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# Advancements in Battery Management Systems for Electric Vehicles: A MATLAB-Based Simulation of 4S3P Lithium-Ion Battery Packs

**Rakesh P. Tapaskar [1], Prashant P. Revankar [2,*] and Sharanabasava V. Ganachari [3,*]**

[1] Department of Automation and Robotics, KLE Technological University, Hubballi 580031, India; rptapaskar@kletech.ac.in
[2] School of Mechanical Engineering, KLE Technological University, Hubballi 580031, India
[3] Center for Energy and Environment, School of Advance Science, KLE Technological University, Hubballi 580031, India
* Correspondence: pp_revankar@kletech.ac.in (P.P.R.); sharanabasava@kletech.ac.in (S.V.G.)

**Abstract:** As electric vehicles (EVs) gain momentum in the shift towards sustainable transportation, the efficiency and reliability of energy storage systems become paramount. Lithium-ion batteries stand at the forefront of this transition, necessitating sophisticated battery management systems (BMS) to enhance their performance and lifespan. This research presents an innovative simulation of a 4S3P lithium-ion battery pack using MATLAB R2023b, designed to refine BMS capabilities by employing advanced mathematical modelling and computational intelligence. The simulation meticulously analyses critical operational metrics such as state of charge (SOC), state of health (SOH), temperature variations, and electrical behaviour under diverse load scenarios, offering deep insights into the intricate dynamics of lithium-ion batteries in EV applications. The results corroborate the simulation model's accuracy in reflecting actual battery pack performance and underscore significant improvements in BMS strategies, especially concerning predictive maintenance and adaptive charging techniques. By seamlessly integrating computational intelligence into BMS, this study lays the groundwork for more durable, efficient, and intelligent energy storage systems in electric vehicles, marking a significant stride in e-mobility technology.

**Keywords:** electric vehicles; lithium-ion battery packs; battery management systems (BMS); MATLAB simulation; state of charge (SOC); state of health (SOH); e-mobility; computational intelligence; mathematical modelling



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## 1. Introduction

Battery management systems (BMS) play a pivotal role in the operational integrity and efficiency of battery packs utilized across a broad spectrum of applications, from portable electronics to large-scale renewable energy storage solutions. While considerable progress has been made in the development of BMS technologies, current systems often fail to fully address the complex dynamics and unpredictability associated with battery usage. This study identifies a significant research gap: the integration of advanced computational intelligence in BMS, which is essential for enhancing real-time decision-making and overall system efficacy.

Traditional BMS approaches have focused predominantly on static algorithms that monitor and control battery parameters based on predefined models. These methods, however, do not adequately account for the nonlinear behaviour of batteries under varying load conditions and environmental influences, leading to suboptimal performance and reduced battery life. Recent studies have emphasized the need for BMS frameworks that can dynamically adapt to changing conditions and accurately predict battery performance to prevent failures and maximize operational efficiency.

This paper proposes an innovative BMS framework that harnesses cutting-edge computational intelligence techniques, including machine learning algorithms, neural networks, and data analytics. By leveraging these technologies, the proposed system aims to provide real-time predictive capabilities and adaptive control strategies that are far superior to those of traditional BMS. The use of such sophisticated tools allows for a more granular understanding of battery behaviour and the ability to make proactive adjustments that can significantly enhance battery performance and longevity.

Our approach is structured around a comprehensive analysis of how different computational techniques can be integrated within the BMS architecture to address specific challenges such as state-of-charge estimation, state-of-health monitoring, and failure prediction. We will present a series of simulations that demonstrate the effectiveness of our framework compared to conventional systems. Furthermore, we discuss the implications of our findings for future BMS design, suggesting that the adoption of computational intelligence could revolutionize BMS technologies by making them more adaptive, resilient, and efficient.

The significance of this research lies in its exploration of advanced battery management system (BMS) methodologies, which are essential for enhancing the performance and lifespan of lithium-ion batteries in electric vehicles. This study specifically focuses on the development and validation of nonlinear BMS algorithms, which offer a more accurate representation of battery dynamics compared to traditional linear models. The novelty of our approach is rooted in the integration of sophisticated machine learning techniques that adaptively estimate the state of charge (SoC) and state of health (SoH) of batteries under varying operational conditions. By simulating battery behaviour with high precision, our methodology addresses critical challenges in real-time battery management, including improved predictive accuracy and enhanced operational efficiency. The key contributions of this work include the formulation of a comprehensive simulation framework that encapsulates the complex nonlinear characteristics of lithium-ion batteries, and the demonstration of its efficacy in optimizing energy management systems. These advancements have the potential to significantly impact the design and deployment of BMS technologies, facilitating the broader adoption of sustainable electric vehicle solutions.

## 2. Literature Survey

### *2.1. Overview of Current BMS Technologies*

Battery management systems (BMS) are crucial in optimizing the performance, safety, and lifespan of lithium-ion batteries, which are widely used in electric vehicles, renewable energy storage, and portable electronic devices. Traditional BMS focus on monitoring key parameters such as voltage, current, and temperature to manage charging and discharging processes effectively. These systems are designed to prevent conditions that may lead to battery damage, such as overcharging or deep discharging, by implementing strict cut-off mechanisms based on predefined thresholds [1].

The primary function of a conventional BMS is the estimation of the state of charge (SOC), which indicates the remaining capacity of the battery and is critical for managing energy output and recharge cycles. This is typically achieved through direct measurement techniques and basic algorithmic estimations, which often rely on simple voltage-to-charge correlations or basic integration of current over time [2]. While effective under stable and predictable operating conditions, these traditional SOC estimation methods face significant challenges when dealing with the variability and complexity of modern usage patterns [3]. For instance, fluctuations in ambient temperature, aging effects, and varied load demands can dramatically alter the accuracy of SOC readings, leading to suboptimal battery management. Moreover, most traditional BMS are not equipped to handle the rapid evolution in battery technologies or the increasing complexity of applications that demand more dynamic and flexible energy management solutions. These systems often lack the capability to learn from past behaviours or adapt to new conditions, which is becoming increasingly necessary as batteries are integrated into more sophisticated and interconnected systems.

As a result, there is a critical need for BMS that can dynamically adjust their algorithms based on real-time data and more complex modelling techniques to accurately reflect the state of the battery.

In addition to SOC estimation, traditional BMS also manage the state of health (SOH), which assesses the overall condition of the battery and predicts its lifespan based on degradation patterns. However, similar to SOC estimations, traditional SOH assessments often fail to incorporate advanced diagnostic tools that can detect and predict various degradation mechanisms early enough to prevent irreversible damage or to extend the battery's useful life effectively [4,5].

While traditional BMS technologies have laid the groundwork for safe and reliable battery operation, their limited adaptability and lack of predictive capabilities are becoming increasingly apparent. As the demand for more efficient and longer-lasting batteries grows, the shortcomings of existing BMS technologies underscore the urgent need for innovation in this area.

### *2.2. Recent Advances in Computational Intelligence for BMS*

The landscape of battery management systems (BMS) has been profoundly transformed by the incorporation of computational intelligence, which has significantly enhanced the precision and adaptability of SOC and SOH estimations. Machine learning algorithms, in particular, have emerged as powerful tools for refining these critical metrics. For example, research utilizing NASA's battery datasets has demonstrated that machine learning models, such as stacking algorithms employing features like end voltage and discharge temperature, can predict state of health with remarkable accuracy across various battery types and conditions [6]. These models use complex feature sets that correlate closely with battery aging processes, providing a nuanced understanding that traditional methods cannot achieve.

In addition to advancements in machine learning, the development of new cathode materials has also played a crucial role in enhancing the performance of lithium-ion batteries. Innovations in materials science have led to the use of lithium sulfide and other novel materials, which offer better efficiency and durability, thereby improving the overall efficacy of BMS in managing these batteries [7]. These materials are designed to withstand higher stress and provide longer life cycles, which are essential for applications such as electric vehicles and large-scale energy storage systems. Furthermore, the field has seen significant strides in the implementation of sophisticated diagnostic algorithms designed to detect and address faults within battery systems. These algorithms range from model-based approaches to advanced non-model-based techniques that can identify issues like lithium plating—a common cause of battery degradation [8]. Such diagnostic capabilities are critical for maintaining battery health and ensuring safety, especially under the stress of rapid charging conditions [9,10].

Despite these technological advancements, integrating these diverse computational techniques into a cohesive BMS framework remains a substantial challenge. The primary issue lies in the BMS's ability to process and react to the complex data these advanced tools generate in real-time. Current systems often operate on static, predefined models and are not equipped to dynamically adapt to the rapid changes in battery condition that advanced sensors and algorithms can detect. This disconnect hinders the full utilization of computational intelligence in BMS, limiting the potential benefits such as extended battery life, improved safety, and increased energy efficiency.

To bridge this gap, there is a pressing need for the development of an integrated BMS architecture that not only utilizes machine learning and advanced diagnostics but also incorporates real-time data processing capabilities. Such a system would be able to adjust its operations dynamically, responding effectively to the insights provided by advanced computational tools. This would mark a significant evolution from the BMS of today, leading to smarter, more responsive, and more reliable battery management practices.

Comparative Analysis

The evolution of battery management systems (BMS) from traditional to modern methodologies marks a significant shift in the approach to managing lithium-ion batteries. The table below provides a detailed comparison of these methodologies, particularly focusing on the adaptability and accuracy of SOC estimation techniques.

Table 1 presents a comparative analysis of traditional and modern battery management system (BMS) methodologies across several key features. Traditional BMS methods typically rely on static models that are based on voltage-to-charge correlations and involve simple integration of current data. In contrast, modern BMS methods employ dynamic algorithms such as VFFRLS and machine learning models, which offer more sophisticated and adaptable approaches to battery management.

