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Review

Next Generation of Electric Vehicles: AI-Driven Approaches for Predictive Maintenance and Battery Management

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Abstract: This review explores recent advancements in electric vehicles (EVs), focusing on the transformative role of artificial intelligence (AI) in battery management systems (BMSs) and system control technologies. While EVs are integral to sustainable transportation, challenges remain in optimising battery longevity, energy efficiency, and safety. AI-driven techniques—such as machine learning (ML), neural networks (NNs), and reinforcement learning (RL)—enhance battery state of health (SOH) and state of charge (SOC) predictions, as well as temperature regulation, offering superior accuracy over traditional methods. Additionally, AI-powered control frameworks optimise energy distribution, regenerative braking, and power allocation under varying driving conditions. Deep RL enables adaptive, self-learning capabilities that improve energy efficiency and extend battery life, even in dynamic environments. This review also examines the integration of the Internet of Things (IoT) and big data analytics in EV systems, enabling predictive maintenance and fleet-level optimisation. By analysing these advancements, this paper highlights AI's pivotal role in shaping next-generation, energy-efficient EVs.

Keywords: artificial intelligence; battery energy management; electric vehicle; internet of things; predictive maintenance; reinforcement learning; state of charge; state of health; system control; sustainable transportation

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1. Introduction

Overview of Sustainable Transportation and Electric Vehicles

The transition to sustainable transportation represents a pivotal step in addressing global environmental and energy challenges. With rising concerns over climate change, air pollution, and diminishing fossil fuel reserves, electric vehicles (EVs) have gained prominence as a cleaner and more energy-efficient alternative to internal combustion engine (ICE) vehicles [1]. However, the environmental benefits of EVs largely depend on the energy mix used for electricity generation. If the electricity powering EV batteries is derived primarily from fossil fuel-based thermal power plants, the reduction in carbon emissions may be negligible, limiting their effectiveness in decarbonisation efforts.

RESs offer a more sustainable alternative but face challenges related to intermittency and instability. Variations in sunlight and wind speed make continuous and stable electricity generation difficult, affecting the reliability of renewable energy for EV charging. To address this issue, integrating battery energy storage systems (BESSs) with renewable energy sources (RESs) can significantly improve energy utilisation and stability, enabling

a more consistent power supply and enhancing the overall efficiency of EV charging infrastructure [2]. This synergy between renewable energy, battery storage, and EVs contributes to reducing reliance on fossil fuels and supports global decarbonisation efforts, further driving the adoption of sustainable mobility solutions. EVs are powered by electric propulsion systems, typically using high-capacity lithium-ion batteries, which are favoured for their superior energy density, efficiency, and relatively lower environmental impact than traditional fuels [3]. The urgency for this transition is evidenced by the consistent rise in global emissions over the past two decades; see Figure 1, which illustrates the annual emissions trend from 2000 to 2023 based on actual data to predict the emissions from 2024 to 2030. The blue line shows that emissions have increased steadily over the years prior to 2023, whilst the green dashed line signifies that from 2024 to 2030, emissions will continue to rise, albeit slightly slower than in earlier years. This trend highlights the importance of implementing effective mitigation strategies to control emissions and address associated environmental concerns. Together, the actual and predicted data provide a comprehensive perspective on historical performance and future expectations.

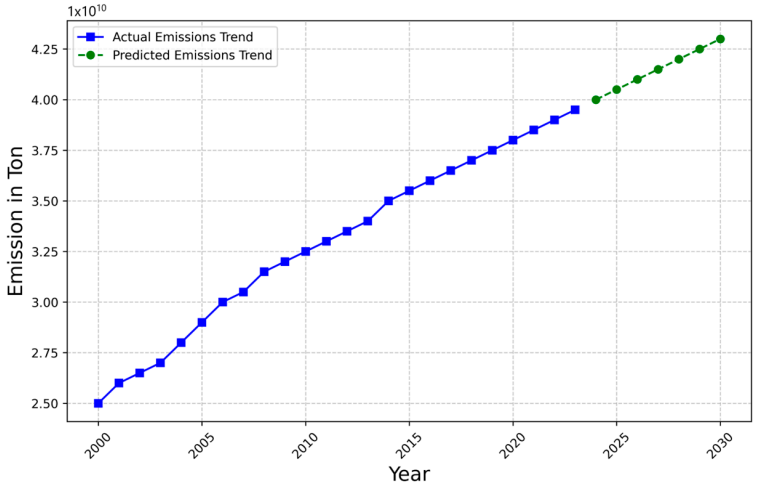


Figure 1. Annual emissions: historical and predicted trends (2000–2030) [4].

Over the recent decade, governments and industrial stakeholders worldwide have invested heavily in promoting EV adoption through incentives such as tax rebates, subsidies, and the development of robust charging infrastructure [5]. For instance, initiatives, including the European Green Deal [6] and China's New Energy Vehicle Programme [7], have catalysed EV deployment at an unprecedented scale [4]. However, challenges persist in range anxiety, charging times, and the long-term sustainability of battery production and recycling processes [8].

Despite the rapid expansion of the EV market, several challenges remain, particularly regarding battery performance, reliability, and lifecycle sustainability. The efficiency and longevity of lithium-ion batteries, which dominate EV energy storage, are affected by factors such as charging infrastructure availability, battery degradation, energy management inefficiencies, and safety concerns. Additionally, integrating RESs for EV charging presents obstacles due to their intermittent and unstable nature, further complicating the widespread adoption of sustainable mobility solutions [9].

Artificial intelligence (AI) and advanced data analytics have emerged as transformative technologies capable of addressing these critical challenges. By leveraging machine learning (ML), deep learning (DL), and reinforcement learning (RL), AI-driven systems can optimise battery performance, enable predictive maintenance, and enhance energy distribution strategies, ultimately improving EV efficiency, reliability, and safety. Moreover, AI-powered BMSs are revolutionising the way state of health (SOH) and state of

charge (SOC) estimations are performed, enabling real-time monitoring and predictive failure analysis.

Furthermore, the rapid advancements in Vehicle-to-Grid (V2G) integration, wireless power transfer (WPT), and smart charging infrastructures indicate a paradigm shift towards a more connected and intelligent transportation ecosystem. Incorporating the Internet of Things (IoT) and big data analytics into EV systems further enhances operational efficiency, enabling seamless communication between vehicles, grid operators, and charging stations. These technological advancements align with the broader vision of smart cities, where EVs serve as dynamic energy assets, supporting grid stability and sustainable energy utilisation.

Given these developments, there is an urgent need for a comprehensive review of AI-driven innovations in EV battery management and system control. This paper aims to analyse the latest advancements in-depth, exploring how AI-powered solutions address key challenges in EV performance, predictive maintenance, and energy optimisation. Thus, it highlights the pivotal role of AI in shaping the next generation of intelligent, energy-efficient, and sustainable EVs, contributing to the global shift towards cleaner and smarter transportation systems.

Purpose

This review, therefore, seeks to systematically evaluate and synthesise the advancements in AI-driven technologies for BMSs and control frameworks within the EV ecosystem. It aims to address the critical challenges associated with performance optimisation, predictive maintenance, safety, and energy efficiency, ultimately supporting the development of next-generation sustainable and connected transportation solutions.

Key Objectives (Research Questions)

1. Identifying Research Gaps:
    - What are the unresolved challenges in optimising EV battery performance, predictive maintenance, and system control?
2. Supporting Decision-Making:
    - What actionable insights can be provided to policymakers and industry leaders to promote innovation and sustainability in the EV sector?
3. Recommending Software Tools:
    - Which AI and IoT tools are essential for predictive analytics, optimisation, and fleet-level integration in EVs?

These objectives align with this study's global aim of evaluating and proposing advancements in AI-driven technologies for EV BMSs and control systems while supporting innovation and sustainability across the industry.

2. Methodological Approach

The first step in this research was to perform a comprehensive search for the relevant literature aligned with the research questions identified. The sources included academic journals, technical articles, policy documents, and other credible publications. Particular care was taken to ensure the selection of high-quality papers, emphasising those resulting from rigorous research methodologies, reliable findings, statistically significant results, and contemporary relevance.

After collecting the literature, the next step involved extracting key points while thoroughly reviewing the details of the publications. These points were carefully summarised to synthesise core ideas, theories, and concepts. This process enabled the identification of the current state of thinking in the field, encompassing cutting-edge ideas, innovative concepts, and prevailing theories. Through this synthesis, the research summarised, discussed,

and critically evaluated the existing knowledge. Additionally, areas of consistency and conflict across the literature were investigated to lay the foundation for structured arguments supporting future research needs. This critical analysis provided in Section 3 offers insights into unresolved challenges and opportunities for advancing the understanding of AI-driven innovations in battery management systems and EV technologies.

This paper then transitions into an overview of BMS, providing a detailed exploration of its key components and functionalities. It examines the critical challenges in battery performance management, such as degradation, safety, and energy efficiency, and establishes the role of BMSs in advancing EV technologies. This leads to a discussion in Section 4 of AI innovations in battery management, which introduces a range of AI techniques, such as ML and DL, and their applications in BMSs, including state estimation, fault detection, and energy optimisation. This section also includes a comparative analysis of different AI approaches based on performance metrics, convergence speed, and computational complexity. Following this, in Section 5, this paper delves into AI-driven optimisation techniques, exploring algorithms such as Genetic Algorithms (GAs), Particle Swarm Optimisation (PSO), Lightning Search Algorithm (LSA), and Whale Optimisation Algorithm (WOA). The strengths, limitations, and comparative insights of these techniques are thoroughly discussed in the context of dynamic battery control and energy management tasks. The subsequent Section 6, discussing advanced AI modelling approaches, examines the role of deep learning models, including LSTM, GRUs, and CNNs, in battery state prediction. It also highlights the applications of Fuzzy Neural Networks (FNNs) and Fuzzy C-Means (FCM) in handling uncertainty and hybrid intelligent systems by combining clustering and regression techniques for improved BMS performance.

The paper, in Section 7, then addresses challenges and future directions, identifying unresolved issues in AI-driven BMSs, such as data dependency, scalability, and computational cost. It discusses emerging trends, including edge computing, digital twins, and cybersecurity, and explores opportunities for future research and practical implementations. Finally, Section 8, the conclusion, summarises the key findings of this study, highlighting AI's contributions to advancing BMS and EV technologies. It also provides final thoughts on future research directions and practical implications, ensuring a cohesive and forward-looking perspective. This structure ensures a logical progression of ideas, from the introduction and methodology to the exploration of AI techniques and challenges, culminating in a discussion of future directions and conclusions. It provides a comprehensive foundation for understanding the advancements and opportunities in AI-driven BMSs for EVs.

