tau \leq 30$$  \hspace{1cm} (21)
in which the traction force is estimated according to Equation (2), but rewritten as
\[ F_{\text{est}} = M_{\text{net}} g f \cos \theta_{\text{ITS}} + \frac{C_d A_f}{21.15} (v_{\text{est}})^2 + M_{\text{net}} g \sin \theta_{\text{ITS}} + (\delta + 1) M_{\text{net}} a_{\text{est}} \]  
(22)
where \( \theta_{\text{ITS}} \) is the road slope provided by ITS, and \( a_{\text{est}} \) is the estimated acceleration based on \( v_{\text{est}} \), as
\[ a_{\text{est}}(s) = \frac{s}{1 + s T_a} v_{\text{est}}(s) \]  
(23)

The acceleration is obtained by differentiating the vehicle speed. In order to remove unnecessary noise, the first filter with a time constant of \( T_a \) is applied. The average power demand \( P_{dmd}^{avg} \) over the evaluation window (30 s) can then be calculated as:
\[ P_{dmd}^{avg} = \frac{1}{T_w} \int_{t}^{t+T_w} P_{dmd}(t + \tau) \, d\tau \]  
(24)

The extra penalty is then determined according to the average power demand \( P_{dmd}^{avg} \) as:
\[ \Delta J = \begin{cases} f_{\text{inh}}, & P_{dmd}^{avg} < P_{\text{thd}} \\ 0, & \text{Otherwise} \end{cases} \]  
(25)
where \( P_{\text{thd}} \) is the threshold power demand level, and \( f_{\text{inh}} \) is the additional cost added to the use of the range extender. These values can be adjusted online. The principle of the extra penalty design is to inhibit the starting of the range extender when the predicted future power demand is low. Via this strategy, the frequency of the range extender’s start–stopping could be reduced. The logic and the calculation flow for the extra penalty calculation are illustrated in Figure 21.

![Figure 21. Logical diagram of the penalty function.](image)

5.3. Results and Discussion of the AECMS with NARX Velocity Prediction

The performance comparison of the vehicle between the CD-CS, A-ECMS and A-ECMS with NARX (AECMS\text{NARX}) strategies, under both WLTC and real-world driving cycles, is summarized in Table 7. It can be observed that the fuel consumption and total energy savings are further improved with AECMS\text{NARX}. Compared with the A-ECMS strategy, the fuel saving rate is improved by 6.7% to 18.2%, depending on the driving cycle characteristics. Further analyses can be performed through a comparison of the range extender’s power distributions. As illustrated in Figure 22, for the WLTC cycle, the
implementation of the penalty function based on NARX velocity prediction significantly shifts the power distribution of the range extender towards a higher-power region, which benefits fuel economy via higher efficiency. For real-world driving cycles, on the other hand, although similar trends are observed, the difference is less obvious compared to the results of WLTC cycles.

Table 7. Summary of vehicle performance comparison.

<table>
<thead>
<tr>
<th>Driving Cycle</th>
<th>Control Strategy</th>
<th>Initial SoC (%)</th>
<th>Final SoC (%)</th>
<th>Cumulative Fuel Consumption (L)</th>
<th>Fuel Savings (%)</th>
<th>$Q_{\text{total}}$ (J)</th>
<th>$Q_{\text{total}}$ Savings (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLTC</td>
<td>CD-CS</td>
<td>40</td>
<td>21</td>
<td>2.57</td>
<td>-</td>
<td>$1.148 \times 10^8$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>A-ECS</td>
<td>40</td>
<td>20.6</td>
<td>2.40</td>
<td>6.6</td>
<td>$1.06 \times 10^8$</td>
<td>3.7</td>
</tr>
<tr>
<td></td>
<td>AECMS$_{\text{NARX}}$</td>
<td>40</td>
<td>20</td>
<td>2.37</td>
<td>7.8</td>
<td>$1.097 \times 10^8$</td>
<td>4.5</td>
</tr>
<tr>
<td>Real-world</td>
<td>CD-CS</td>
<td>40</td>
<td>21</td>
<td>1.88</td>
<td>-</td>
<td>$9.174 \times 10^7$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>A-ECS</td>
<td>40</td>
<td>19.9</td>
<td>1.71</td>
<td>9</td>
<td>$8.798 \times 10^7$</td>
<td>4.1</td>
</tr>
<tr>
<td></td>
<td>AECMS$_{\text{NARX}}$</td>
<td>40</td>
<td>19.6</td>
<td>1.70</td>
<td>9.6</td>
<td>$8.789 \times 10^7$</td>
<td>4.2</td>
</tr>
</tbody>
</table>

Figure 22. Comparison of range extender power distribution in the studied cases.