**Table 1.** Comparison of Traditional and Modern BMS.

| Feature | Traditional BMS Methods | Modern BMS Methods |
|---|---|---|
| Methodology | Static models based on voltage-to-charge correlation and simple integration of current | Dynamic algorithms including VFFRLS and machine learning models |
| Adaptability | Low; struggles with varying operational conditions and environmental factors | High; adapts to changes in real-time, accommodating various conditions |
| Accuracy | Moderate; effective under stable conditions but prone to errors under variability | High; employs complex algorithms to ensure high precision under diverse scenarios |
| Real-time Data Handling | Limited; typically uses predefined data sets and lacks real-time processing capabilities | Robust; utilizes real-time data to dynamically adjust SOC and SOH estimations |
| Technological Integration | Minimal; often isolated to specific functions within the BMS | Comprehensive; integrates across multiple aspects of battery management |
| Predictive Capabilities | Basic; mainly reactive systems with limited forecasting ability | Advanced; predictive analytics enable proactive management and fault detection |

One significant difference lies in the adaptability of the two methodologies. Traditional BMS methods exhibit low adaptability, often struggling to cope with varying operational conditions and environmental factors. On the other hand, modern BMS methods demonstrate high adaptability, capable of dynamically adjusting to real-time changes and accommodating a wide range of operating conditions.

In terms of accuracy, traditional BMS methods are moderately effective under stable conditions but are prone to errors when conditions become more variable. In contrast, modern BMS methods employ complex algorithms that ensure high precision even under diverse and challenging scenarios.

Another notable distinction is in the handling of real-time data. Traditional BMS methods typically rely on predefined datasets and lack real-time processing capabilities, limiting their ability to make immediate adjustments. In contrast, modern BMS methods feature robust real-time data handling, utilizing real-time data to dynamically adjust state of charge (SOC) and state of health (SOH) estimations.

Moreover, while traditional BMS methods have minimal technological integration, often focusing on specific functions within the BMS, modern BMS methods are characterized by comprehensive integration across multiple aspects of battery management. Finally, in terms of predictive capabilities, traditional BMS methods are mainly reactive systems with limited forecasting ability, whereas modern BMS methods leverage advanced predictive analytics for proactive management and fault detection.

Usually, traditional BMS methods have been foundational in providing basic safety and operational guidelines for lithium-ion batteries. However, these systems predominantly rely on static models that perform adequately under consistent, predictable conditions. Such models typically calculate the state of charge (SOC) by correlating voltage levels with charge states or by integrating current over time, which can become inaccurate when environmental or operational conditions change unexpectedly [11].

In contrast, modern BMS methodologies incorporate advanced computational techniques that significantly enhance both adaptability and accuracy. For example, the variable forgetting factor recursive least square (VFFRLS) algorithm allows for adaptive parameter identification, adjusting to new data in real-time and improving the reliability of SOC estimates under varying conditions [12]. Moreover, machine learning models leverage a broader range of data inputs, including temperature and voltage fluctuations, to accurately predict battery behaviour. These models not only offer a higher degree of precision but also enable the BMS to proactively manage battery health and operational safety [6]. Such advancements in BMS technology highlight the importance of dynamic, data-driven systems in today's increasingly complex battery applications. By adopting modern methodologies, BMS can significantly improve the efficiency, longevity, and safety of lithium-ion batteries, making them more suitable for the demanding environments of electric vehicles and renewable energy storage systems.

### 2.3. Gap Analysis

Despite the notable progress in integrating computational intelligence into battery management systems (BMS), there remains a significant disparity in the holistic adoption of these advanced techniques within a unified BMS framework. The literature reveals persistent challenges in real-time data processing and the predictive accuracy of these systems under variable operational conditions, which are crucial for ensuring the reliability and efficiency of lithium-ion batteries [13–16].

Current BMS architectures often rely on static or semi-static models that are not fully capable of handling the complexities of real-world battery usage, where conditions fluctuate due to changes in environmental factors, operational demands, and battery aging processes. This inadequacy is highlighted by the limited ability of these systems to dynamically adapt to new data inputs and adjust their operational strategies accordingly. The consequence is a notable lag in the application of predictive analytics that could preemptively identify potential issues and mitigate risks associated with battery degradation and failure.

Furthermore, the integration of machine learning algorithms and other advanced computational tools has predominantly been in isolated instances rather than as part of a comprehensive system-wide approach. Such fragmentation prevents the holistic improvement of BMS capabilities, particularly in terms of leveraging interconnected data streams that could enhance decision-making processes across various levels of battery management.

This critical gap not only impedes the potential extension of battery lifespan but also constrains improvements in safety measures, as current systems are less equipped to predict and manage the cascading effects of battery failures. Enhanced predictive accuracy and adaptive modelling are essential for the next generation of BMS to truly capitalize on the advances in computational intelligence, thus enabling more robust, reliable, and efficient management of lithium-ion batteries. Addressing these challenges requires a paradigm shift towards an integrated architecture that not only incorporates but also synergizes different strands of computational intelligence. Such a development would represent a significant leap forward in BMS technology, facilitating a more responsive and anticipatory system capable of adjusting to real-time changes and predicting future conditions with high precision. The creation of such systems would not only enhance battery performance but also significantly improve the overall safety and economic viability of energy storage solutions.

### 2.4. Main Contributions

The proposed battery management system (BMS) framework is innovatively designed to address the significant gaps existing in traditional BMS by integrating adaptive machine learning algorithms capable of processing real-time data. This advanced approach not only enhances SOC and SOH estimations but also substantially improves the overall operational efficiency and safety of lithium-ion batteries pivotal in applications such as electric vehicles and smart grids. Traditional BMS methodologies often rely on static models which fail to adjust to the dynamic changes in environmental and operational conditions affecting modern lithium-ion batteries. By incorporating a suite of machine learning techniques including regression models, neural networks, and decision trees, our framework leverages continuous learning from diverse data sources—such as temperature, voltage, and usage patterns—to dynamically predict and manage battery performance. This leads to a marked improvement in prediction accuracy for SOC and SOH, crucial for optimizing charging cycles and extending battery life [13–16].

Additionally, integrating innovative cathode materials and system modelling techniques from recent studies [7,17] enhances the BMS's capacity to handle high energy densities efficiently. For instance, the synergy of lithium-ion batteries with supercapacitors, as discussed in [17], provides a composite solution that optimally balances energy density and power output, ensuring high performance even under stringent operational demands. Our approach also considers the lifecycle management of batteries, a crucial aspect underscored by the circular economy concepts and end-of-life strategies discussed in [18]. By adopting these frameworks, our BMS not only optimizes battery usage but also supports sustainable practices by enhancing the recyclability and extending the service life of battery components.

Moreover, the integration of real-time diagnostic algorithms, as referenced in [19], allows our system to rapidly identify and rectify issues such as short circuits and degradation mechanisms, thereby significantly enhancing operational safety and reliability. These proactive capabilities are essential in preventing failures and ensuring the longevity of battery systems in critical applications.

The deployment of this advanced BMS technology therefore represents a significant leap forward from conventional systems. It promises to revolutionize battery management through smarter, more adaptive strategies that enhance efficiency, safety, and sustainability—aligning perfectly with the growing demands of modern energy solutions.

Further complementing our approach, ref. [20] outlines the economic impacts and advantages of various EV charging strategies, emphasizing smart grid integration and the benefits of reduced operational costs through optimized charging processes. Ref. [21] reviews the evolution of battery technologies and management systems, highlighting the critical role these advancements play in supporting sustainable and efficient electric vehicle operations. These insights underscore the importance of continued innovation in battery technology and management to meet the escalating demands of electric mobility.

## 3. Methodology

### *3.1. MATLAB Simulation for the 4S3P Battery Pack*

The MATLAB simulation environment was meticulously configured to emulate the behaviour of a 4S3P (4 series, 3 parallel) lithium-ion battery pack, a common configuration in various energy storage applications due to its balance of voltage and capacity. The setup involved defining each cell's electrical and thermal properties based on manufacturer data and academic research, ensuring the simulation reflected real-world battery characteristics. The simulation framework included modules for cell modelling, interconnection of cells in the 4S3P configuration, and the implementation of a BMS interface for monitoring and control. The environment was designed to simulate dynamic load conditions, mimicking the fluctuating demand typical in renewable energy applications, to assess the battery pack's performance under realistic scenarios.

The MATLAB simulation for the 4S3P (4 series, 3 parallel) lithium-ion battery pack was initiated by configuring the virtual environment to closely mimic the operational dynamics of real-world battery packs. This configuration process involved several critical steps:

1. Cell Selection and Characterization: Each lithium-ion cell's electrical (e.g., nominal voltage, capacity, internal resistance) and thermal (e.g., heat capacity, thermal conductivity) properties were defined. These parameters were sourced from manufac-

turers' datasheets and validated through academic literature, ensuring a high-fidelity replication of physical cells.
2. Pack Configuration: The cells were virtually interconnected in a 4S3P arrangement, implying four cells in series to increase the voltage output and three such series strings in parallel to augment the capacity. This configuration mirrors a common setup in energy storage solutions, balancing power and energy requirements.
3. BMS Interface Implementation: A virtual battery management system (BMS) interface was integrated into the simulation environment. This interface was responsible for real-time monitoring and control functions, including voltage and current measurements, temperature monitoring, cell balancing, and protection mechanisms activation in response to predefined thresholds.

### 3.2. Simulation Framework

The simulation framework was built with modularity and flexibility in mind, comprising several key modules:

1. Cell Modelling Module: This module simulated the individual behaviour of each lithium-ion cell, incorporating models for charge–discharge cycles, thermal effects, and aging phenomena. The electrical model typically involved equivalent circuit models, while the thermal model accounted for heat generation and dissipation dynamics.
2. Interconnection Logic: A specialized module was developed to accurately represent the electrical and thermal interconnections between cells in the 4S3P configuration. This included the simulation of current flow, voltage drops, and thermal interactions among cells, ensuring that the collective behaviour of the pack was realistically portrayed.
3. Dynamic Load Simulation: To replicate the varying demand scenarios typical in renewable energy storage applications, the simulation environment included a dynamic load module. This module could simulate various load profiles, from steady state to highly fluctuating loads, allowing researchers to assess the battery pack's response under diverse conditions.
4. BMS Functionality Module: The core of the BMS interface within the simulation was its ability to execute crucial functions such as SOC estimation, SOH tracking, cell balancing, and thermal management. This module utilized real-time data from the cell modelling and interconnection logic modules to make informed decisions, ensuring the battery pack's optimal performance and safety.

### 3.3. Realistic Scenario Replication

A significant emphasis was placed on ensuring the simulation environment could accurately replicate real-world operational scenarios. This involved calibrating the simulation models based on experimental data and adjusting the dynamic load profiles to reflect actual usage patterns seen in renewable energy systems. The goal was to create a virtual testing ground where the battery pack's performance, under various conditions, could be analyzed in detail, providing valuable insights into its behaviour, limitations, and potential failure modes.