3. Exploring BMSs in EVs: Types, Technologies, and Challenges

3.1. The Role of BMSs in EV Performance

A critical component underpinning EVs' performance, safety, and longevity is the BMS. The BMS acts as the brain of the EV battery pack and is responsible for monitoring, controlling, and safeguarding the battery's operation. It plays a pivotal role in ensuring that the battery operates within safe parameters, preventing risks such as overheating, overcharging, and deep discharge, which can lead to severe degradation or failure [10]. The key functions of the BMS include SOC estimation, which provides a real-time measure of the battery's energy reserves, and SOH assessment, which evaluates the battery's overall condition and capacity over time. Accurate SOC and SOH predictions are essential for optimising energy usage, enhancing the driving range, and addressing critical user concerns [11].

Traditional BMS designs often rely on deterministic models and rule-based algorithms derived from electrochemical principles. While effective in controlled scenarios, these approaches struggle to adapt to the complexities and variability of real-world driving

conditions, where factors such as temperature fluctuations, uneven charging cycles, and ageing dynamics introduce significant uncertainties [12]. This limitation has prompted the exploration of advanced computational methods to improve the precision and adaptability of BMS functionalities.

3.2. Emerging Significance of AI in EV Systems

AI has emerged as a transformative force in EV technology, particularly in designing and operating battery management and system control systems. By leveraging AI techniques such as ML, DL, and RL, researchers and engineers are developing more accurate, adaptive, and efficient BMS solutions to overcome the limitations of traditional models [13]. Figure 2 presents a comprehensive framework for battery energy management in EVs, incorporating monitoring, control, and advanced intelligence. Key input parameters such as temperature, voltage, and current are used to evaluate battery performance and safety. Essential functions include battery cell monitoring, power management, estimation of the SOC and SOH, and the prediction of the Remaining Useful Life (RUL). Advanced thermal management, fault diagnosis, discharge control, secure data acquisition, and cell balancing enhance reliability and efficiency. The framework also integrates communication and networking systems for seamless data flow. AI and control systems are central to the framework, employing real-time data for predictive analytics, optimisation, and decision-making. This holistic approach ensures safe, efficient, intelligent BEM for EVs.

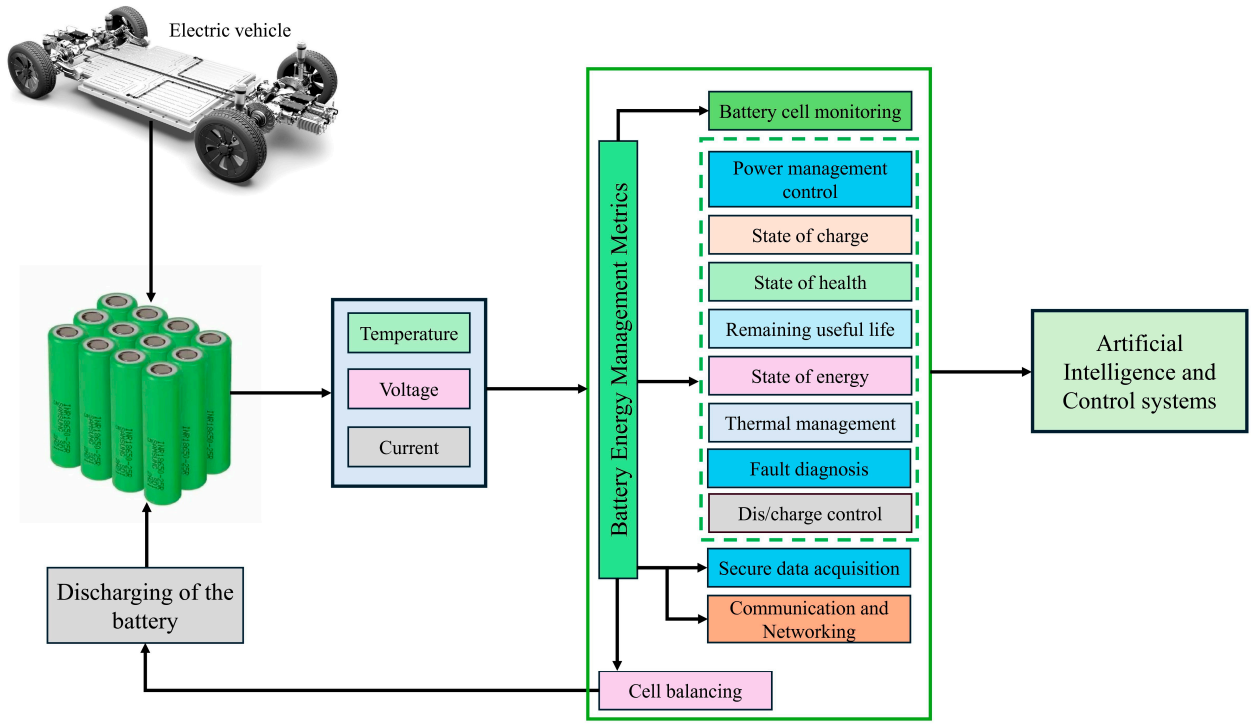


Figure 2. Framework for BEM and control in EVs.

AI-driven innovations provide real-time and predictive capabilities crucial for managing EV batteries' intricate dynamics. For instance, ML algorithms trained on historical and real-time data can predict the SOC and SOH more accurately than traditional methods, accounting for temperature variations, load fluctuations, and battery ageing. Neural networks (NNs), in particular, have proved to be effective in modelling complex, non-linear relationships within battery systems, enabling more precise thermal regulation and fault detection [14]. RL introduces self-learning capabilities to BMSs and system controls, allowing for dynamic optimisation of energy distribution, power allocation, and regenerative

braking strategies under varying driving conditions. This adaptive approach significantly enhances energy efficiency and extends battery life, even in unpredictable operational environments [15].

Integrating IoT and big data analytics further amplifies AI's potential in EV systems. IoT-enabled vehicles generate vast amounts of operational data, which can be harnessed to improve the training of AI models. This, in turn, enables predictive maintenance and fleet-level optimisation. For instance, predictive algorithms can pre-emptively identify battery faults or degradation, reducing maintenance costs and enhancing safety. At the fleet level, AI enables dynamic energy management across multiple EVs, unlocking new possibilities for commercial and public transportation applications [16]. The global emissions trend shown in the figure reinforces the urgency for transformative changes in transportation systems. As EV adoption is scaled up globally, advancements in AI-driven BMSs and system controls become crucial not only for enhancing the efficiency and reliability of individual vehicles but also for addressing broader environmental challenges. Integrating AI, IoT, and big data will play a pivotal role in optimising EV performance, supporting the transition to a low-carbon economy, and paving the way for a sustainable future with connected transportation. The following section considers the different types of EVs, technologies, and challenges.

3.3. Diverse Electric Vehicle Types: A Comprehensive Comparison

EVs encompass a range of categories, each with distinct characteristics and operational frameworks. These include BEVs, HEVs, PHEVs, and FCEVs. Understanding the differences among these types is fundamental to appreciating the diversity and functionality of EV technology [17].

1. Battery Electric Vehicles (BEVs): BEVs operate solely on electricity, using energy stored in rechargeable batteries, producing zero emissions during operation and having larger battery capacities to enhance driving range. Current BEVs can typically travel between 160 and 500 km on a single charge, depending on battery specifications, and require ancillary technology and vehicle design [17]. Driving conditions also significantly influence the range and energy efficiency of BEVs. For instance, wet weather may require windscreen wipers, while maintaining comfort during extreme temperatures necessitates operating heating or cooling systems. Similarly, driving at night increases energy consumption due to using headlights and other lighting systems. These additional energy demands underscore the importance of efficient energy management and robust battery systems in ensuring optimal performance across diverse driving scenarios [18].
2. Hybrid Electric Vehicles (HEVs): HEVs combine an ICE with an electric motor powered by energy generated during braking or by the ICE. Unlike PHEVs, HEVs cannot be charged from an external power source and rely entirely on self-sufficient charging systems within the vehicle [17].
3. Plug-in Hybrid Electric Vehicles (PHEVs): PHEVs share similarities with HEVs but offer the added charging capability through an external electrical source. This enables a greater electric-only driving range while retaining the backup support of a traditional ICE, making them a versatile choice for users transitioning to EV technology [19].
4. Fuel Cell Electric Vehicles (FCEVs): FCEVs use hydrogen as their primary energy source, generating electricity through chemical reactions within a fuel cell. These vehicles emit only water vapour as a by-product and are a sustainable solution for reducing carbon emissions. However, the limited availability of hydrogen infrastructure poses a barrier to their widespread adoption [19].

Each type of EV addresses unique transportation needs and environmental objectives, contributing collectively to the broader aim of reducing fossil fuel dependency and GHG emissions.

3.4. Innovations in EV Charging: Methods and Technologies

The efficiency and practicality of charging systems are critical to the widespread adoption of EVs. Various methods have been developed to cater to user needs, ranging from rapid convenience charging to those delivering long-term energy sustainability. These methods are seen in Figure 3 and include battery swapping, wireless power transfer (WPT), and conduction charging (CC), each with distinct advantages and limitations [20].

1. Battery swapping allows EV users to exchange a depleted battery for a fully charged one at designated Battery Swapping Stations (BSSs). This method eliminates the waiting time associated with conventional charging. BSSs often integrate renewable energy sources (RESs), such as solar or wind, to further enhance sustainability. However, this approach involves challenges such as high infrastructure costs, the need for standardised battery designs, and elevated operational expenses due to station operators' ownership of the station's battery [21].
2. Wireless power transfer (WPT) employs electromagnetic induction to transmit energy between two coils, one embedded in the road and the other installed in the vehicle. This technology offers unparalleled convenience, enabling charging without physical connections and even when the vehicle is being driven. Despite these benefits, WPT charging faces challenges such as efficiency losses, communication latency between the vehicle and the transmitter, and the high costs associated with infrastructure development [21]. In addition to efficiency losses, improving wireless charging interoperability is critical to ensuring the widespread adoption of WPT systems. Interoperability refers to the ability of different transmitter and receiver devices to function seamlessly while maintaining output performance within specified parameters. If the transmitter and receiver are not properly matched, the system may fail to achieve the required charging performance, leading to significant power losses or, in some cases, complete charging failure. Poor interoperability not only reduces charging efficiency but also increases energy wastage, limiting the effectiveness of WPT technology in real-world applications. Therefore, developing standardised communication protocols and hardware compatibility measures is essential to improving WPT efficiency and reliability [22].