6. Summary and Conclusions

A proper energy management strategy is an effective means to improve fuel economy in hybrid vehicles. This study presents a practical method to realize the global optimization of energy management in REVs, whereby the equivalent factor is dynamically optimized by the traffic information provided by ITS, and the control of the start–stopping of the range extender is further optimized through the utilization of NARX network-based velocity prediction. The studied vehicle operation conditions are restricted to a case in which the vehicle is not able to finish the planned trip when driven only by the battery, and range extender must be switched on to achieve the target SoC. On the other hand, traffic information in the planned route is a necessary input for the proposed strategy. Although cases where all needed traffic information is must be studied, these are not included in the scope of this research. Based on the established model and the proposed strategy, the vehicle performance under WLTC and real-world driving cycles is investigated via the simulation method. The following conclusions can be drawn:
(1) The proposed A-ECMS strategy is able to adjust the equivalent factor dynamically in relation to different power demands and battery SoCs. Then, the operation of the range extender can be optimized. Fuel consumption savings up to 9% can be achieved compared to the base CD-CS strategy under the studied real-world driving cycles. Its effectiveness is clearly shown;

(2) The proposed A-ECMS strategy achieves better fuel-saving performance under real-world driving cycles compared to WLTC. The fuel consumption saving under WLTC cycles is 6.6%, while it reaches up to 9% for real-world driving cycles. This is due to the fact that a more concentrated high-power region, and less range extender start–stop activity, are presented in the latter. Considering the variance in the values of battery SoC at the destination, the total energy savings are 3.7% and 4.1% for WLTC and real-world driving cycles, respectively;

(3) The predicted velocity of the NARX network effectively adheres to the real velocity. The maximum error is well under 3.5 m/s, which is significantly lower than that arising in the traffic flow speed provided by ITS;

(4) The energy saving performance is further improved by implementing a velocity prediction-based penalty function in the A-ECMS strategy. Control of the range extender’s start–stopping can then be optimized, with the fuel saving rate improving by 6.7% to 18.2% compared to the base A-ECMS strategy. This updated strategy is more effective when used in WLTC cycles, where the power distribution of the range extender is significantly shifted towards the higher-power region, with higher efficiency.

Although the effectiveness of the proposed strategies in this paper is well demonstrated, further improvements are still required. Firstly, the determination of the optimal equivalent factor relies on the traffic information provided by ITS, but in some cases, complete traffic information may not be available. The strategy has to be updated to cover these scenarios. Secondly, the proposed penalty function in the A-ECMS strategy was less efficient under the studied real-world driving cycles, where the high-power demand region was more concentrated. Further improvements should be carried out to broaden the effective range of this strategy. Thirdly, the utilization of the proposed strategy in REVs with other types of power source (such as hydrogen fuel cells) should be investigated.

Author Contributions: Investigation and writing original draft: W.L.; methodology: H.Z.; project administration: B.Z.; supervision: Y.W.; resources: Y.X.; software and visualization: K.X.; writing—review and editing: R.Z. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