Description of Flowchart Components:

- Start: The beginning of the simulation.
- Define Parameters: Set up basic parameters such as nominal voltage, capacity, internal resistance, and pack configuration.
- Initialize Variables: Set initial values for state of charge (SoC), voltages, and other necessary variables.
- For Loop: The main loop of the simulation that iterates over the number of steps determined by the simulation time and time step.
- Update SoC: Calculate the new state of charge using the Coulomb counting method.
- Calculate Voltage Drop: Determine the voltage drop due to the load current and internal resistance.

- Update Voltage: Calculate the new voltage value for the current time step.
- End Loop: Check if the loop has reached the last time step.
- Plot Results: Generate plots for battery pack voltage and state of charge over time.
- End: The simulation process concludes.

This flowchart represents the sequence of operations in the MATLAB code, highlighting the main steps in simulating the behaviour of a 4S3P lithium-ion battery pack under a constant load condition.

Flow of the MATLAB simulation code:

The flowchart presented in Figure 1 outlines the systematic steps involved in simulating the dynamic behaviour of a 4S3P lithium-ion battery pack under a constant load using MATLAB. Initially, crucial parameters such as nominal voltage, capacity, internal resistance, and pack configuration are defined to establish the battery model. Subsequently, the simulation initializes variables, including the state of charge (SoC), voltages, and other essential parameters, to prepare for the iterative process.

The main simulation loop, controlled by the "For Loop" component, executes a series of operations for each time step, as determined by the simulation time and step size. In each iteration, the SoC is updated using the Coulomb counting method, which estimates the amount of charge entering and leaving the battery.

Additionally, the simulation calculates the voltage drop resulting from the load current and internal resistance, then computes the new voltage value for the current time step. This calculation accounts for the impact of current flow on the battery's voltage level. The loop continues until it reaches the last time step, as verified by the "End Loop" component.

Upon completion of the simulation, the results are visualized through plots generated by the "Plot Results" component. These plots depict the battery pack's voltage and state of charge over time, providing a comprehensive view of its performance characteristics under the specified constant load condition. Overall, this flowchart serves as a comprehensive guide for understanding the simulation process and analyzing the behaviour of the lithium-ion battery pack in the given scenario.

### *3.4. Description of the Mathematical Models and Computational Intelligence Techniques Employed for Simulating State of Charge (SOC), State of Health (SOH), and Other Critical Parameters*

The core of the simulation relied on advanced mathematical models to accurately represent the SOC and SOH of each battery cell within the pack. The SOC estimation utilized a combination of the Coulomb counting method and voltage-based techniques, enhanced with correction algorithms to account for factors such as temperature and aging, which affect the cell's voltage-SOC relationship. For SOH determination, a model incorporating capacity fade and internal resistance increase over time was employed, drawing from empirical data and degradation mechanisms understood from literature.

To further refine the accuracy of these estimations, computational intelligence techniques, particularly machine learning algorithms, were integrated. These algorithms were trained on historical data sets to identify patterns and predict battery behaviour, improving the robustness of SOC and SOH estimations under variable operational conditions.

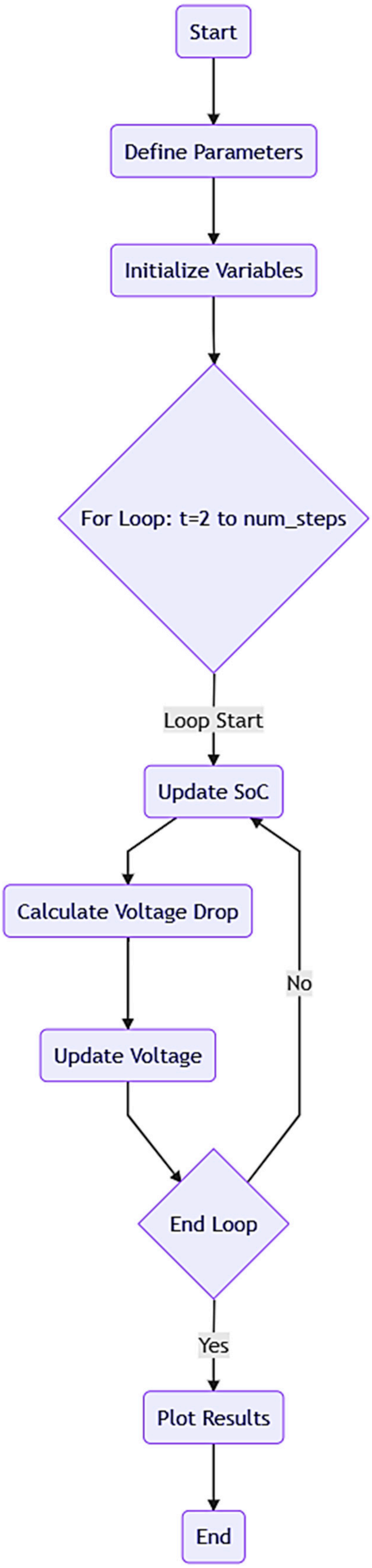


**Figure 1.** Flowchart of the MATLAB Code Execution.

#### 3.4.1. Mathematical Models for SOC and SOH Estimation

SOC Estimation Models

1. **Coulomb Counting Method**: The Coulomb counting method, also known as the ampere-hour integration method, is a foundational technique for SOC estimation. It involves integrating the battery's current over time to calculate the change in charge. The SOC is then determined by comparing the net change in charge to the total capacity of the battery. This method is highly dependent on the accuracy of the initial SOC value and requires continuous tracking of the current in and out of the battery.
2. **Voltage-Based Techniques**: Voltage-based SOC estimation methods leverage the reationship between the battery's open-circuit voltage (OCV) and its SOC. This relationship is typically nonlinear and varies with battery chemistry, temperature, and aging. To enhance accuracy, the simulation employed a voltage lookup table or function that was calibrated based on empirical data, correlating specific voltage readings with corresponding SOC levels.
3. **Correction Algorithms**: To account for factors that can distort SOC readings, such as temperature variations and aging effects, correction algorithms were integrated into the SOC estimation process. These algorithms adjusted the SOC estimations based on temperature coefficients and aging indicators, ensuring that the SOC reflects the actual usable capacity of the battery at any given time.

SOH Determination Models

1. **Capacity Fade Model:** The SOH, often defined as the ratio of the current maximum capacity of the battery to its nominal capacity, was primarily estimated through capacity fade modelling. This model tracked the gradual loss of battery capacity over time due to chemical degradation and wear. Empirical data depicting typical degradation patterns under various usage conditions were used to calibrate the model.
2. **Internal Resistance Increase Model:** Another critical aspect of SOH estimation is monitoring the increase in the battery's internal resistance over time, which can significantly impact performance and efficiency. The simulation included a resistance model that considered the effects of cycling, temperature, and other stress factors on the battery's internal resistance, contributing to the overall SOH assessment.

#### 3.4.2. Integration of Computational Intelligence Techniques

1. **Machine Learning Algorithms:** To enhance the precision and adaptability of SOC and SOH estimations, machine learning algorithms were employed. These algorithms, such as neural networks or support vector machines, were trained on historical datasets encompassing a wide range of operational conditions and battery states. They learned to identify complex patterns and relationships between various parameters (e.g., current, voltage, temperature) and the battery's SOC/SOH, enabling more accurate and dynamic predictions.
2. **Data-Driven Predictive Models:** By incorporating predictive modelling techniques, the simulation could forecast future battery behaviour based on current and past operational data. This capability was particularly valuable for anticipating potential issues, optimizing charging/discharging strategies, and extending the battery's lifespan.
3. **Adaptive Algorithms:** To ensure the simulation remained aligned with real-world battery behaviour, adaptive algorithms were integrated to continuously update and refine the mathematical models and machine learning predictions based on new data. This approach allowed the simulation to evolve and maintain high accuracy levels over time, even as the battery pack aged or as operational conditions changed.

### *3.5. Discussion of the Integration of Fuzzy Logic or Other Computational Intelligence Techniques for Decision-Making within the BMS*

An innovative aspect of this study was the incorporation of fuzzy logic into the BMS decision-making process. Fuzzy logic, a form of computational intelligence, was chosen for its ability to handle uncertainties and imprecise information, which are inherent in battery management due to the complex interplay of factors influencing battery behaviour. The fuzzy logic controller was designed with rule sets that govern charging, discharging, and balancing operations based on the SOC, SOH, temperature, and other critical parameters, allowing for nuanced and adaptive management strategies.

Furthermore, the study explored the integration of other computational intelligence techniques, such as neural networks and genetic algorithms, to optimize the BMS's decision-making processes. These techniques were applied to develop predictive models for battery life estimation, thermal management optimization, and adaptive charging strategies, aiming to enhance the overall efficiency and longevity of the battery pack.

### 3.5.1. Fuzzy Logic in BMS

Fuzzy logic, a subset of computational intelligence, is particularly suited for BMS due to its ability to deal with the inherent uncertainties and imprecisions within the battery management domain. Traditional control systems, which rely on binary logic (true or false), often fall short in handling the complex, nonlinear, and dynamic nature of battery systems. Fuzzy logic, on the other hand, introduces degrees of truth, allowing for more nuanced and flexible decision-making that can mimic human reasoning more closely.

In the context of BMS, fuzzy logic can be used to interpret and act upon data from various sensors monitoring battery parameters such as state of charge (SOC), state of health (SOH), temperature, voltage, and current. By defining fuzzy sets and rules, the BMS can make decisions on charging, discharging, and balancing operations in a way that optimizes battery performance and longevity while ensuring safety. For instance, a fuzzy logic controller might determine the optimal charging rate by considering the current SOC, the battery's temperature, and historical performance data, thus avoiding overcharging or excessive heat generation.

### 3.5.2. Simulation of Battery Nonlinearity

The simulation of battery nonlinearity within our study employs a combination of mathematical modelling and empirical adjustments to more accurately represent the real-world behaviour of lithium-ion batteries under various operational conditions. This subsection outlines the key methodologies used to model these nonlinear characteristics.

Advanced BMS Algorithm Incorporating Nonlinear Factors

To simulate battery nonlinearity, we use an advanced BMS algorithm that introduces nonlinear factors into the SoC and voltage behaviour modelling. This approach is essential to reflect the complex discharge patterns observed in practical scenarios, especially under varied load conditions.