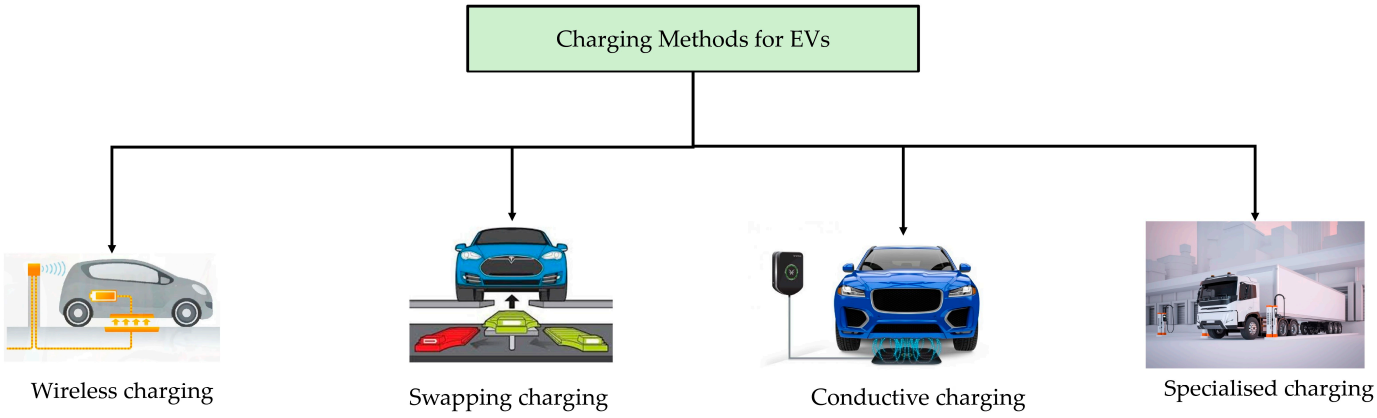


Figure 3. EV charging methods.

3. Conductive charging (CC) requires a physical connection between the EV and the power grid. CC is divided into three levels [21]:

- Level 1 and Level 2 charging is suitable for residential and commercial use and offers slower charging rates that are less taxing on the grid.
- Level 3 charging, also known as fast charging, provides rapid energy replenishment but may result in grid components' instability, voltage fluctuations, and a shortened lifespan.

CC can also facilitate V2G technology, allowing EV batteries to supply energy back to the grid. This capability helps stabilise the grid during peak demand but may contribute to battery degradation over time.

4. Specialised charging for heavy vehicles is a unique system, including overnight depot charging and pantograph charging, typically employed for electric buses and trucks [21].
   - Overnight depot charging enables vehicles to recharge during off-peak hours, minimising grid impact.
   - Pantograph charging uses automated connections to provide high-power charging, either from the top (off-board pantographs) or bottom (on-board pantographs), catering for the high energy demands of public transport.

Each charging method addresses specific user scenarios, but challenges such as standardisation, infrastructure costs, and grid impact remain critical areas for research and development. Also, an optimised combination of these methods will likely be necessary to meet the diverse demands of future EV markets.

3.5. Overcoming Challenges in Fuel Cell EVs and Hybrid EV Adoption

Despite their potential to reduce GHG emissions and the reliance on fossil fuels, technological, economic, and infrastructural barriers hinder the widespread adoption of FCEVs and HEVs [23]. Figure 4 outlines the main obstacles associated with FCEVs and HEVs. These include high manufacturing costs, durability and performance limitations, and inadequate hydrogen infrastructure, notwithstanding that hydrogen production poses challenges. High initial costs, the limited energy density of renewable sources, insufficient refuelling and recharging infrastructure, and prolonged recharging times for plug-in hybrid models hinder widespread adoption. Addressing these challenges is critical to facilitating the adoption of FCEVs and HEVs as a component of sustainable transportation policy.

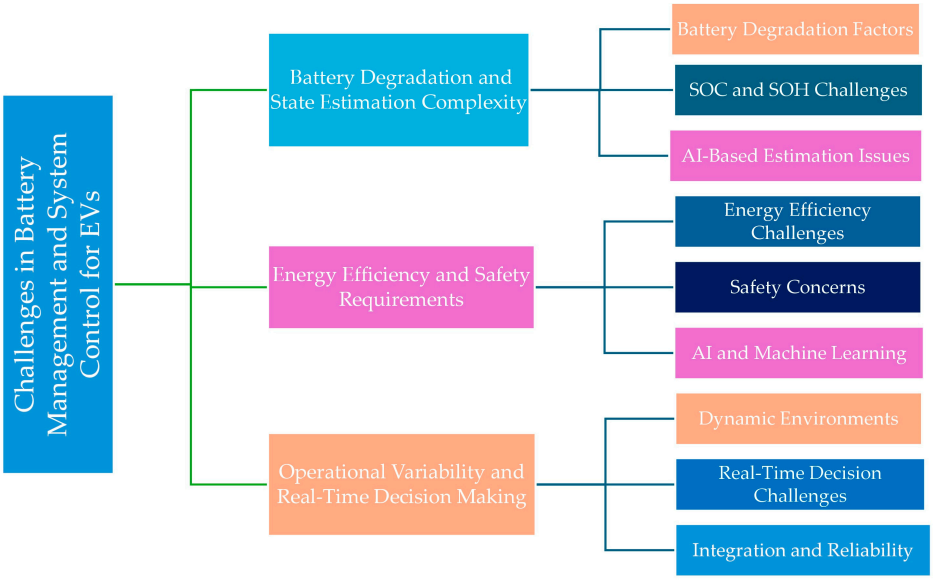


Figure 4. Challenges for FCEVs and HEVs discussed in this research.

3.5.1. Fuel Cell Electric Vehicles (FCEVs): Unlocking the Potential of Hydrogen

1. High Production Costs: Manufacturing fuel cells remains a primary barrier to FCEV commercialisation. The US Department of Energy (DoE) aims to reduce fuel cell costs to USD 40 per kilowatt by 2025 and eventually to USD 30 per kilowatt. Achieving this goal requires balancing cost reduction with maintaining performance and durability, a difficult trade-off given the reliance on expensive materials such as platinum catalysts [24].
2. Durability and Performance Limitations: Current fuel cells often fall short of durability targets. For example, many fail to sustain performance beyond 5000 operational cycles, while the DOE targets over 8000 h of operation. Improving durability without compromising cost efficiency remains a critical challenge [25,26].
3. Hydrogen Infrastructure: The limited availability of hydrogen refuelling stations poses a significant barrier to FCEV adoption. Developing a widespread, cost-effective hydrogen infrastructure requires substantial investment and coordinated policy support [27].
4. Hydrogen Production Challenges: Most hydrogen is currently derived from fossil fuels, undermining FCEVs' environmental benefits. Transitioning to green hydrogen, which is produced using renewable energy, is essential but requires advancements in production technology and cost reductions [27].

Fuel Cell Electric Vehicles (FCEVs) present a promising solution for reducing carbon emissions; however, several challenges hinder their widespread adoption. These include high production costs, durability and performance limitations, hydrogen infrastructure constraints, and hydrogen production challenges. Additionally, Prognosis and Health Management (PHM) for fuel cells is crucial in ensuring FCEVs' long-term reliability and commercial viability.

One of the primary concerns is the limited lifespan of Proton Exchange Membrane Fuel Cells (PEMFCs), which degrades over time due to complex operational conditions and component ageing. This gradual performance deterioration eventually reaches a minimum acceptable threshold, restricting the commercialisation potential of PEMFC-based FCEVs. Moreover, the recovery phenomenon of reversible voltage loss further complicates life prediction models, making it essential to develop advanced monitoring and diagnostic techniques.

The advancements in PHM systems enable proactive interventions by predicting fuel cell degradation patterns and implementing corrective measures before failure occurs. By leveraging data-driven approaches and AI-based predictive models, PHM can enhance SOH monitoring, optimise maintenance schedules, and extend the operational lifespan of PEMFCs. These innovations improve the economic feasibility of FCEVs, making them a more viable solution for sustainable transportation.

3.5.2. Hybrid Electric Vehicles (HEVs): Balancing Complexity and Affordability

1. High Initial Costs: Integrating advanced powertrains in HEVs increases manufacturing costs. Economies of scale and technological innovations are needed to make these vehicles more affordable for consumers [28].
2. Limited Energy Density of Renewable Sources: The energy density of RESs used in HEVs is relatively low. Advanced energy storage technologies and improvements in energy density are essential to overcome this limitation [28].
3. Refuelling and Recharging Infrastructure: The lack of robust infrastructure to support HEV operations, including alternative fuel stations and rapid charging systems, limits their convenience and market appeal. Developing such infrastructure is costly and requires substantial investment [29,30].

4. Recharging Time for Plug-In HEVs: PHEVs require improved fast charging systems to minimise recharge time. Advances in battery technology, such as developing lightweight, high-capacity lithium-ion batteries, are crucial for addressing this issue [29].

FCEVs and HEVs represent critical steps towards sustainable transport, but addressing these challenges requires coordinated research, technology development, and infrastructure investment efforts. Achieving scalability and cost efficiency will be key to their successful integration into the global automotive market.

4. AI-Driven Innovations in BMSs

A BMS is an integrated hardware and software framework designed to ensure the optimal functioning of a battery system. A typical BMS includes a range of components such as cell voltage balancing mechanisms, fuel gauge monitors, cut-off field-effect transistors, cell voltage monitors, state machines, temperature sensors, and real-time clocks. These components are configured differently across systems, from basic analogue front ends with microcontrollers for monitoring and balancing to fully autonomous, stand-alone solutions [31]. Figure 5 illustrates a cloud-based framework for managing data and control systems in the BMS of EVs. Data from multiple EVs is transmitted to servers, which then interface with a centralised cloud computing system. This system facilitates a range of critical functions, including secure data acquisition, reliable data communication, and the application of AI algorithms for predictive analysis and decision-making. The cloud infrastructure supports advanced control systems and ensures seamless integration with the BMS to optimise performance, enhance reliability, and ensure safety. This decentralised approach enables real-time monitoring and management, paving the way for more efficient and scalable EV operations.

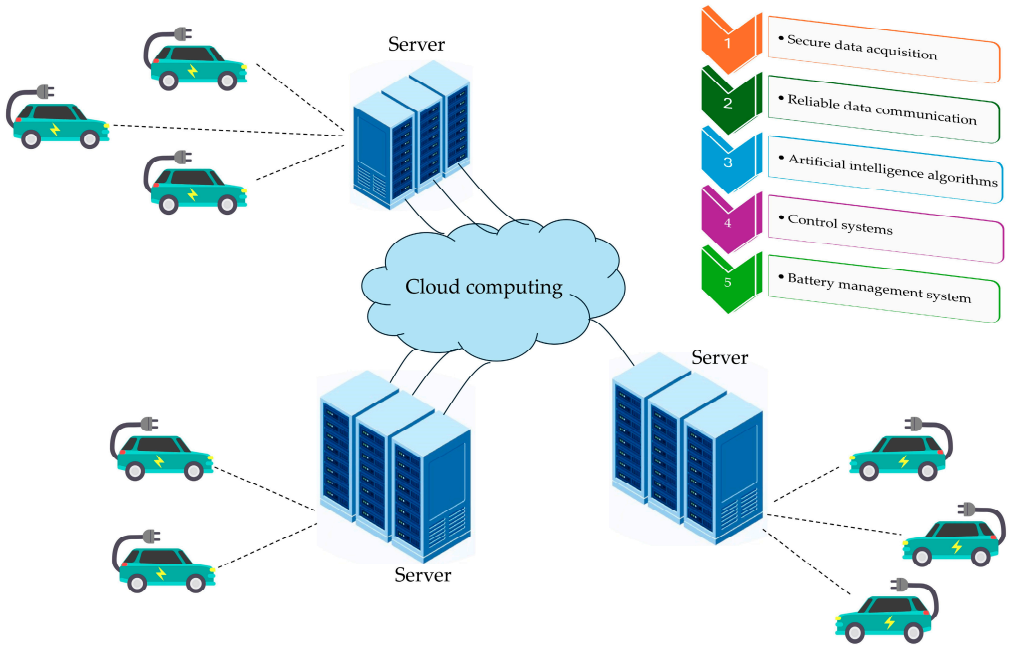


Figure 5. Cloud-based data management and control framework for BMS of EVs in this research.