Acronyms

APU Auxiliary Power Unit
A-ECMS Adaptive ECMS
AECMS\textsubscript{NARX} Adaptive ECMS with NARX
AI Artificial Intelligence
BSFC Brake Specific Fuel Consumption
CD-CS Charge-Depleting and Charge-Sustaining
DP Dynamic Programming
DLL Dynamic Link Library
ECMS Equivalent Fuel Consumption Minimization Strategy
EMS Energy Management Strategy
EV Electric Vehicle
FFNN Feed Forward Neural Networks
FPLG  Free-Piston Linear Generator  
GA  Genetic Algorithm  
GPS  Global Positioning System  
HEV  Hybrid Electrical Vehicle  
ICE  Internal Combustion Engine  
ISG  Integrated Starter–Generator  
ITS  Intelligent Transportation Systems  
MGT  Micro Gas Turbine  
NARX  Nonlinear Auto-Regressive network with External input  
NN  Neural Networks  
OCV  Open Circuit Voltage  
OEM  Original Equipment Manufacturer  
PMSM  Permanent Magnet Synchronous Motor  
PHEV  Plug-in Hybrid Electric Vehicle  
REV  Range-extended Electric Vehicle  
RF  Random Forest  
SoC  State of Charge  
SVM  State Vector Machine  
UDDS  Urban Dynamometer Driving Schedule  
WLTC  Worldwide Light-duty Test Cycle  

<table>
<thead>
<tr>
<th>Nomenclatures</th>
<th>Description</th>
<th>Nominal Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbols</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_f$</td>
<td>Frontal area (m$^2$)</td>
<td>2.45</td>
</tr>
<tr>
<td>$C_d$</td>
<td>Air drag coefficient</td>
<td>0.285</td>
</tr>
<tr>
<td>$F_t$</td>
<td>Traction force (N)</td>
<td></td>
</tr>
<tr>
<td>$F_i$</td>
<td>Inertia force (N)</td>
<td></td>
</tr>
<tr>
<td>$F_w$</td>
<td>Air drag force (N)</td>
<td></td>
</tr>
<tr>
<td>$F_s$</td>
<td>Slope drag force (N)</td>
<td></td>
</tr>
<tr>
<td>$F_r$</td>
<td>Rotating drag force (N)</td>
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<tr>
<td>$f$</td>
<td>Rolling resistance coefficient</td>
<td></td>
</tr>
<tr>
<td>$g$</td>
<td>Acceleration constant of gravity (m/s$^2$)</td>
<td>9.81</td>
</tr>
<tr>
<td>$h_{fuel}$</td>
<td>Low heat capacity of gasoline (J/g)</td>
<td>44,000</td>
</tr>
<tr>
<td>$i_0$</td>
<td>Main reduction ratio</td>
<td>11.591</td>
</tr>
<tr>
<td>$I$</td>
<td>Total cost of fuel and electricity</td>
<td></td>
</tr>
<tr>
<td>$j_{inh}$</td>
<td>Additional cost adding to the use of range extender</td>
<td></td>
</tr>
<tr>
<td>$k_{opt}$</td>
<td>Optimum equivalent factor (g/kwh)</td>
<td></td>
</tr>
<tr>
<td>$I_L$</td>
<td>Charging/discharging current of the battery (A)</td>
<td></td>
</tr>
<tr>
<td>$l_{seg}$</td>
<td>Segment length (m)</td>
<td></td>
</tr>
<tr>
<td>$l_{rmn}$</td>
<td>Remaining distance to destination (m)</td>
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</tr>
<tr>
<td>$M_c$</td>
<td>Car curb weight (kg)</td>
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</tr>
<tr>
<td>$M_f$</td>
<td>Full load weight (kg)</td>
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<tr>
<td>$M_{nml}$</td>
<td>Nominal weight (kg)</td>
<td>2106</td>
</tr>
<tr>
<td>$N_{cyl}$</td>
<td>Cylinder number (-)</td>
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</tr>
<tr>
<td>$N_{max}^{ICE}$</td>
<td>Engine maximum speed (r/min)</td>
<td>5000</td>
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<tr>
<td>$N_{max}^{motor}$</td>
<td>Motor maximum speed(r/min)</td>
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<tr>
<td>$P_{batt}$</td>
<td>Battery power (kw)</td>
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</tr>
<tr>
<td>$P_d$</td>
<td>Demand vehicle power (W)</td>
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</tr>
<tr>
<td>$P_{peak}^{ICE}$</td>
<td>Engine peak power (kw)</td>
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<tr>
<td>$P_{ICE}$</td>
<td>Engine power (kw)</td>
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<tr>
<td>$P_{ICE}^{*}$</td>
<td>ECMS solution of engine power (kw)</td>
<td></td>
</tr>
<tr>
<td>$P_{AECMS}^{motor}$</td>
<td>A-ECMS solution of engine power (kw)</td>
<td></td>
</tr>
<tr>
<td>$P_{peak}^{motor}$</td>
<td>Motor peak power (kw)</td>
<td>170</td>
</tr>
<tr>
<td>$P_{batt}^{mol}$</td>
<td>Motor nominal power (kw)</td>
<td>65</td>
</tr>
<tr>
<td>$P_m$</td>
<td>Driver demand power (kw)</td>
<td></td>
</tr>
<tr>
<td>$P_{est}^{m}$</td>
<td>Estimated power demand (kw)</td>
<td></td>
</tr>
<tr>
<td>$P_{avg}^{PS}$</td>
<td>Average power demand (kw)</td>
<td></td>
</tr>
</tbody>
</table>
\( P_{\text{thd}} \) \quad \text{Threshold power of the range extender (kw)}