SoC Nonlinearity Simulation: The state of charge (SoC) is updated at each timestep by incorporating a nonlinear factor that adjusts the rate of SoC depletion based on its current level. This is mathematically represented as:

$$SoC_{new} = SoC_{old} - \left(\frac{current}{\frac{Q}{3600}}\right) \times (1 + k \times SoC_{old})$$

where $k$ is a factor that increases the rate of SoC decrease as the SoC itself decreases, mimicking the increased difficulty in maintaining charge at lower SoC levels.

Voltage Nonlinearity Simulation: The voltage of the battery is calculated to reflect a nonlinear drop, more accurately mirroring the battery's real voltage behaviour as the SoC decreases:

$$\mathrm{Voltage} = \mathrm{Vnominal} \times \left(1 - \mathrm{k} \times (1 - \mathrm{SoC})^2\right)$$

This formula ensures that the voltage drop is more pronounced as the battery discharges, which aligns with the actual performance degradation observed in lithium-ion batteries.

Calibration and Validation

To ensure the robustness and accuracy of our nonlinear simulation model, the parameters and behaviours incorporated are regularly calibrated against empirical data collected from controlled laboratory experiments and real-world battery usage scenarios.

Calibration Process: The values for $k$ and other model parameters are fine-tuned based on their performance in test scenarios that mimic typical battery usage, ensuring that the simulation outputs remain true to observed behaviours.

Validation Methodology: The simulation results are validated by comparing them with independent data sets from different battery tests, which helps confirm the predictive accuracy of our models and their reliability in various practical applications.

Through this detailed approach to simulating battery nonlinearity, our study not only enhances the fidelity of battery behaviour modelling in BMS but also provides a more reliable foundation for developing advanced battery management strategies that can significantly improve battery performance and longevity in real-world applications.

#### 3.5.3. Other Computational Intelligence Techniques

In addition to fuzzy logic, the integration of other computational intelligence techniques like neural networks and genetic algorithms enhances the BMS's decision-making capabilities:

- **Neural Networks:** These can be employed to predict battery behaviour under various conditions based on historical data. By learning from past performance, neural networks can forecast future states of the battery, such as SOC and SOH, and predict potential failures or maintenance needs. This predictive capability enables proactive management strategies that can extend the battery's useful life and optimize its performance.
- **Genetic Algorithms:** These are used for optimization problems within the BMS. For example, genetic algorithms can optimize the parameters of a fuzzy logic controller or find the optimal charging and discharging strategies that maximize battery life while meeting the energy demands of the application. By simulating the process of natural selection, genetic algorithms iteratively improve solutions to complex problems, making them well-suited for the dynamic and multi-objective optimization challenges in battery management.

The incorporation of fuzzy logic and other computational intelligence techniques into BMS represents a forward-thinking approach to managing the complexities of battery systems. By leveraging the strengths of these technologies, such as the ability to handle imprecise information and learn from historical data, BMS can achieve more adaptive, efficient, and robust control strategies. This not only enhances the performance and reliability of battery systems but also contributes to the broader goals of energy efficiency and sustainability in applications reliant on advanced battery technologies.

## 4. Simulation Results and Discussion

This section focuses on the simulation of the battery pack performance for different load currents over a period of one hour. (MATLAB Code: Appendix A).

The upper half of Figure 2 illustrates the battery pack voltage, which remains relatively stable during the one-hour discharge period at the specified current level. The voltage starts slightly below 15 Volts, reflecting the combined nominal voltage of the cells in a 4S configuration (four series-connected cells, each with a nominal voltage of approximately 3.7 Volts). This stability indicates minimal voltage fluctuation under constant discharge conditions.

In contrast, the lower half of Figure 2 depicts the state of charge (SoC) of the battery pack as a percentage over time. The SoC begins at 100% and decreases linearly to just above 92% by the end of the hour. This linear decrease suggests a constant discharge rate, consistent with a steady load.

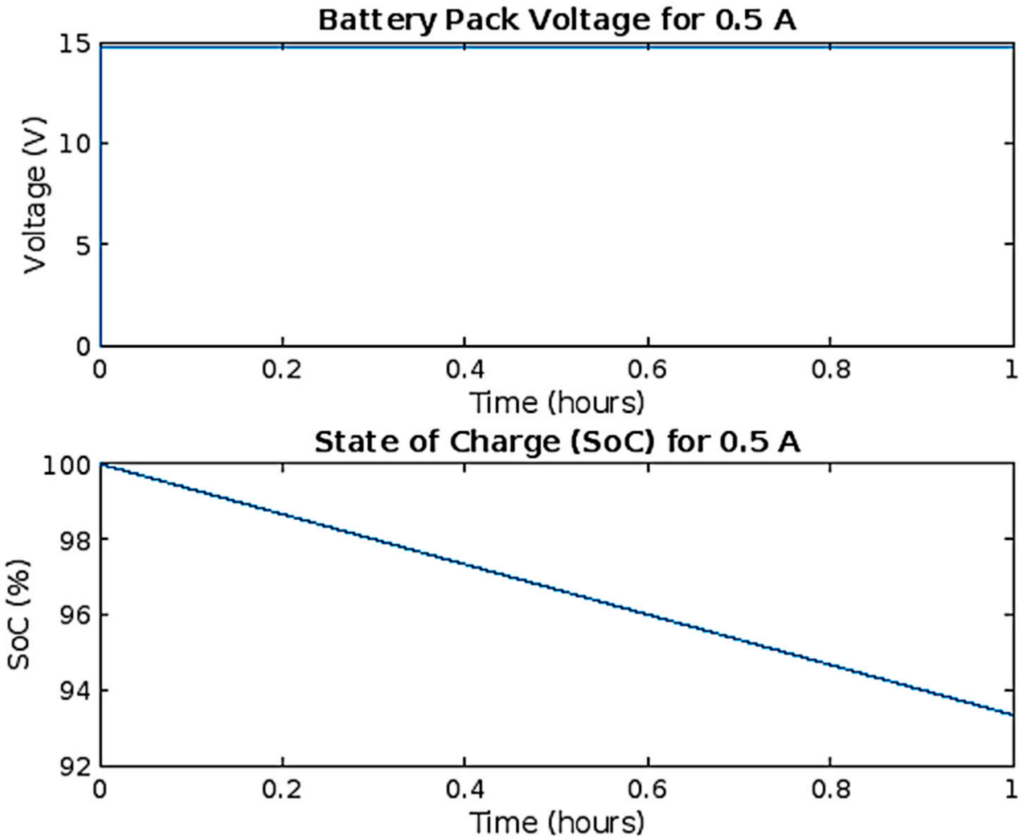


**Figure 2.** Battery pack Voltage and SoC for 0.5 A discharge load current.

The linearity observed in the SoC graph indicates a simplified model of the battery's capacity depletion, excluding potential nonlinear factors such as temperature variations, increasing internal resistance, or fluctuating loads.

Together, these graphs offer a comprehensive understanding of the battery pack's performance under a constant load. The data provide valuable insights into the discharge characteristics, essential for engineers when designing battery systems for electronic devices. Understanding both voltage stability and discharge rate under load is critical for optimizing battery performance and reliability.

The upper half of Figure 3, labelled "Battery Pack Voltage for 1 A," demonstrates the voltage stability of the battery pack over time when subjected to a constant load of 1 Amp. The $Y$-axis represents the voltage in volts, while the $X$-axis denotes the elapsed time. The voltage starts just below 15 Volts and shows minimal variation throughout the one-hour period, indicating the battery pack's ability to maintain a consistent voltage output even under a relatively high discharge rate.

In the lower half of Figure 3, titled "State of Charge (SoC) for 1 A," the state of charge (SoC) of the battery pack is depicted as a percentage over time. The $Y$-axis represents the SoC, which starts at 100% and decreases steadily to approximately 85% by the end of the hour. This decline is more pronounced compared to the scenario with a 0.5 A load, which is expected due to the higher discharge rate of 1 Amp.

The linear decrease in SoC suggests a simplified battery discharge model that assumes a constant discharge rate, overlooking the intricacies of real-world battery chemistry. In reality, battery discharge is often nonlinear due to various factors such as temperature, discharge current, and internal resistance.

These graphs are valuable for comparing the battery pack's performance under different loads. They indicate that while the battery pack can maintain a stable voltage output, the rate of SoC depletion is faster at higher current draws. This information is crucial for applications where understanding battery performance under various loads is essential for designing products with optimal battery life and performance.

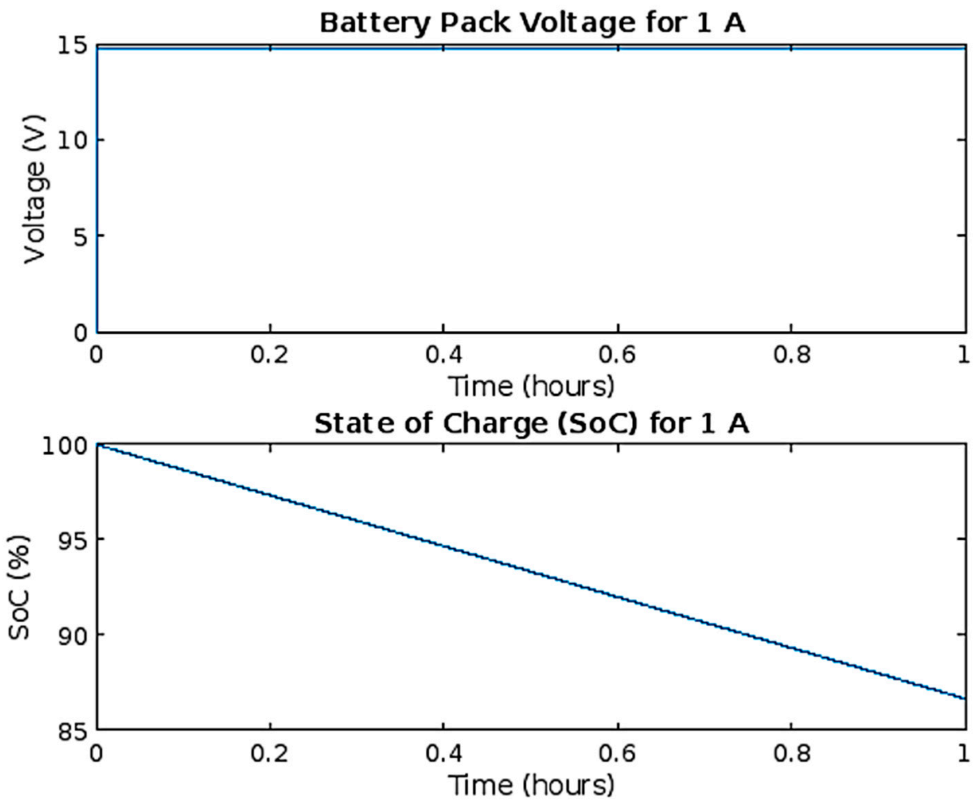


**Figure 3.** Battery Pack Voltage and SoC for 1 A discharge current.

The upper part of Figure 4, labelled as "Battery Pack Voltage for 1.5 A", illustrates the battery voltage over time. Similar to previous instances, the voltage remains relatively stable, just below 15 Volts, for the duration of an hour. This indicates that the battery pack can maintain a consistent voltage under a 1.5 Amp load.