In EVs, the BMS incorporates sensors, actuators, and controllers to safeguard batteries and maintain operational parameters within safe voltage, current, and temperature ranges. The primary hardware architectures of BMSs are modular, centralised, or distributed. Layered structures for monitoring and managing battery states also have been proposed. Functionalities within BMSs are supported by a network of sensors throughout the battery pack, enabling efficient data collection, real-time processing, and communication with

vehicle control processors [32]. Modern BMS solutions prioritise enhanced safety by integrating additional sensors, allowing for accurate warnings and controls to prevent overcharging, over-discharging, and overheating. Systems rely on sensors to monitor and measure critical battery parameters, including voltage, current, and temperature. However, practical challenges such as space constraints and cost affect the scalability of these measures beyond laboratory settings. Essential components for efficient state tracking include a data modelling, acquisition system (DAQ) and secure data storage [33].

Charge and Cell Management: A subsystem known as the charge controller regulates the charging and discharging process. Cell balancing is crucial for equalising the cells within a battery pack and ensures uniform SOC levels across cells, thereby preventing overcharging or over-discharging. Improved balancing strategies rely on precise SOC calculations for each cell. Additionally, balancing may involve variable resistors to address internal resistance variations. Efficient internal communication within the BMS is critical, typically achieved via a Controller Area Network (CAN) bus. Intelligent batteries with embedded microchips facilitate enhanced communication with users and chargers, often supported by radio or other communication technologies [34].

Thermal Management: Temperature discrepancies within battery packs significantly impact cell reliability and performance, necessitating the inclusion of thermal management modules. Maintaining a uniform and optimal temperature across cells is critical to enhancing battery longevity and performance [34].

Software Functions: The software in a BMS acts as the system's brain, managing equipment functions, interpreting sensor data, and enabling predictive decision-making. Key software capabilities include switching controls, sampling rate monitoring, cell balance management, and dynamic safety circuit configuration. Web-based data analysis enables continuous battery function updates, whilst automated and reliable data analysis supports SOC and SOH estimation and fault detection. A user-friendly interface ensures the information is easily accessible, providing insights on battery life, operational constraints, and recommendations for replacements or repairs. Advanced techniques such as fuzzy systems, artificial neural networks (ANNs), and state-space models are often used for precise state evaluations [35].

Key Functionalities: BMS functionalities can be broadly categorised as follows [36]:

1. Protection: Preventing extreme temperatures, over-discharge, overcurrent, overcharge, and short circuits.
2. High-Voltage Control and Sensing: Monitoring temperature, voltage, current, thermal management, and fault detection.
3. Diagnostics: Estimating the state of life (SOL) and SOH, and detecting potential abuse.
4. Performance Management: Calculating power limits, equalising cells, and SOC estimation.
5. Interface: Enabling data recording, communication, reporting, and range estimation.

Traditional BMSs often rely on fixed control algorithms that remain unchanged throughout the battery's lifespan. However, given the operational lifespan of EV batteries, typically 5–10 years, environmental and operational changes may necessitate adjustments to these algorithms to maintain optimal performance. AI-based strategies, such as ML algorithms, are increasingly popular due to their ability to enhance responsiveness and adaptability [33]. Accurate SOC and SOH calculations are critical for ensuring the BMS communicates effectively with users and protects the battery. These metrics influence decisions to avoid overcharge and over-discharge, mitigating risks such as battery failure or explosion. AI-driven techniques, including NNs and fuzzy logic, are well suited to address these challenges. ML algorithms offer dynamic state estimations, enabling proactive fault detection and system optimisation. These strategies not only improve battery safety and reliability but also extend battery lifespan by adapting to changing conditions over time.

4.1. Advanced Deep Learning Techniques for Battery State Prediction: Artificial Neural Network (ANN)

An ANN consists of interconnected nodes or neurons functioning similarly to the human brain. Structurally, an ANN typically includes input, hidden, and output layers, each containing neurons configured based on system requirements. ANNs demonstrate self-adaptive and self-learning capabilities, enhancing their performance with the Backtracking Search Algorithm (BSA) and Backpropagation Neural Network (BPNN). Based on experimental data, the backpropagation technique is often employed to train ANNs. Recorded data are processed through the input layer, weighted, and summed, after which a sigmoid activation function is applied. The algorithm then adjusts weights iteratively to minimise Mean Squared Error (MSE) [37].

ANNs are highly effective in estimating battery states. For example, the Hybrid Pulse Power Characterisation (HPPC) test identifies battery parameters of a first-order equivalent circuit model, which can then train a multi-layer BPNN. This approach also enables accurate SOH estimation. Choi et al. [38] implemented a multi-layer perceptron (MLP) model using data from 300 lithium (Li-ion) batteries. The model, validated through training and testing datasets, successfully used the predicted capacity information for SOC estimation, achieving high accuracy compared to actual SOC measurements.

4.1.1. BPNN Optimising Accuracy

A BPNN, a type of ANN, employs supervised learning for training. Backpropagation operates by adjusting the weights and biases of an NN to minimise the discrepancy between its predicted outputs and the actual values from a given training dataset. This adjustment process occurs iteratively, progressively allowing the network to reduce errors and improve accuracy with each iteration [39]. BPNNs have demonstrated the ability to predict battery states, such as the SOC and SOH, with high levels of statistical significance, often exceeding 95% accuracy in relevant studies. They also excel in optimising energy usage and ensuring efficient power management in BMSs. By leveraging their capacity to adapt to non-linear battery behaviour, BPNNs play a critical role in enhancing battery safety, extending lifespan, and improving overall performance. Their ability to learn and adapt enables BMSs to predict battery life with acceptable levels of accuracy, anticipate potential failures, and manage charging and discharging processes effectively. These predictive capabilities improve battery safety, extend lifespan, and enhance overall performance. The key advantages of BPNNs include their adaptability to non-linear battery behaviour, capacity to process complex data, and potential for real-time decision-making. However, challenges such as the need for large datasets, susceptibility to overfitting, and difficulty interpreting their "black-box" decision-making process persist. Nonetheless, BPNNs remain a critical technology for optimising BMSs in EVs, driving significant improvements in efficiency and reliability [40]. BPNNs are particularly effective in capturing the complex relationships inherent in battery data, making them well suited for SOC estimation. Additionally, they excel at handling non-linear patterns and adapting to dynamic battery conditions.

Despite these strengths, BPNNs require large volumes of labelled training data, are susceptible to overfitting, and may demand substantial computational resources, limiting their feasibility for real-time applications. Careful data preparation, model fine-tuning, and efficient resource allocation are essential to maximise their benefits in battery management. BPNNs have been employed in a range of BMS applications. Vidal et al. [41] applied BPNNs for SOC estimation of lithium iron, Fe, phosphate (LFP) and lead–acid (LA) batteries, assessing their model across five light vehicle test cycles. They reported RMSE values of 0.33% for LFP and 0.84% for lead acid batteries.

4.1.2. Radial Basis Function Neural Network (RBFNN): Non-Linear Excellence

An RBFNN is an ANN that employs radial basis functions as activation mechanisms. RBFNNs are versatile and have been applied in a range of domains, including pattern recognition, function approximation, and clustering. They have demonstrated considerable effectiveness in SOC estimation for BMSs. For instance, Wu et al. [24] introduced an enhanced RBFNN-based approach for estimating the SOH of lithium-ion batteries, achieving a maximum estimation error of $\pm 4\%$.

Despite their advantages, RBFNNs require careful parameter optimisation to ensure optimal performance, particularly in determining the placement of the radial basis functions. This can make their setup process more demanding. Nonetheless, their capacity to detect complex patterns and non-linear relationships in battery data makes them a valuable tool in NN research and ML. In the context of BMSs for EVs, RBFNNs are highly effective at capturing non-linear dependencies within battery data, enabling more precise state estimation and improved system performance. These outcomes extend battery lifespan through better charge management, enhancing safety by predicting faults or anomalies and optimising energy utilisation [42].

4.1.3. Extreme Learning Machines (ELMs): Fast and Scalable Solutions

ELMs are a type of ML algorithm designed for supervised learning tasks, particularly within NNs. Introduced as an alternative to gradient-based training methods, ELMs focus on reducing the computational complexity associated with training NNs, particularly in terms of training time. Unlike traditional networks such as Feedforward Neural Networks (FNNs) or BPNNs, where both input-to-hidden and hidden-to-output connections require training, ELMs adopt a distinctive approach by randomising the input-to-hidden layer weights and biases. These parameters are assigned randomly and remain fixed, eliminating the need for iterative updates in this layer.

The hidden-to-output layer weights, on the other hand, are determined analytically through a single-step computation, often by solving a least-squares optimisation problem. This method significantly reduces training time while maintaining competitive performance compared to traditional methods. By decoupling the training process for the two layers, ELMs avoid challenges such as slow convergence, vanishing gradients, and the need for extensive hyperparameter tuning, which are common in gradient-based methods. This distinctive approach not only accelerates the training process but also simplifies implementation, making ELMs particularly well suited for applications requiring rapid predictions with large datasets [43]. Their scalability, high training speed, and robust generalisation make them particularly useful in BMS applications. For example, Li et al. [44] developed a cloud-based BMS using an ELM combined with data preprocessing, yielding errors of 3% for the SOC and 2% for the terminal voltage. ELMs are instrumental in swiftly predicting battery states, optimising charging and discharging strategies, and improving energy management in EVs. Their benefits include high training speed, minimal parameter tuning, and resistance to overfitting, making them efficient for processing large datasets. However, ELMs' reliance on randomly generated hidden layer parameters can reduce interpretability and create challenges in fine-tuning performance. Despite these limitations, ELMs remain essential for advancing BMSs in EVs, enhancing reliability, performance, and energy efficiency [45].

4.1.4. Random Forest (RF): A Robust Tool for Predictive BMS

RF is a widely used ML algorithm that excels in both classification and regression tasks. It operates by constructing multiple decision trees during training and combining their outputs—taking the majority vote for classification or averaging predictions for regression.

In BMS applications, RF offers significant advantages due to its versatility and robust performance across various tasks. RF models have demonstrated impressive accuracy in predicting key battery performance metrics. For example, RF has been used to predict the SOH and RUL of lithium-ion (Li-ion) batteries, achieving a mean error of 1.8152%, as reported by Wang et al. [46], outperforming traditional models specifically designed for Li-ion batteries. Additionally, RF has been applied to SOC estimation for different Li-ion battery chemistries. RF is also robust against overfitting due to its ensemble approach and requires minimal hyperparameter tuning, making it an efficient tool for diverse tasks. These tasks include predicting battery performance metrics, facilitating efficient charge and discharge control, and aiding in fault detection. However, the computational complexity of RF models can pose challenges in real-time applications with strict response time requirements [47].