\( Q_{\text{cap}} \) \quad \text{Battery capacity (Ah)} 114

\( Q_{\text{tot}} \) \quad \text{Total energy cost (J)}

\( R_{\text{cap}} \) \quad \text{Tire rolling radius (m)} 0.341

\( \text{SoC}_{\text{seg}} \) \quad \text{Target SoC of the segment (%)}

\( \text{SoC}_{\text{endseg}} \) \quad \text{SoC at the end of segment (%)}

\( \text{SoC}_{\text{ini}} \) \quad \text{Initial SoC of the battery (%)}

\( \text{SoC}_{\text{tgt}} \) \quad \text{Target SoC at the end of route (%)}

\( \text{SoC}_{\text{ev}} \) \quad \text{Target SoC above which for pure EV mode (%)}

\( \text{SoC}_{\text{rev}} \) \quad \text{Target SoC below which for range-extended mode (%)}

\( T_{\text{d}} \) \quad \text{Demand electric machine torque (Nm)}

\( T_{\text{s}} \) \quad \text{SoC calculation time step (s)}

\( T_{\text{peak}}_{\text{ICE}} \) \quad \text{ICE Engine peak torque (Nm)} 142

\( T_{\text{peak}}_{\text{mot}} \) \quad \text{Motor peak torque (Nm)} 310

\( U_{\text{nom}} \) \quad \text{Battery nominal voltage (V)} 3.67

\( U_{\text{max}} \) \quad \text{Battery maximum voltage (V)} 452.4

\( v \) \quad \text{Vehicle speed in (m/s)}

\( \tilde{v}_{\text{est}} \) \quad \text{Estimated vehicle speed (m/s)}

\( \tilde{v}_{\text{d}} \) \quad \text{Mean velocity in past \( d \) seconds before time \( t \) (m/s)}

\( \tilde{v}_{\text{m}} \) \quad \text{Mean velocity in next \( m \) seconds at time \( t \) (m/s)}

\( \tilde{v}_{\text{d}+m} \) \quad \text{Predicted velocity in next \( m \) seconds at time \( t \) (m/s)}

\( v_{\text{d}} \) \quad \text{Velocity in the past \( d \) seconds before time \( t \) (m/s)}

\( v_{\text{fuel}} \) \quad \text{Fuel flow rate (L/s)}

\( V_{\text{dspl}} \) \quad \text{Engine displacement (cm\(^3\)) 1500}

\( a \) \quad \text{Vehicle acceleration (m/s\(^2\))}

\( \theta \) \quad \text{Road slope (degree)}

\( \rho \) \quad \text{Standard air density (kg/m\(^3\)) 1.29}

\( \rho_{\text{fuel}} \) \quad \text{Density of gasoline fuel (g/L)} 745

\( \delta \) \quad \text{Rotating quality conversion coefficient 0.03}

\( \eta_{\text{e}} \) \quad \text{Effective efficiency of the transmission}

\( \eta_{\text{t}} \) \quad \text{Transmission efficiency 0.95}

\( \Omega_{\text{rt}} \) \quad \text{Route information from ITS}

References