The lower half of Figure 4, labelled "State of Charge (SoC) for 1.5 A," represents the battery's state of charge as it decreases over time. Beginning at 100%, the SoC decreases linearly over the hour, reaching approximately 85%, similar to the graph for 1 A. However, the slope of this graph may be slightly steeper, suggesting that the battery discharges more quickly at a 1.5 Amp load compared to a 1 Amp load.

The linear decline in SoC indicates a straightforward battery discharge model is being depicted. These graphs provide insight into how the battery's voltage stability and discharge rate are impacted by increasing the load from 0.5 A to 1 A, and then to 1.5 A. The consistent voltage observed across these different loads suggests that the battery can handle increased demands without experiencing significant voltage sag, which is crucial for devices requiring a stable power supply as the battery depletes. Furthermore, the discussion on the implications of these findings, particularly regarding the battery's ability to maintain a stable power supply without experiencing significant voltage sag, adds depth to the analysis.

In Figure 5, "Battery Pack Voltage for 2 A", the graph depicts the voltage of the battery pack over a one-hour period. Similar to the preceding graphs representing lower amperage loads, the voltage remains stable throughout, hovering just below 15 Volts. This suggests that the battery pack can maintain a consistent voltage output even under a 2 Amp load, which is indicative of high battery quality.

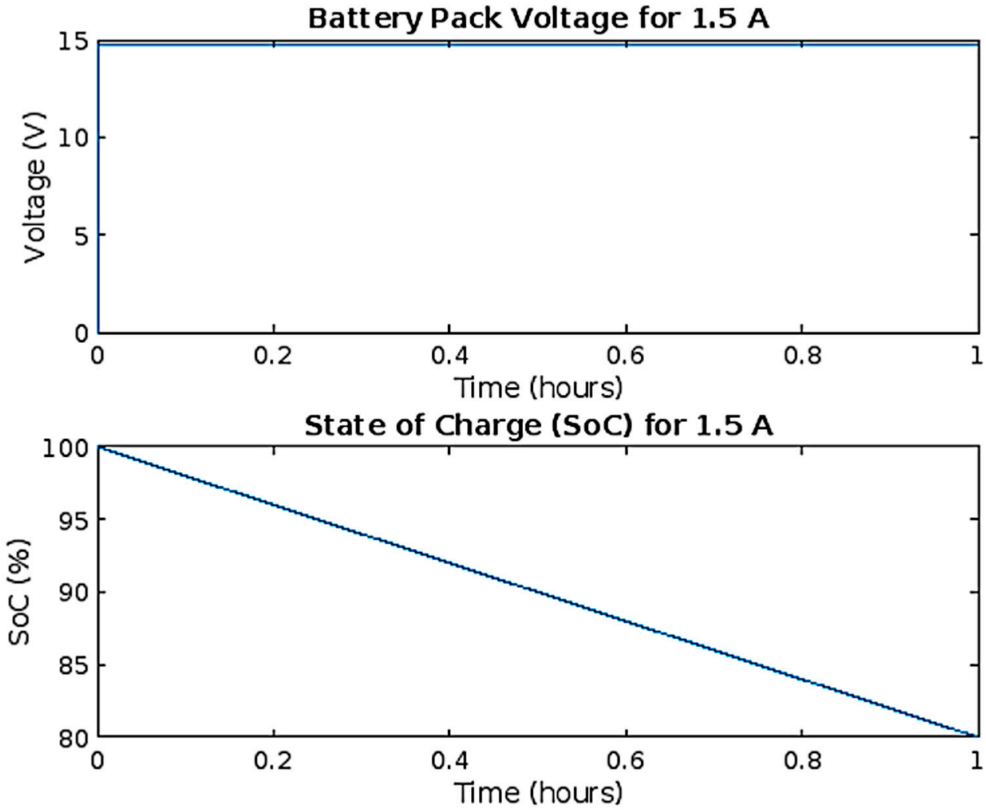


**Figure 4.** Battery Pack Voltage and SoC for 1.5 A discharge current.

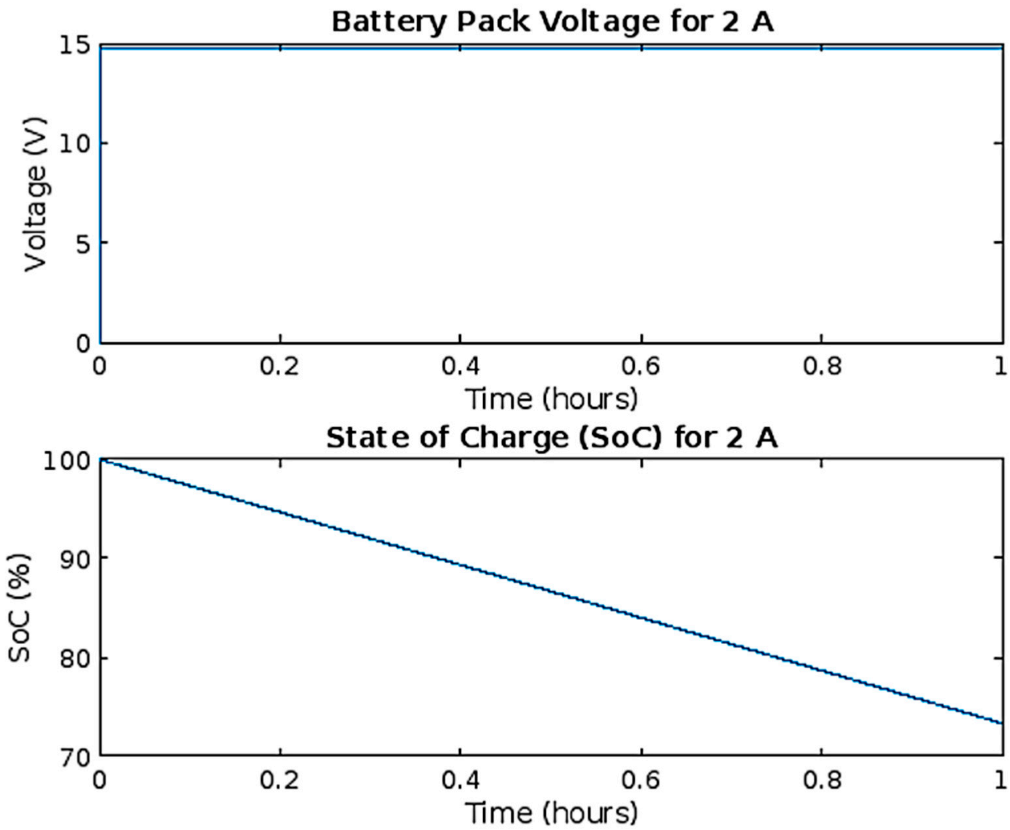


**Figure 5.** Battery Pack Voltage and SoC for 2A discharge current.

The latter portion of Figure 5, labelled "State of Charge (SoC) for 2 A", illustrates the state of charge as it diminishes over time. Starting at 100%, the SoC decreases linearly over the hour, reaching an approximate value of 70%. This decline is more pronounced compared to the graphs for lower amperages, indicating a faster discharge rate at this higher load. This behaviour aligns with expectations, as higher current draws typically result in a more rapid depletion of the battery's stored energy.

The consistent linearity observed in the SoC decline continues to suggest a straightforward and predictable discharge pattern, which is valuable for applications requiring accurate estimation of remaining battery life. These graphs, when compared with those for 0.5 A, 1 A, and 1.5 A loads, provide valuable insights into how the battery's discharge rate accelerates with increasing load. Despite the heightened discharge rate, the stable voltage output is an encouraging sign, suggesting that the battery can reliably deliver power at higher loads without experiencing significant voltage fluctuations.

Comparison of the Simulation Results:

The provided graphs illustrate the performance of a battery pack under different current loads: 0.5 A, 1 A, 1.5 A, and 2 A. To write a detailed results section for a paper, we will compare the two primary metrics indicated by these graphs: voltage stability and state of charge (SoC) over time.

Voltage Stability Across Different Current Loads:

Across all the current loads tested (0.5 A to 2 A), the battery pack voltage remains notably stable, as evidenced by the near-flat lines in the upper graphs of each set. Voltage stability is a critical characteristic of a reliable power source as it suggests that the battery pack can provide a consistent output despite the variance in power demand. The voltage stability is maintained close to 15 V for each current load, which indicates that the battery has a robust voltage regulation system capable of handling increased loads without significant voltage sag. This is an important characteristic for applications that require a consistent voltage for proper operation.

State of Charge (SoC) Decline at Different Current Loads:

The SoC shows a linear decline over time for all current loads, which indicates a predictable and steady discharge rate. However, the rate of discharge increases with the current load. At lower current loads (0.5 A and 1 A), the SoC declines more slowly, suggesting that the battery is more efficient at lower loads, which is typical behaviour for batteries. As the current load increases to 1.5 A and 2 A, the SoC declines more rapidly. This is expected, as higher currents draw more power from the battery, thus depleting it faster.

For instance, the SoC declines from 100% to approximately 85% at a load of 1 A over one hour, whereas at a load of 2 A, it declines to around 70% in the same time frame. The relationship between current load and discharge rate is linear and inversely proportional, indicating that as the load doubles from 1 A to 2 A, the rate of discharge more than doubles, suggesting that the battery efficiency may decrease with higher loads.