4.1.5. Recurrent Neural Network (RNN): Capturing Time-Series Dynamics

RNNs are a type of ANN designed to process sequential data by maintaining an internal state or memory. Unlike traditional feedforward networks, where information flows only from input to output, RNNs feature cyclic connections that allow them to model dynamic temporal behaviours. The application of RNNs in BMSs has gained traction in recent years due to their ability to process time-series data, making them invaluable for analysing and improving battery performance. By capturing temporal dependencies and sequential patterns, RNNs are particularly useful for understanding battery degradation over time [48]. For example, Tao et al. [49] used an RNN model for SOC estimation in EVs, highlighting its accuracy, robustness against measurement uncertainties, and adaptability to battery ageing cycles. These features make RNNs more efficient than alternative models. The advantages of RNNs include their ability to handle sequential data effectively, learn temporal dependencies, and perform well in time-series prediction tasks. However, the challenges include susceptibility to vanishing or exploding gradient problems, which can impede learning over long sequences, and the need for substantial computational resources when working with deep architectures or large datasets. Despite these challenges, RNNs remain pivotal in advancing BMSs for EVs, contributing to improved efficiency, safety, and sustainability [50].

4.1.6. Gaussian Process Regression (GPR): Precision Through Probabilistic Modelling

GPR is a non-parametric, probabilistic technique commonly used for regression tasks in ML and statistics. Its strength lies in its ability to model complex, non-linear relationships between inputs and outputs flexibly. In BMSs, GPR has proven invaluable for forecasting battery behaviour, enhancing performance, and managing uncertainty in real-world conditions. Its applications extend from EVs to renewable energy storage, where precise predictions of battery degradation and remaining lifespan are critical for operational efficiency. For instance, Meng et al. [51] proposed a GPR-based end-of-life (EOL) prediction model. They observed that GPR offered greater accuracy and narrower uncertainty margins than other models. Similarly, Li et al. [52] used GPR with electrochemical impedance spectroscopy (EIS) data and charging cycle counts to predict the SOH, achieving improved accuracy when adding these features to the model. GPR contributes significantly to improving battery health monitoring and resource management. However, GPR requires access to the full training dataset during predictions, leading to higher computational demands for large datasets and challenges in scaling to high-dimensional data. Despite these limitations, GPR remains a versatile and powerful tool for optimising EVs' BMSs [53].

4.1.7. Support Vector Machines (SVMs): A Reliable Workhorse for Classification and Regression

SVMs are supervised learning algorithms primarily used for classification and regression tasks. In classification scenarios, SVMs identify an optimal decision boundary to separate data into distinct categories, while in regression, they estimate continuous outcomes. In BMS applications, SVMs offer several advantages, including high accuracy, robustness against noise and outliers, and adaptability to high-dimensional data. However, it also has drawbacks, such as sensitivity to parameter tuning, computational complexity, and difficulty handling unbalanced datasets. For example, Patil et al. [54] applied a multistage SVM approach to predict the RUL, demonstrating faster computations suitable for real-time scenarios. SVMs aid in modelling battery behaviour, predicting states, and detecting faults effectively. Its benefits include efficient handling of high-dimensional data, robustness against overfitting, and flexibility in using various kernel functions to capture non-linear relationships. However, its computational intensity, reliance on appropriate kernel selection, and parameter sensitivity can pose challenges. Despite these challenges, SVMs remain a critical tool in optimising BMSs for EVs, significantly improving battery management and performance [55].

4.1.8. Reinforcement Learning (RL): Adaptive and Dynamic Decision-Making

RL is an ML paradigm in which an agent learns to make decisions by interacting with an environment and maximising cumulative rewards. Inspired by the trial-and-error learning seen in humans and animals, RL dynamically adapts to optimise outcomes in real time. RL has shown great potential in BMSs by enabling adaptive and dynamic control strategies. For example, Heba et al. [56] reviewed RL-based EV charging systems, highlighting their advantages over traditional methods like BPNNs and RBFNNs, which require extensive training data and may struggle with real-time feasibility. Chaoui [57] proposed an RL-based framework for resource allocation, achieving SOC equalisation and extending battery life. Minho et al. [58] developed an RL-based SOC estimation model, demonstrating improved training accuracy with large datasets and validating the approach using charge–discharge simulation data. RL optimises charging and discharging strategies by adapting to dynamic conditions, enhancing energy efficiency, and prolonging battery life. Its advantages include learning directly from interactions with the environment, adapting to changing conditions, and optimising strategies without requiring labelled data. However, challenges include the need for significant training data, high computational demands, and careful design of reward mechanisms. Despite these hurdles, RL holds significant promise in revolutionising BMSs for EVs, contributing to improved energy management, safety, and operational efficiency.

In summary, Figure 6 provides a comparative analysis of error rates (RMSE, AAE, and MAE) across eight ML models applied to BMSs. Among these, the RBFNN exhibited the lowest RMSE of 0.34% [59], indicating its superior accuracy in tasks such as SOC and SOH estimation. The BPNN also demonstrated strong performance with an RMSE of 0.78% [47], while RF achieved an RMSE of 0.382% [60], accompanied by a low MAE of 0.193%, reflecting its robust precision in real-world scenarios. On the other hand, the ELM and GPR showed moderate error rates, with RMSE values of 2.5% [46] and 3.9% [60], respectively, indicating their capability to handle non-linear battery data effectively. However, the RNN recorded the highest RMSE at 6.0% [61], highlighting potential challenges in processing sequential data, particularly under dynamic battery conditions. The SVM and RL achieved RMSE values of 2.0% [62] and 1.5% [57], respectively, showcasing their balanced trade-offs between accuracy and computational feasibility. The additional metrics, such as the AAE of 0.23% [59] for the RBFNN and the MAE of 0.0204% [63] for GPR, further highlight these

models' precision in specific applications. These results suggest that the RBFNN and RF excel in accuracy for SOC and SOH predictions, while the ELM and SVM offer scalable solutions for tasks with moderate precision requirements. In contrast, RNNs, despite their ability to process temporal data, may require further optimisation to reduce errors in dynamic scenarios.

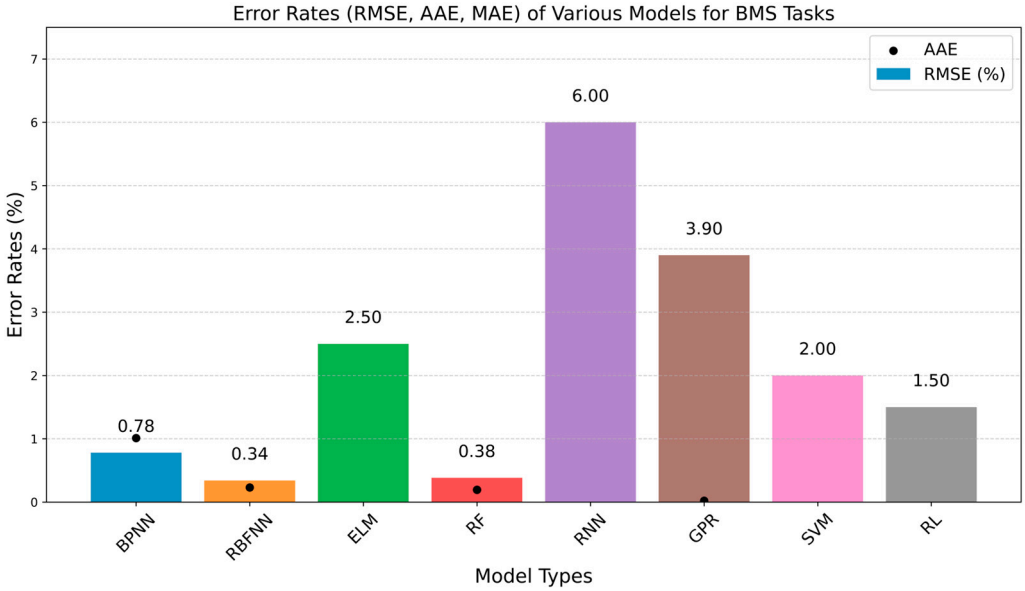


Figure 6. Error rate comparison of ML models for BMS in this research.

4.2. Deep Neural Network (DNN): Unlocking Advanced Battery Insights

A DNN is an advanced type of ANN consisting of multiple interconnected layers of nodes, typically structured with an input layer, one or more hidden layers, and an output layer. Chemali et al. [41] utilised a DNN to estimate SOC across various EV drive cycles and temperature conditions, achieving an MAE of 1.10% at 25 °C after validating results on several datasets. Lipu et al. [64] provided a detailed review of DNNs' applications in BMSs, illustrating how DNNs effectively estimate the SOC, SOH, and RUL with high precision, thereby enhancing battery safety, reliability, and lifespan. However, the performance of DNN models heavily relies on the availability of extensive datasets. Zafar et al. [65] developed a three-layer DNN model to estimate the SOC in lithium-ion batteries, leveraging a large dataset that covered real-world EV batteries under varying temperature conditions. The experimental results demonstrated an MSE and RMSE of 0.1% and 0.3%, respectively. While DNNs are highly versatile for various BMS applications, they face challenges such as overfitting, difficulty in model optimisation, and the lack of interpretability in safety-critical scenarios. A DNN in BMSs enhances resource management efficiency, improves safety by detecting anomalies or failures, and accurately predicts battery degradation. Key advantages include learning complex data patterns, efficiently processing large datasets, and reducing the need for manual feature engineering. However, challenges such as high computational demands, overfitting risks with intricate architectures, and dependency on large amounts of data remain significant. Despite these limitations, DNNs are pivotal in advancing BMSs for EVs, significantly improving performance, reliability, and battery health management [37].

4.2.1. Long Short-Term Memory (LSTM): Capturing Temporal Dynamics

LSTM is an advanced RNN architecture designed to overcome the vanishing and exploding gradient problems associated with standard RNNs. LSTM excels at processing

sequential data, making it particularly well suited for time-series analysis, including tasks related to BMSs. LSTMs are highly effective for SOC estimation, fault detection, and optimisation in BMSs due to their ability to model long-term dependencies in battery data. For example, Basnet and Ali [66] applied LSTM to cybersecurity for EV charging stations on the 5G platform, achieving nearly 100% detection accuracy for cyberattacks. Applying LSTMs in BMSs enhances accuracy in forecasting battery health, improves resource management efficiency, and captures long-term dependencies necessary for understanding battery behaviour. Their strengths include effectively handling sequential data, mitigating gradient issues, and adapting to variable-length sequences. However, LSTMs also have limitations, including increased computational complexity, difficulty interpreting the learned representations, and high data requirements for training. Despite these challenges, LSTMs are vital in optimising BMSs for EVs, contributing to enhanced reliability, performance, and safety [67].