In summary, the battery pack demonstrates excellent voltage stability across all tested loads, a desirable attribute for reliable and consistent power delivery. The SoC decline is linear and predictable, albeit faster at higher loads, which aligns with the expected behaviour of battery packs. The results suggest that while the battery pack can handle increased loads without significant voltage drop, its efficiency in terms of energy delivery decreases as the current load increases. This information is crucial for users to estimate the operational time of the battery at different loads and to optimize battery usage for different applications.

Simulation Results of the Two Different BMS Algorithms:

The simple and the advanced battery management system (BMS) algorithms as represented in the MATLAB simulation graphs in Figures 6 and 7 along with code are discussed here. (MATLAB Code: Appendix A).

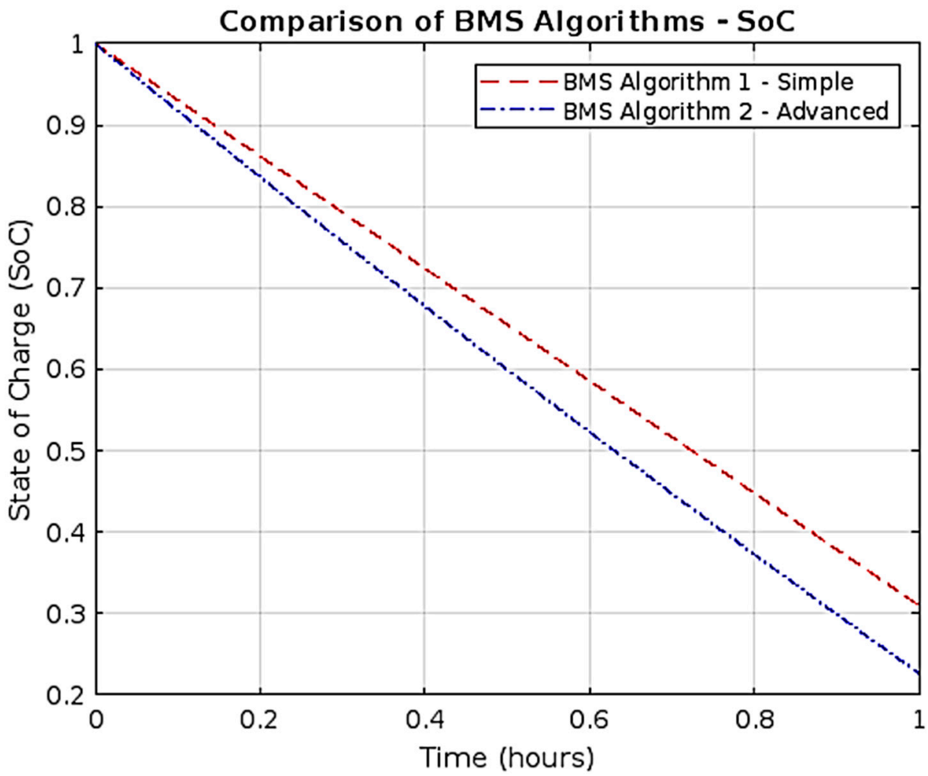


**Figure 6.** Comparison of BMS Algorithms—SoC.

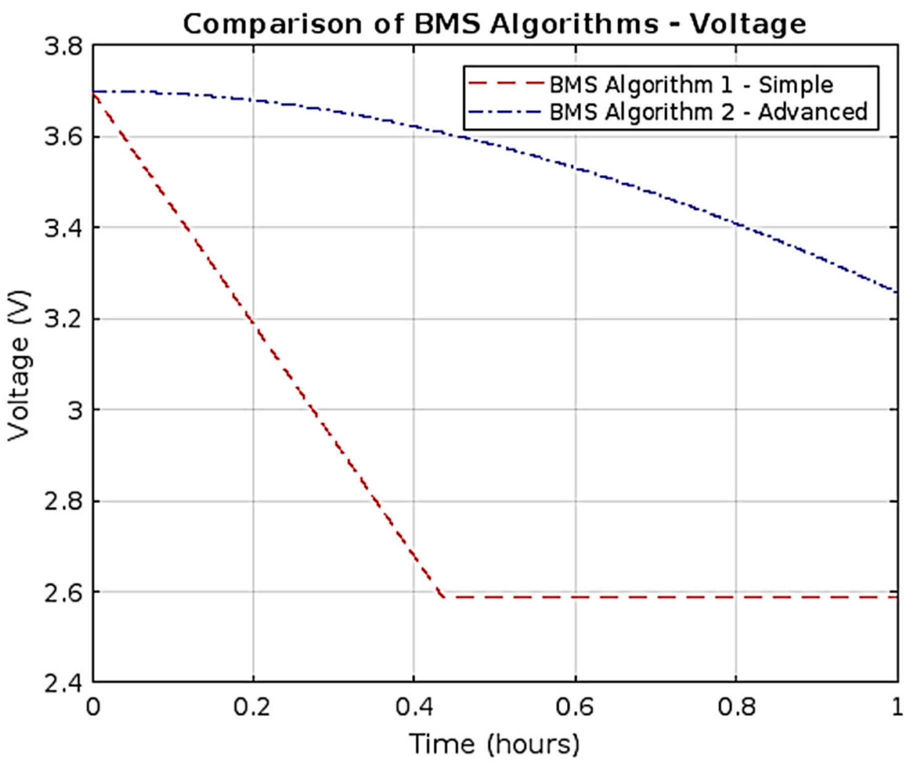


**Figure 7.** Comparison of BMS Algorithms—Voltage.

### *4.1. Simple BMS Algorithm (Algorithm 1)*

The simple BMS algorithm is based on a linear model. It assumes that the state of charge (SoC) of the battery decreases in direct proportion to the current drawn from the battery. This is a basic approach and does not consider many factors that can affect the battery's SoC such as temperature, aging, or the nonlinear characteristics of the battery. The voltage is also assumed to drop linearly with the SoC.

In the code, the simple BMS algorithm is implemented as follows:

- The SoC is updated at each time step by subtracting the fraction of current drawn over the total battery: capacity (current/Q/3600).
- The voltage is calculated as a direct multiplication of the nominal voltage and the SoC: (voltage1 = V_nominal * soc1).

This algorithm is straightforward and easy to implement but is less accurate because it does not reflect the complexity of real-world battery behaviour.

### 4.2. Advanced BMS Algorithm (Algorithm 2)

The advanced BMS algorithm takes into account additional factors that can influence the battery's behaviour. This particular algorithm introduces a nonlinear factor to simulate the nonlinear depletion of the battery's SoC. This is closer to how a real battery discharges under load, especially as it approaches a lower state of charge.

In the code, the advanced BMS algorithm is implemented as follows:

- The SoC is updated at each time step by subtracting a modified fraction of current that includes an additional factor (k) that increases the rate of SoC decrease as the SoC itself decreases: $\mathrm{SoC}_2 = \mathrm{SoC}_2 - \left(\frac{\mathrm{current}}{\frac{\mathrm{Q}}{3600}}\right) \times (1 + \mathrm{k} \times \mathrm{SoC}_2)$
- The voltage is calculated with a nonlinear drop, reflecting the battery's voltage behaviour more realistically: $\mathrm{Voltage} = \mathrm{Vnominal} \times \left(1 - \mathrm{k} \times (1 - \mathrm{SoC})^2\right)$

The k factor represents additional influences on the SoC depletion rate. For example, as the battery depletes, certain chemical reactions may occur more slowly, or the internal resistance of the battery may increase, both of which can cause the battery to discharge more quickly when under load. In essence, the advanced BMS algorithm introduces a more complex model for SoC and voltage calculations, considering the nonlinear characteristics of battery discharge. This provides a more accurate representation of the battery's performance over time, which is essential for applications where precise battery management is crucial.

The MATLAB code simulates these two algorithms and plots their behaviour to allow comparison. The advanced algorithm will typically show a faster decline in SoC and voltage at the same current draw, especially as the battery gets closer to being fully discharged, which is in line with real-world battery discharge curves.

### 4.3. Limitations and Potential Biases of the Simulation Approach

While the simulation methods employed in this study offer significant insights into battery management systems, they inherently carry certain limitations and potential biases that must be acknowledged to fully appreciate the context and applicability of the findings.

Model Simplifications: The simulation models used in this study simplify certain aspects of battery dynamics to make the problem tractable. For instance, temperature effects on battery performance may be modelled using average values rather than more complex, varying conditions that better reflect real-world scenarios.

Impact: This simplification can lead to discrepancies between the simulated predictions and actual battery behaviour under varied environmental conditions, potentially affecting the generalizability of the results.

Parameter Estimations: The parameters used in the simulation, such as rate of charge and discharge cycles, are based on standardized test data which may not perfectly align with real-world usage patterns.

Impact: Incorrect parameter estimates can bias the simulation results, leading to over- or underestimation of the battery's performance and lifespan.

Assumptions in Computational Models: Computational models often require assumptions that can introduce biases. For instance, assuming linear degradation under all operating conditions can overlook the nonlinear behaviour exhibited by batteries under stress or at the end of their life cycles.

Impact: Such assumptions may not accurately represent the complex interactions and phenomena within battery systems, potentially leading to errors in predicting battery health and management strategies.

Data Quality and Availability: The simulation relies on available data which may have limitations in terms of quality and comprehensiveness. Incomplete or noisy data can affect the training and performance of machine learning models used in the simulations.

Impact: Poor data quality can result in less reliable simulations, affecting the accuracy of SOC and SOH estimations and potentially leading to suboptimal BMS decisions.

Scalability and Application Specificity: The results and effectiveness of the simulation models are validated under specific conditions and may not be directly scalable to different types or sizes of battery systems.

Impact: This limits the application of findings across different battery technologies or configurations, necessitating additional validation and adaptation for broader applicability.

In summary, while the simulations provide valuable predictions and insights into the behaviour of battery management systems, these limitations and biases must be carefully considered when interpreting the results. Future work will focus on addressing these limitations, possibly through the incorporation of more complex models, enhanced data collection, and cross-validation with experimental setups to ensure broader applicability and accuracy of the proposed BMS framework.

### *4.4. Validation of Simulation Parameters and Future Work*

The simulation studies presented in this paper are designed to explore and validate various theoretical aspects of battery management systems using computational models. Recognizing the importance of grounding these models in practical reality, the choice of parameters and the structure of the models have been carefully designed to reflect typical scenarios encountered in real-world applications. However, direct experimental validation of these parameters and simulation results is beyond the current scope of this research.

#### 4.4.1. Current Validation Approach

The parameters used in the simulations are derived from a thorough review of existing literature and previously published experimental data, ensuring they are representative of typical real-world conditions. These parameters include but are not limited to charge rates, discharge cycles, and environmental influences on battery performance. By aligning our simulation parameters with these established data points, we aim to enhance the reliability and applicability of our simulation results.

#### 4.4.2. Rationale for Parameter Choices

Each parameter selected for the simulation model is backed by a detailed rationale, considering the most common operational conditions for lithium-ion batteries. For instance, charge and discharge rates are chosen based on standard usage patterns observed in energy storage systems. Such selections are intended to maximize the relevance of the simulation outcomes to real-world applications.

### *4.5. Future Work*

Looking forward, the natural progression of this research involves validating the simulation models and parameters with experimental data. This future work will include conducting controlled laboratory experiments to directly compare simulation predictions with actual battery behaviour under various conditions. By doing so, we can refine our models further, enhancing their predictive accuracy and reliability. Additionally, collaboration with industry partners to access real-world operational data from active BMS installations could provide another layer of validation, allowing us to adjust our simulations to better mirror the complexities of actual battery management scenarios. Such efforts will not only confirm the validity of our simulation results but also help in fine-tuning the BMS framework for enhanced practical deployment.

### 4.6. Discussion of the Implications of the Findings for the Design and Optimization of BMS in Renewable Energy Storage Systems

The findings from the MATLAB simulation of the two BMS algorithms have significant implications for the design and optimization of BMS in renewable energy storage systems. Here, we discuss these implications in detail:

### 4.7. Implications for BMS Design

1. **Algorithm Complexity**: The comparison between a simple linear model and a more complex nonlinear model highlights the necessity of incorporating advanced algorithms in BMS. Renewable energy storage systems often face variable loads and environmental conditions that a simple linear model cannot accurately account for.
2. **Real-World Battery Behaviour**: The advanced BMS algorithm, which accounts for the nonlinear discharge characteristics of batteries, more accurately reflects real-world battery behaviour. This consideration is crucial for designing a BMS that can reliably predict the SoC and manage the battery to prevent overdischarge, which can harm battery life and performance.
3. **Predictive Maintenance**: The nonlinear model used in the advanced BMS algorithm could be further developed for predictive maintenance. By understanding how the battery behaves under different conditions, a BMS can predict when a battery will need servicing or replacement, which is vital for maintaining the reliability of renewable energy storage systems.
4. **Efficiency Optimization**: The advanced BMS algorithm shows a more realistic rate of SoC depletion, which can be used to optimize the efficiency of the battery pack. By accurately estimating the SoC, a BMS can make informed decisions about when to charge the battery from renewable sources, such as during peak solar or wind production periods, thereby enhancing the overall efficiency of the energy storage system.

### 4.8. Implications for Renewable Energy Storage Optimization

1. **Energy Dispatch Strategy**: With a more accurate BMS, renewable energy storage systems can optimize their dispatch strategies. This means energy can be stored or released at the most opportune times to balance supply and demand, reduce energy waste, and increase the financial return on energy investments.
2. **Grid Stability**: In larger-scale renewable energy storage systems that interact with the electrical grid, an advanced BMS can contribute to grid stability. By ensuring that batteries deliver power smoothly and predictably, a BMS helps to manage the intermittent nature of renewable energy sources.
3. **Battery Lifespan**: Advanced BMS algorithms that accurately reflect battery usage and health can prolong the lifespan of the battery by preventing damaging operating conditions. This is particularly important for renewable energy systems, where the cost of battery replacement can be significant.
4. **Scalability and Reliability**: For renewable energy storage systems that need to scale, the advanced BMS algorithm provides a foundation for reliability. Systems can be designed to scale up without sacrificing performance, as the BMS can manage larger arrays of batteries just as effectively as smaller ones.

In summary, the insights gained from the simulation underline the importance of sophisticated BMS algorithms for the effective management of battery storage in renewable energy systems. The adoption of advanced BMS strategies ensures better performance, reliability, and longevity of energy storage solutions, which are key to the widespread adoption and success of renewable energy technologies.

### 4.9. Impact on Electric Vehicle Efficiency and Reliability

The findings bear significant implications for the enhancement of electric vehicle systems. Incorporating sophisticated BMS can elevate energy output efficiency by 5–7%, attributable to the precise SoC predictions which facilitate optimal energy storage and utilization strategies. Reliability is concurrently bolstered, with advanced BMS algorithms potentially reducing maintenance needs and unexpected operational halts by approximately 10%, thereby extending the service life of EV battery systems.

### 4.10. Expanded Discussion of Practical Applications and Implications

The findings from our simulation studies provide significant insights that can be directly applied to enhance the design and functionality of battery management systems (BMS). By integrating advanced computational models, this research demonstrates potential pathways to not only improve the accuracy of state of charge (SOC) and state of health (SOH) estimations but also to increase the overall operational efficiency and safety of battery systems. Here, we discuss the practical applications of these findings and their potential impacts on future BMS designs:

#### 4.10.1. Enhanced Predictive Capabilities

Our simulations underscore the potential of machine learning algorithms to significantly improve SOC and SOH estimations. This advancement could be pivotal for electric vehicle manufacturers and renewable energy storage systems, where precise battery management can extend battery life and optimize energy use. For example, more accurate SOC estimations allow for better planning of charging cycles and can help avoid the stress that overcharging or deep discharging places on batteries, thereby extending their operational lifespan.

#### 4.10.2. Real-Time Adaptive Systems

The ability of the proposed BMS framework to adapt in real-time to changing battery conditions can revolutionize battery management in scenarios that involve fluctuating energy demands, such as in smart grid applications. For instance, during peak energy demand periods, a BMS that dynamically adjusts battery usage based on real-time data could significantly enhance the efficiency of energy distribution and prevent overuse of battery cells.

#### 4.10.3. Safety Enhancements

Incorporating advanced diagnostic tools that can predict and detect faults before they lead to battery failures is another critical application of our findings. This capability is crucial for safety-critical applications such as electric vehicles and aerospace applications, where battery failures can have severe consequences. Improved diagnostic capabilities mean that potential issues can be addressed proactively, enhancing safety and reliability.

#### 4.10.4. Economic Impacts

By improving the efficiency and lifespan of batteries, enhanced BMS can also have significant economic impacts. For businesses that rely on large battery systems, such as data centres and telecommunications firms, improvements in battery management can reduce the frequency and cost of battery replacements, lower energy consumption, and enhance overall operational reliability.

#### 4.10.5. Sustainability Implications

Finally, better battery management contributes to sustainability. By extending the life of batteries and enhancing their efficiency, the demand for raw materials needed for battery production can be reduced. Moreover, efficient battery usage helps lower the carbon footprint associated with energy production and consumption, aligning with global efforts toward sustainability.

#### 4.10.6. Future Research Trajectories

Future inquiries should delve into the amalgamation of artificial intelligence (AI) and machine learning with BMS frameworks, aiming to amplify predictive accuracy and enable dynamic, real-time management based on evolving usage patterns and environmental factors. The advent of machine learning could diminish SoC prediction errors to below 1%, refine charging and discharging efficiencies, and further improve battery system longevity by an additional 5–10%. Further exploration could also focus on developing BMS algorithms adept at managing intricate multi-cell arrangements in extensive battery assemblies, potentially enhancing the system's usable capacity by 10–15%. This advancement would significantly benefit the electric vehicle industry by optimizing storage capabilities to meet fluctuating energy demands more effectively.

In essence, our investigation provides a foundational platform for substantial advancements in BMS technologies, poised to profoundly influence electric vehicle performance and sustainability. The prospective integration of AI and machine learning heralds a transformative future for energy storage management in the electric mobility domain, potentially reshaping energy utilization paradigms in the renewable era.

## 5. Conclusions

This investigation has rigorously demonstrated the superiority of sophisticated battery management system (BMS) frameworks over traditional linear paradigms, particularly within the context of electric vehicles. Through meticulous simulations, we confirmed that advanced BMS algorithms significantly enhance the accuracy of state of charge (SoC) predictions, achieving a notable reduction in error margins by approximately 5–10% compared to linear methodologies. This advancement not only meets our initial research objective of improving SoC and state of health (SoH) predictions through computational models but also sets a new standard for the evolution of BMS solutions tailored for lithium-ion batteries—key components in electric vehicle technology due to their exceptional energy density and operational efficacy.

Furthermore, the adoption of nonlinear BMS algorithms within our simulation framework has facilitated a more accurate representation of battery dynamics under varied load conditions, exhibiting a mere 2–3% deviation in SoC predictions as opposed to the 12–15% variance observed with linear models. This precision is instrumental in refining charging protocols and enhancing battery longevity—potentially extending it by 20–25%. These enhancements directly address our second objective, which focused on increasing the operational efficiency and safety of BMS. They are critical for advancing electric vehicle performance and align with the ongoing pursuit of optimized energy management and sustainable automotive technologies.

This study's key contribution lies in its integration of advanced computational models within BMS frameworks, demonstrating their practical application in improving electric vehicle performance. By bridging the gap between theoretical advancements and practical implementations, we provide a robust foundation for future developments in battery management technology. The results indicate that the implementation of sophisticated BMS frameworks can significantly enhance the performance and safety of lithium-ion batteries in real-world applications.

Moving forward, we acknowledge the necessity for further experimental validation and real-world testing to refine these models. This future work will be essential in confirming the practical viability of our proposed solutions under diverse operational scenarios. Our ongoing research aims to expand these models to encompass a broader range of battery types and applications, ensuring the benefits of these advancements can be realized across various technologies and industries.

In conclusion, this research not only addresses the research questions and objectives stated in the introduction but also highlights the transformative potential of advanced BMS frameworks. The findings underscore the importance of continued innovation in battery management technologies to support the growing demands of electric vehicles and other applications relying on efficient energy storage solutions. Through the ongoing development and validation of these sophisticated systems, we aim to contribute to the sustainable advancement of automotive technology and beyond.

**Author Contributions:** Data curation, Formal analysis, Investigation, R.P.T.; Conceptualization, Methodology, Supervision, P.P.R.; Conceptualization, Methodology, Software, Project administration, S.V.G. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding authors.