4.2.2. Gated Recurrent Units (GRUs): Efficient Sequential Modelling

GRUs are a variant of RNNs designed to efficiently model dependencies in sequential data. They serve as a computationally simpler alternative to LSTMs while delivering similar performance in capturing long-range dependencies. GRUs have been applied to various BMS tasks. For example, Zhang et al. [68] proposed an SOH model using GRUs with an enhanced learning rate optimised by a sparrow search algorithm. This approach was tested for both single batteries and battery packs, demonstrating strong adaptability and performance. However, while efficient, GRUs may struggle to capture the intricate non-linear dynamics of battery behaviour fully. Similar to other RNN architectures, GRUs require large amounts of labelled data, which can be a limitation in data-scarce contexts. Additionally, their abstract nature can hinder interpretability in safety-critical applications where understanding model decisions is vital. GRUs contribute to modelling temporal dependencies in battery data, enabling precise predictions of battery states, optimising charging/discharging strategies, and improving fault detection. Despite these obstacles, GRUs are an efficient and valuable tool in advancing BMSs for EVs, significantly improving battery reliability, performance, and health management [64].

4.2.3. Convolutional Neural Network (CNN): Extracting Spatial Features in BMSs

CNNs are DL models specifically designed to process structured grid-like data, such as images and videos. While primarily associated with computer vision tasks, CNNs have also demonstrated potential in natural language processing and speech recognition. Their ability to automatically extract spatial features makes them adaptable to a range of applications. Although CNNs are not traditionally linked with BMS, they have shown promise in tasks such as SOC and SOH estimation, as well as regulating temperature conditions in EV batteries. The performance of CNNs in BMSs depends on factors like data quality, the network architecture, and the system's specific requirements. CNNs face challenges in BMS applications, including their high computational demands, especially for larger and more complex architectures, and their limited interpretability due to their hierarchical structure. Despite these limitations, CNNs remain a powerful and promising tool for optimising BMSs in EVs, contributing to improved battery health monitoring, resource management, and overall system performance [69].

4.2.4. Alternative AI Approaches: Expanding the Scope of BMS

Neuro-Fuzzy Logic (NFL) Systems—Bridging Logic and Learning: NFL alone is often inadequate for estimating the SOC and SOH of battery packs. Traditionally, research in adaptive battery control focused on either NNs or fuzzy logic. However, recent studies increasingly integrate these two approaches to leverage their combined strengths. NNs

complement fuzzy logic by providing dynamic solutions to BMS challenges, reducing reliance on static models and experimental data. The neuro-fuzzy logic approach uses input–output training data to refine fuzzy system parameters [70].

Expert Systems (ESs)—Rule-Based Intelligence: ESs consist of a feature data repository, a knowledge base, reasoning and explanation mechanisms, a knowledge acquisition module, and a user interface. ES is particularly useful in managing fault symptom information, which is processed into a unified format for fault analysis. For example, ESs guide state estimation and security analysis in energy management systems by incorporating real-time or operator-initiated execution commands. State estimation, an integral part of ESs, identifies and eliminates erroneous data while providing accurate measurements across transmission networks. This ensures actionable insights from analogue measurement data, which would otherwise overwhelm operators in raw form. ESs thus improve data reliability and support operators in making informed decisions [71].

Support Vector Machines (SVMs): SVMs have been widely applied in SOC estimation. For example, voltage and current were used as inputs for SOC calculation, while subsequent studies incorporated temperature alongside these variables to train SVM models for SOC estimation. SVMs offer advantages over CNNs, including superior generalisation and avoidance of local minimisation issues due to their reliance on solving quadratic programming problems for global optimisation. In battery management, a two-step approach involves SVM training followed by virtual testing to calculate SOH metrics such as capacity and resistance. For instance, SVM models were trained using current, temperature, and SOC as inputs and voltage as the output, serving as look-up tables for predicting battery performance. The virtual test results mimic standard performance testing, enabling resistance and capacity estimation with high precision [72].

Evolutionary Algorithms (EAs)—Nature-Inspired Problem Solvers: EAs are recommended for addressing emerging BMS challenges. For instance, multigene genetic programming has been used to model lithium-ion battery capacity at the nanoscale. In contrast, the non-dominated sorting Genetic Algorithm II (NSGA-II) has optimised battery pack enclosure designs, demonstrating improved performance. When integrated with other AI systems, NSGA-II further enhances results, showcasing EAs' effectiveness in EV systems for monitoring performance and ensuring safety. EAs are preferred for their ability to solve non-convex optimisation problems with multiple local optima and their flexibility in handling multi-objective tasks. Typical EA processes involve iterative population-based operations, including reproduction, fitness evaluation, and selection, until stopping criteria are met. EAs thus offer robust solutions for complex optimisation in BMS applications [73].

Hybrid Intelligent Systems (HISs): HISs combine AI techniques to optimise energy and time management for EVs and PHEVs. These systems guide drivers in selecting energy-efficient routes and driving profiles, reducing energy consumption and travel time. Using clustering methods, hybrid models categorise datasets into groups with similar characteristics, enabling tailored regression models for each cluster. This structure improves overall model performance, with the number of clusters determined through topology evaluation. For example, k-means clustering is often used in the grouping phase, followed by regression modelling with an ANN due to its ability to predict non-linear system outputs. Although HIS models integrate multiple AI methods, they consistently outperform traditional regression approaches. By leveraging clustering and intelligent regression techniques, HIS enhances predictive accuracy in battery management, offering superior results in performance and efficiency [50].

In summary, Figure 7 provides a comparative analysis of the performance metrics of various AI approaches used in BMSs, focusing on two key metrics: RMSE and efficiency improvements (%). Among the AI approaches, LSTM achieves the lowest RMSE of 0.50% [74],

demonstrating its exceptional accuracy in modelling and prediction tasks. Similarly, GRU performs well, with an RMSE of 0.70% [75], reflecting its ability to handle sequential dependencies in data effectively. In contrast, CNN records a higher RMSE of 2.33% [76], suggesting potential limitations in handling temporal data compared to recurrent-based methods such as LSTM and GRU. SVM demonstrates moderate accuracy with an RMSE of 1.00% [72], showcasing its capability to generalise well across specific use cases. In terms of efficiency improvements, the orange bars reveal that HISs deliver the highest improvement of 15%, making them the most effective for optimising energy usage and extending battery lifespan. EAs follow closely, achieving a notable efficiency improvement of 12% [73], highlighting their adaptability in solving complex optimisation problems. LSTM and GRUs provide moderate efficiency improvements of 10% and 8%, respectively, while the CNN, NFL, and SVM achieve relatively lower improvements ranging from 5% to 7% [76].

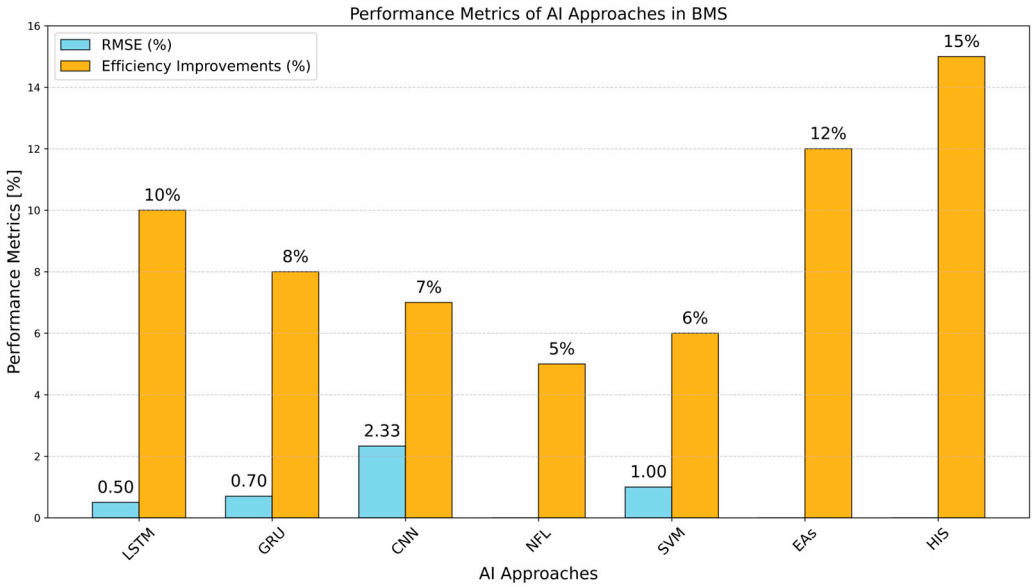


Figure 7. Comparison of performance metrics of AI approaches in BMSs in this research.

4.3. Optimisation Algorithms: Driving Efficiency in Battery Management

4.3.1. Genetic Algorithm (GA): Optimising Battery Performance Through Evolutionary Strategies

GAs are optimisation techniques inspired by natural selection and genetics principles. As a subset of EAs, GAs use mechanisms along with selection, crossover, mutation, and survival of the fittest to solve complex optimisation and search problems. GAs have been widely applied in BMSs for optimisation, state estimation, and control tasks. Ma et al. [49] proposed a GA-optimised BPNN model for SOC estimation in lithium-ion batteries, reducing the errors caused by the Kalman filter's linearisation process. The model achieved high accuracy, with a maximum error of 0.0121 under the dynamic stress test (DST) drive cycle. However, challenges include high computational demands, parameter tuning sensitivity, and premature convergence risk. Addressing these limitations requires careful algorithm design and parameter selection. Using GAs in BMSs improves battery resource management, prolongs battery lifespan, and enables effective exploration of large solution spaces. Their flexibility and robustness make them valuable for solving non-linear and multi-objective optimisation problems. Nonetheless, computational intensity and sensitivity to initial parameter settings remain hurdles for broader applications [15].

4.3.2. Particle Swarm Optimisation (PSO): Collective Intelligence for Energy Management

PSO is a metaheuristic inspired by the social behaviours of flocks of birds or schools of fish. It operates by simulating the movement and interaction of particles within a multi-dimensional search space to find optimal solutions. PSO has been extensively used in BMS applications. For instance, Li et al. [77] employed PSO to enhance SOC and SOH estimation in lithium-ion batteries, integrating it with SVM's kernel functions to achieve flexible and accurate results under the DST cycle. Lipu et al. [78] introduced a PSO-optimised Non-Linear Autoregressive with Exogenous Inputs (NARX) model for SOC estimation under varying EV drive cycles and temperatures. The model demonstrated significant improvements in accuracy, reducing the RMSE and MAE by 53% and 50%, respectively, compared to the standalone NARX algorithm. Despite its advantages, PSO faces challenges such as sensitivity to noisy data, potential convergence to suboptimal solutions, and reliance on parameter tuning. Effective handling of these issues requires robust noise filtering and diversity maintenance during optimisation. PSO's key strengths lie in its simplicity, ability to navigate high-dimensional spaces, and effectiveness in solving non-linear optimisation problems. However, careful design is required to avoid premature convergence and ensure robust handling of complex optimisation landscapes [64].

4.3.3. Lightning Search Algorithm (LSA): Rapid Optimisation for Dynamic Battery Control

The LSA is a metaheuristic inspired by natural lightning phenomena. It is designed to quickly converge to optimal or near-optimal solutions, making it suitable for time-sensitive optimisation tasks. Hannan et al. [79] proposed an LSA-based SOC estimation model for lithium-ion batteries, demonstrating superior accuracy, flexibility, and resilience under diverse operating conditions compared to state-of-the-art methods. While the LSA performs well across various optimisation tasks and high-dimensional search spaces, it faces limitations in solving complex, multimodal problems. Additionally, its balance between exploration and exploitation may require refinement for specific applications. The LSA contributes to BMSs by efficiently navigating search spaces and providing rapid optimisation solutions. Its advantages include quick convergence and consistent performance, but challenges related to complex problem-solving and parameter tuning persist.

4.3.4. Whale Optimisation Algorithm (WOA): Cooperative Strategies for Battery System Optimisation

Humpback whales' social hunting behaviours inspire the WOA, designed to solve many optimisation problems with simplicity and adaptability. Wu et al. [80] applied the WOA for SOC estimation, optimising battery parameters to enhance prediction accuracy. The WOA is known for its robust exploration and exploitation balance, which reduces the likelihood of becoming trapped in local optima. It also features a low number of control parameters, simplifying implementation. However, the WOA's performance can be sensitive to parameter settings and may be outperformed by more sophisticated algorithms for high-dimensional problems. Additionally, its convergence speed can be slower in some scenarios. Despite these limitations, the WOA offers a flexible and efficient approach for BMS applications, contributing to better resource management and enhanced battery health.

4.3.5. Rules-Based Approaches: Structured Logic for Reliable Battery Management

Fuzzy Neural Network (FNN): A FNN is a hybrid model combining fuzzy logic and ANNs. It leverages fuzzy logic's interpretability with NNs' learning capabilities to address problems involving uncertainty, imprecision, and incomplete data [81]. However, its complexity can lead to significant computational requirements during training and inference. Additionally, tuning fuzzy membership functions and network parameters is challenging, potentially reducing interpretability in highly complex models. Zahid

et al. [81] proposed a SOC estimation model based on a subtractive clustering neuro-fuzzy system. Using 10 EV drive cycles, the model outperformed traditional methods like BPNNs and ELMs in accuracy, with inputs including temperature, power loss, and battery thermal factors. FNNs are particularly effective for addressing uncertainty in BMSs while maintaining adaptability and reliability.

Fuzzy C-Means (FCM): FCM is a clustering algorithm that extends traditional k-means by allowing data points to belong to multiple clusters with varying degrees of membership. Hu et al. [82] developed a GA-enhanced FCM model for clustering, integrated with recursive least squares to estimate parameters and backpropagation learning for optimisation. The proposed method demonstrated improved accuracy and robustness compared to traditional fuzzy modelling techniques. FCM is beneficial for handling fuzzy or uncertain data in BMSs, offering improved flexibility and interpretability. However, challenges such as computational complexity and parameter tuning may arise, requiring careful design and integration with other methods.

In summary, Figure 8 compares convergence speed and computational complexity levels for various optimisation algorithms used in BMSs. The LSA achieves the highest convergence speed with a score of 5 [79], indicating its ability to converge to optimal or near-optimal solutions quickly. However, it also exhibits the highest complexity level of 5, highlighting the significant computational demands associated with this approach, particularly for high-dimensional optimisation problems. The GA and PSO show balanced performance, with convergence speeds of 3 [49] and 4 [77], respectively, and complexity levels of 4 and 3. PSO, in particular, offers a good balance between speed and complexity, making it a viable choice for tasks with moderate computational resources and time constraints. The WOA demonstrates a convergence speed of 3 and a complexity level of 3 [80], suggesting moderate performance in both metrics. Its balance between speed and complexity makes it suitable for less time-sensitive tasks or scenarios with limited computational capacity. The FNN [81] and FCM [82] algorithms exhibit slower convergence speeds 2, indicating a more gradual optimisation process. Nevertheless, these methods have relatively high complexity levels of 5 and 4, respectively, due to their intricate computations and the need for significant tuning parameters. These algorithms are more appropriate for tasks requiring detailed modelling and precision, albeit at the cost of computational efficiency.

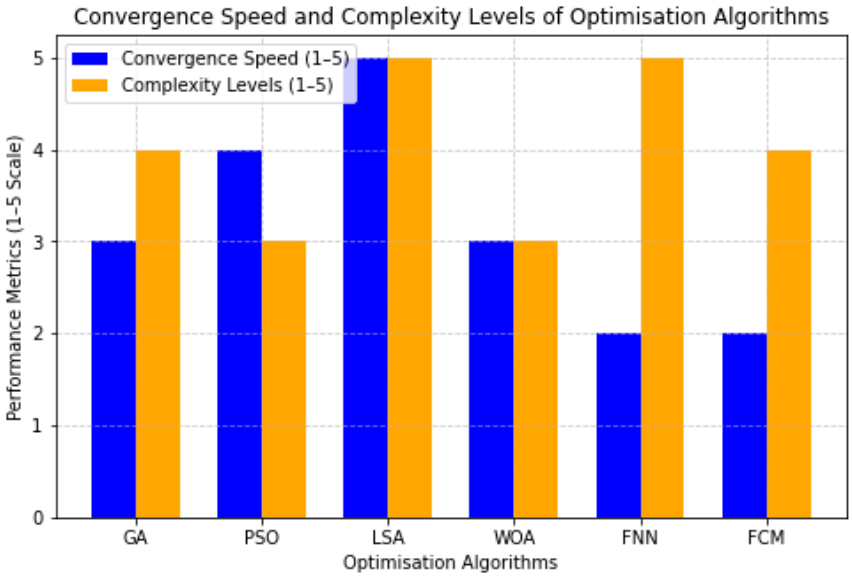


Figure 8. In this research, a comparison of convergence speed and computational complexity for various optimisation algorithms in BMSs is made.

4.4. SOH and SOC Estimation Approaches

Accurate SOH and SOC estimation are critical for optimising BMSs in EVs. While AI-driven approaches, such as ML, DL, and NNs, have demonstrated superior adaptability and predictive capabilities, traditional experimental measurement approaches remain fundamental for real-time and high-precision estimations.

4.4.1. Experimental Measurement-Based SOH and SOC Estimation

Several experimental techniques are commonly used for SOH and SOC estimation:

- Coulomb Counting Method: This approach calculates the SOC by integrating the charge and discharge currents over time. While it is simple and widely used, it accumulates errors over time due to current sensor inaccuracies [83].
- Open-Circuit Voltage (OCV) Method: The SOC is estimated based on the battery's voltage when no load is applied. Although accurate under stable conditions, this method requires long relaxation times, making it impractical for real-time applications [84].
- Electrochemical Impedance Spectroscopy (EIS): This technique analyses battery impedance at different frequencies to infer the SOH and SOC. It provides valuable insights into battery degradation but requires specialised equipment and is computationally intensive [84].
- Non-Destructive Ultrasonic Reflection Wave Technique: This method is emerging for joint SOC and temperature estimation. Ultrasonic waves are transmitted through the battery, and their reflections are analysed to determine the SOC and internal temperature. This approach enhances safety by detecting thermal runaway risks early. Compared to AI-based methods, ultrasonic techniques offer high accuracy, real-time response, and early fault detection without requiring extensive historical training data. However, practical implementation challenges, such as sensor placement and signal processing complexity, still need further development [85].

4.4.2. Comparison: AI-Driven vs. Experimental Methods

While AI-based methods offer superior adaptability and predictive maintenance capabilities, experimental approaches—especially non-destructive ultrasonic techniques—are promising for real-time safety monitoring, thermal runaway prevention, and enhanced SOC/SOH accuracy, as shown in Table 1. Integrating AI models with experimental validation, a hybrid approach could offer the best balance between accuracy, real-time application, and long-term reliability in next-generation BMSs.

Table 1. Comparison of experimental measurement and AI-driven approaches for battery state estimation across key performance metrics.

Aspect	Experimental Measurement Approaches	AI-Driven Approaches	References
Accuracy	High (for controlled conditions)	High (adaptive to real-world conditions)	[86]
Real-Time Capability	Limited (OCV needs relaxation time, EIS requires processing)	High (fast prediction based on training data)	[87]
Adaptability	Low (fixed equations and assumptions)	High (self-learning, adapting to new conditions)	[88]
Data Requirement	Low (real-time sensor readings)	High (large datasets required for training)	[89]
Computational Demand	Moderate to High (depending on method)	High (complex neural networks and models)	[90]
Predictive Capability	Limited (reactive, relies on direct measurements)	Strong (can predict degradation and failures in advance)	[91]
Safety Enhancement	High (ultrasonic methods detect thermal risks)	Moderate (depends on data quality and model accuracy)	[92]

4.5. Trends and Future Challenges in AI for BMSs

The increasing adoption of advanced ML models, edge computing, and digital twin technologies characterises the evolution of AI in BMSs. Edge AI is emerging as a transformative trend, enabling local real-time processing of battery data, which reduces latency and dependence on cloud infrastructure. Digital twins of battery systems also are gaining traction, allowing for precise simulations of battery behaviour under different scenarios, which aids the development of more robust and efficient BMSs. In addition, AI algorithms are being refined to handle the complexities of next-generation batteries, including solid-state and lithium–sulphur chemistries. These new technologies require sophisticated models to improve prediction accuracy by accommodating their unique behaviours, including energy density, thermal stability, and lifecycle characteristics [23].

Despite these advancements, challenges persist. The scalability of AI solutions for diverse EV models and operating conditions remains a significant barrier. Furthermore, developing comprehensive datasets that adequately represent real-world conditions is resource-intensive, and the proprietary nature of battery technologies often limits data availability. The increasing complexity of AI models also raises concerns about interpretability and transparency, particularly when these systems are deployed in safety-critical applications. Cybersecurity is an additional area of concern. As AI-powered BMSs become integral to EV operations, they are increasingly vulnerable to cyber threats, necessitating robust security protocols to protect both vehicle performance and user data.

4.6. Advantages and Shortcomings of AI Technologies in BMSs for EVs

Advantages

1. Enhanced Precision: AI algorithms improve the accuracy of state estimations (e.g., SOC, SOH), enabling better decision-making and optimised battery usage.
2. Predictive Maintenance: AI-powered fault detection systems can identify potential failures early, reducing downtime and maintenance costs.
3. Energy Efficiency: AI-driven optimisation techniques, such as RL and DL, enhance battery performance, extend lifespan, and reduce energy waste.
4. Scalability for Fleets: AI enables efficient energy management across connected EV fleets, balancing grid demands and promoting renewable energy integration.
5. Real-Time Adaptation: AI models can adjust to dynamic operational conditions, ensuring robust performance under varying scenarios.