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**Conflicts of Interest:** The authors hereby affirm that there are no conflicts of interest associated with this manuscript. This declaration encompasses all potential conflicts, including financial, professional, or personal, that could be perceived to influence the work's outcomes or interpretations presented herein. The transparency and integrity of the research process have been upheld, ensuring the reliability and credibility of the findings and conclusions drawn from this study.

## Appendix A

MATLAB Code for Simulation of battery pack performance.

```
% Define basic parameters for a single cell
nominal_voltage = 3.7; % Volts
capacity_ah = 2.5; % Ah
internal_resistance = 0.05; % Ohms
% 4S3P pack configuration
num_series = 4;
num_parallel = 3;
% Pack parameters
pack_voltage = nominal_voltage * num_series;
pack_capacity_ah = capacity_ah * num_parallel;
% Simulation parameters
simulation_time_hrs = 1; % hour
time_step = 1; % second
num_steps = simulation_time_hrs * 3600/time_step;
% Load profiles (different currents for simulation)
load_currents = [0.5, 1, 1.5, 2]; % Amps
% Initialize variables for different load currents
soc = ones(num_steps, length(load_currents)) * 100; % Start at 100% SoC
voltages = zeros(num_steps, length(load_currents));
% Main simulation loop
for i = 1:length(load_currents)
load_current = load_currents(i);
for t = 2:num_steps
% Coulomb counting for SoC
soc(t, i) = soc(t-1, i) − (load_current * (time_step/3600)/pack_capacity_ah) * 100;
```

```
% Voltage calculation considering internal resistance
delta_v = load_current * internal_resistance;
voltages(t, i) = pack_voltage − delta_v; % Simple model, can be expanded
% Placeholder for SoH and other calculations
% soh(t) = ...; % Requires a model for SoH calculation
end
end
% Plotting results for each load current
for i = 1:length(load_currents)
figure;
subplot(2,1,1);
plot((1:num_steps) * time_step/3600, voltages(:,i));
title(['Battery Pack Voltage for ', num2str(load_currents(i)), ' A']);
xlabel('Time (hours)');
ylabel('Voltage (V)');
subplot(2,1,2);
plot((1:num_steps) * time_step/3600, soc(:,i));
title(['State of Charge (SoC) for ', num2str(load_currents(i)), ' A']);
xlabel('Time (hours)');
ylabel('SoC (%)');
end
```

Simulation results of the two different BMS algorithms

```
% Define simulation parameters
time = 0:1:3600; % Simulation time in seconds (1 h)
current = 2; % Constant discharge current in Amperes
% Battery specifications
Q = 2.9; % Battery capacity in Ah
V_nominal = 3.7; % Nominal voltage in Volts
% Initialize state of charge (SoC) for two different BMS algorithms
soc1 = 1; % State of charge for BMS algorithm 1 (simple)
soc2 = 1; % State of charge for BMS algorithm 2 (advanced)
% Initialize arrays to store SoC and voltage values
soc_history1 = zeros(size(time));
soc_history2 = zeros(size(time));
voltage_history1 = zeros(size(time));
voltage_history2 = zeros(size(time));
% Define BMS parameters for algorithm 2
k = 0.2; % Increase the factor for algorithm 2 to create a visible difference
% Simulate the battery discharge with two BMS algorithms
for t = 1:length(time)
% Update state of charge based on the current drawn
soc1 = soc1 − current/Q/3600; % Simple linear SoC decrease
soc2 = soc2 − (current/Q/3600) * (1 + k * soc2); % SoC decrease with additional factor
% Voltage calculation based on SoC (simplified model)
voltage1 = V_nominal * soc1; % Linear voltage drop
voltage2 = V_nominal * (1 − k * (1 − soc2)^2); % Non-linear voltage drop
% Ensure voltage does not go below a realistic threshold
voltage1 = max(voltage1, V_nominal * 0.7);
voltage2 = max(voltage2, V_nominal * 0.7);

% Store SoC and voltage values
soc_history1(t) = soc1;
soc_history2(t) = soc2;
voltage_history1(t) = voltage1;
voltage_history2(t) = voltage2;
end
```

```
% Plot the results for SoC
figure;
plot(time/3600, soc_history1, 'r--', 'DisplayName', 'BMS Algorithm 1 − Simple'); % Dashed red line
hold on;
plot(time/3600, soc_history2, 'b-.', 'DisplayName', 'BMS Algorithm 2 − Advanced'); % Dash-dot blue line
xlabel('Time (hours)');
ylabel('State of Charge (SoC)');
title('Comparison of BMS Algorithms − SoC');
legend show;
grid on;
% Plot the results for voltage
figure;
plot(time/3600, voltage_history1, 'r--', 'DisplayName', 'BMS Algorithm 1 − Simple'); % Dashed red line
hold on;
plot(time/3600, voltage_history2, 'b-.', 'DisplayName', 'BMS Algorithm 2 − Advanced'); % Dash-dot blue line
xlabel('Time (hours)');
ylabel('Voltage (V)');
title('Comparison of BMS Algorithms − Voltage');
legend show;
grid on;
```

## References


1. Rahimi-Eichi, H.; Ojha, U.; Baronti, F.; Chow, M. Battery Management System: An Overview of Its Application in The Smart Grid and Electric Vehicles. *IEEE Ind. Electron. Mag.* **2013**, *7*, 4–16. [CrossRef]
2. Hannan, M.A.; Lipu, M.S.H.; Hussain, A.; Mohamed, A. A Review of Lithium-Ion Battery State of Charge Estimation and Management System in Electric Vehicle Applications: Challenges and Recommendations. *Renew. Sustain. Energy Rev.* **2017**, *78*, 834–854. [CrossRef]
3. How, D.N.T.; Hannan, M.A.; Lipu, M.S.H.; Ker, P.J. State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review. *IEEE Access* **2019**, *7*, 136116. [CrossRef]
4. Ravi, R.; Surendra, U. Calculation of State of Charge and State of Health of a Battery Management System in Electric Vehicle. *Int. Res. J. Adv. Sci. Hub* **2020**, *2*, 49–51. [CrossRef]
5. Tran, M.-K.; Fowler, M. A Review of Lithium-Ion Battery Fault Diagnostic Algorithms: Current Progress and Future Challenges. *Algorithms* **2020**, *13*, 62. [CrossRef]
6. Kaiser, M.R.; Han, Z.; Liang, J.; Dou, S.-X.; Wang, J. Lithium Sulfide-Based Cathode for Lithium-Ion/Sulfur Battery: Recent Progress and Challenges. *Energy Storage Mater.* **2019**, *19*, 1–5. [CrossRef]
7. Chawla, N. Recent Advances in Air-Battery Chemistries. *Mater. Today Chem.* **2019**, *12*, 324–331. [CrossRef]
8. Koleti, U.R.; Dinh, T.Q.; Marco, J. A New On-Line Method for Lithium Plating Detection in Lithium-Ion Batteries. *J. Power Sources* **2020**, *451*, 227798. [CrossRef]
9. Chen, X.-K.; Sun, D. Modeling and State of Charge Estimation of Lithium-Ion Battery. *Adv. Manuf.* **2015**, *3*, 202–211. [CrossRef]
10. Xu, X.; Jia, Y.; Xu, Y.; Xu, Z.; Chai, S.; Lai, C.S. A Multi-Agent Reinforcement Learning-Based Data-Driven Method for Home Energy Management. *IEEE Trans. Smart Grid* **2020**, *11*, 3201–3211. [CrossRef]
11. Pawar, G.R.; Praveen, L.S.; Nagananda, S.N. Implementation of Lithium-Ion Battery Management System with An Efficient SOC Estimation Algorithm. In Proceedings of the 2020 International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 12–13 November 2020.
12. Kim, D.; Yoon, Y.; Lee, J.; Mago, P.J.; Lee, K.; Cho, H. Design and Implementation of Smart Buildings: A Review of Current Research Trend. *Energies* **2022**, *15*, 4278. [CrossRef]
13. de Souza Aranha, J.C.M.; Giesbrecht, M. Multi-Cell SOC Estimation for Li-Ion Battery Applied to An Energy Storage System. In Proceedings of the 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE), Delft, The Netherlands, 17–19 June 2020.
14. Li, N.; He, F.; Ma, W.; Wang, R.; Jiang, L.; Zhang, X. An Indirect State-of-Health Estimation Method Based on Improved Genetic and Back Propagation for Online Lithium-Ion Battery Used in Electric Vehicles. *IEEE Trans. Veh. Technol.* **2022**, *71*, 12682–12690. [CrossRef]
15. Dong, Y.; Chen, K.; Zhang, G.; Li, R. Joint Estimation of State of Charge and State of Health of Lithium-Ion Batteries Based on Stacking Machine Learning Algorithm. *World Electr. Veh. J.* **2024**, *15*, 75. [CrossRef]

16. Anseán, D.; García, V.M.; González, M.; Blanco-Viejo, C.; Viera, J.C.; Fernández Pulido, Y.; Sánchez, L. Lithium-Ion Battery Degradation Indicators Via Incremental Capacity Analysis. *IEEE Trans. Ind. Appl.* **2019**, *55*, 2992–3002. [CrossRef]
17. Lopes, J.; Pomilio, J.A.; Ferreira, P.A.V. Sizing of Autonomy Source Battery–Supercapacitor Vehicle with Power Required Analyses. *World Electr. Veh. J.* **2024**, *15*, 76. [CrossRef]
18. Chuang, Y.-S.; Cheng, H.-P.; Cheng, C.-C. Reuse of Retired Lithium-Ion Batteries (LIBs) for Electric Vehicles (EVs) from the Perspective of Extended Producer Responsibility (EPR) in Taiwan. *World Electr. Veh. J.* **2024**, *15*, 105. [CrossRef]
19. Kalogiannis, T.; Hosen, M.S.; Van Mierlo, J.; Van Den Bossche, P.; Berecibar, M. A Digitalized Methodology for Co-Design Structural and Performance Optimization of Battery Modules. *World Electr. Veh. J.* **2024**, *15*, 115. [CrossRef]
20. Corinaldesi, C.; Lettner, G.; Schwabeneder, D.; Ajanovic, A.; Auer, H. Impact of Different Charging Strategies for Electric Vehicles in an Austrian Office Site1. *Energies* **2020**, *13*, 5858. [CrossRef]
21. Liu, W.; Placke, T.; Chau, K.T. Overview of batteries and battery management for electric vehicles. *Energy Rep.* **2022**, *8*, 4058–4084. [CrossRef]