Shortcomings

1. Data Dependency: AI models require large, high-quality datasets for training and validation, which can be difficult and expensive.
2. Model Complexity: Sophisticated algorithms often lack interpretability, challenging verifying their decisions in safety-critical contexts.
3. Scalability Issues: Current AI solutions may struggle to adapt to diverse battery chemistries, EV models, and real-world conditions.
4. Cybersecurity Risks: AI-driven BMSs are vulnerable to cyberattacks, which could compromise battery safety and vehicle operation.

4.7. Shortcomings and Challenges of Applying AI in BMSs for EVs

The application of AI in BMSs is not without challenges, particularly regarding ensuring robustness, scalability, and safety.

1. Data Limitations: The development of effective AI models relies on comprehensive datasets that capture the diverse operating conditions of EV batteries. However, ob-

taining such datasets is both time-consuming and costly. Additionally, the proprietary nature of many battery technologies restricts access to critical data.

2. Model Generalisability: AI models are often optimised for specific battery chemistries or vehicle types, limiting their ability to generalise across different systems. This hinders their scalability and widespread adoption.
3. Complexity and Interpretability: Advanced AI algorithms, while powerful, are often perceived as "black boxes," making it difficult for developers and end-users to understand or trust their decision-making processes. This lack of transparency is a significant concern in applications where safety is paramount.
4. Computational Demands: AI-powered BMSs require substantial computational resources, particularly for real-time monitoring and optimisation, which may increase hardware costs and energy consumption.
5. Cybersecurity Vulnerabilities: As BMSs become more reliant on AI and interconnected systems, they face heightened risks of cyberattacks. Ensuring robust security measures is critical to safeguarding the integrity and functionality of these systems.
6. Regulatory and Standardisation Barriers: The lack of unified standards for AI integration in BMSs complicates development and deployment efforts, particularly across different regions and manufacturers.

Addressing these challenges will require interdisciplinary collaboration between academia, industry, and regulatory bodies. Future efforts should prioritise the development of interpretable, secure, and energy-efficient AI models while ensuring their scalability and applicability across diverse battery technologies and operating conditions.

4.8. Limitations of AI Integration in On-Board Vehicle Systems

While AI has demonstrated significant potential in enhancing BEM and vehicle control, integrating AI models directly into on-board vehicle systems presents several challenges. The effectiveness of AI-driven solutions depends on their ability to process real-time data, optimise decision-making, and operate under resource-constrained conditions. However, several limitations hinder the seamless deployment of AI on board:

1. Computational Constraints and Energy Overhead: Most AI algorithms require substantial computational power, particularly DL, NNs, and RL. On-board vehicle processors have limited hardware resources, and real-time AI operations can significantly increase power consumption, reducing overall energy efficiency. Unlike cloud-based AI, which can leverage high-performance GPUs and distributed computing, on-board AI must operate with energy-efficient embedded processors [88].
2. Real-Time Processing and Latency Issues: AI-driven state estimation (SOC, SOH) and energy optimisation require continuous real-time data processing from vehicle sensors, BMSs, and powertrain components. However, latency issues arise when large-scale data streams need to be processed locally. Complex AI models may struggle to meet the strict timing requirements for instantaneous decision-making, particularly in dynamic driving conditions.
3. Data Dependency and Model Generalisation: AI models require high-quality training data to perform accurately. However, real-world driving conditions vary significantly, introducing unpredictable factors that AI may not have encountered during training. This lack of generalisation capability leads to potential errors in battery performance prediction, energy distribution, and fault diagnosis. Additionally, obtaining diverse, high-resolution datasets for continuous model refinement remains challenging [84].
4. Cybersecurity and Data Privacy Risks: AI models in EVs rely on extensive vehicle-to-infrastructure (V2I) and V2G communication, increasing cybersecurity vulnerabilities. Unsecured AI decision-making could be manipulated by adversarial attacks, lead-

ing to incorrect battery state predictions, compromised control systems, or energy inefficiencies. Moreover, exchanging sensitive vehicle data raises privacy concerns, requiring robust encryption and secure AI frameworks [79].

5. Hardware Cost and Scalability Challenges: Deploying advanced AI processors and embedded computing units in EVs increases manufacturing costs, limiting their accessibility for mid-range and budget EV models. Scaling AI across multiple vehicle architectures remains challenging, particularly as hardware capabilities differ across brands and models [79].

4.9. The Role of Cloud-Based AI and Distributed Computing

To overcome these limitations, a distributed AI architecture leveraging cloud computing and edge AI is emerging as a viable solution. Instead of executing complex AI models directly on board, cloud-based AI enables the following:

High-performance computing—Offloads AI tasks to powerful cloud servers, reducing computational strain on vehicles [92].

Seamless AI updates and scalability—AI models can continuously update and adapt to new driving data across multiple EVs.

Optimised real-time processing—Edge AI systems can handle low-latency tasks locally, while cloud AI manages high-complexity learning models.

Infrastructure Requirements for Cloud-Based AI in EVs: The success of distributed AI integration in EVs depends on the following:

- High-speed connectivity (5G, IoT-based networks) to enable real-time AI processing with minimal delay.
- Advanced encryption and AI-driven cybersecurity to protect sensitive vehicle data from cyber threats.
- Standardised cloud AI platforms to ensure interoperability across different EV manufacturers and battery technologies [79].

5. Challenges in Battery Management and System Control for EVs

Figure 4 highlights the major challenges in battery management and system control for EVs. These challenges are categorised into three key areas. Firstly, the Battery Degradation and State Estimation Complexity Section includes issues such as battery degradation factors, difficulties in estimating the SOC and SOH, and the limitations of AI-based estimation techniques. Secondly, the Energy Efficiency and Safety Requirements Section covers challenges in optimising energy efficiency, addressing safety concerns, and integrating AI and ML for predictive analytics and decision-making. Lastly, the Operational Variability and Real-Time Decision-Making Section involves managing dynamic environments, overcoming real-time decision challenges, and ensuring integration and reliability across EV subsystems. Addressing these challenges is crucial for improving battery performance, safety, and operational efficiency in EVs, and more details are provided below.

5.1. Battery Degradation and State Estimation Complexity

One of the most critical challenges in EVs is managing battery degradation, which directly impacts vehicle performance, range, and lifespan. Lithium-ion batteries, the dominant energy storage solution in EVs, are susceptible to capacity fade and increased internal resistance over time due to repeated charge–discharge cycles, temperature fluctuations, and operational stress. Understanding and predicting the degradation mechanisms—such as Solid Electrolyte Interphase (SEI) layer formation, lithium plating, and thermal instability—remain complex tasks, requiring advanced analytical models and monitoring systems [93].

Estimation of the SOH and SOC to a high level of accuracy is essential for efficient battery management, yet achieving this task is challenging. SOC estimation involves determining the remaining charge available in the battery, which varies dynamically depending on load, temperature, and discharge rates [94]. SOH estimation, on the other hand, assesses the overall health of the battery relative to its original capacity and performance. Traditional estimation techniques, such as Coulomb counting and open-circuit voltage methods, are often limited by their reliance on idealised conditions and inability to account for real-world operational variability. While promising, AI-driven approaches face challenges, particularly in the training of models, given the diversity and quality of data. Battery degradation data are often sparse or specific to specific chemistries, making generalised AI models difficult to develop [95].

5.2. Energy Efficiency and Safety Requirements

Achieving high energy efficiency in EVs is essential for extending driving range and minimising energy consumption, particularly in urban environments and under variable driving conditions. However, this goal is constrained by inefficiencies in energy conversion, power delivery, and thermal management systems [96]. The regenerative braking system, for instance, must capture and store energy effectively without overburdening the battery or reducing its lifespan. Optimising energy usage across subsystems, such as HVAC (heating, ventilation, and air conditioning), further complicates this challenge [97].

Safety concerns are another critical aspect of EV battery management. Lithium-ion batteries are highly sensitive to overcharging, deep discharging, and thermal runaway, which can result in catastrophic failures such as fires or explosions. Managing these risks requires precise monitoring and control of temperature, voltage, and current at both the cell and pack levels. Fault detection systems must operate in real time to identify and address potential issues before they escalate, yet such systems often struggle with false positives or delayed responses. Meeting these energy efficiency and safety requirements demands balancing performance optimisation against operational safeguards. While AI and ML can help improve predictive capabilities and decision-making, challenges persist in ensuring these solutions are robust, interpretable, and compliant with regulatory standards [98].

5.3. Operational Variability and Real-Time Decision-Making

EVs operate in highly dynamic environments, where driver behaviour, road conditions, and ambient temperature can significantly influence battery performance. This operational variability presents a major challenge for both BMSs and overall system controls. For example, sudden acceleration or frequent stop-and-go traffic patterns can cause rapid fluctuations in battery load, requiring the BMS to adapt in real time to maintain optimal performance and prevent degradation [99]. Real-time decision-making in EV systems involves complex trade-offs between competing objectives, such as extending battery life, maximising energy efficiency, and ensuring vehicle safety. Traditional rule-based and deterministic models are often inadequate for handling these trade-offs, particularly in unpredictable conditions. AI-driven control systems, such as those employing RL, show potential for adaptive decision-making, yet they face challenges in terms of computational latency and robustness to outlier scenarios [100].

Moreover, implementing real-time decision-making systems requires seamless integration across multiple subsystems, including the powertrain, battery, and thermal management systems. Data from these subsystems must be processed and analysed with minimal latency, necessitating advanced edge computing capabilities and efficient algorithms. Ensuring reliability in real-time systems is particularly challenging in extreme operating environments, such as high temperatures or remote areas with limited connec-

tivity. Ensuring reliability in real-time systems involves developing robust and efficient control frameworks capable of processing and responding to data from multiple subsystems, such as the powertrain, battery, and thermal management, even under challenging conditions. In extreme temperatures, both high and low, maintaining operational efficiency becomes critical. High temperatures can lead to overheating, risking performance degradation or safety issues such as thermal runaway, while low temperatures reduce battery efficiency due to slower chemical reactions. In remote areas with limited connectivity, the lack of communication networks poses additional challenges, as data cannot always be transmitted to centralised systems for analysis. To address this, vehicles must rely on on-board edge computing systems to perform real-time decision-making locally, ensuring reliability without depending on external networks [101]. The next section discussions AI-driven innovations in BMSs, such as charge and cell management, thermal management and software functions.

6. IoT and Big Data Integration in EVs

Integrating the IoT and big data analytics within EVs is revolutionising the automotive industry by providing unprecedented connectivity and data-driven insights. These technologies enable real-time monitoring, predictive analytics, and system-wide optimisation, addressing battery management, maintenance, and fleet operations challenges. This section examines how IoT and big data enhance AI models, facilitate predictive maintenance, and optimise fleet-level operations. Figure 9 showcases a cloud-based big data management framework for EVs. Data are collected from various EV subscribers and processed through the cloud, transforming raw information into actionable insights. The system utilises big data's key dimensions—volume (scale of data), velocity (analysis of data flow), variety (structured and unstructured data), and veracity (data uncertainty)—to enable efficient processing and analysis. The framework supports three primary objectives: enhancing AI models through IoT-enabled data collection, predictive maintenance and fault diagnosis, and fleet-level optimisation for connected EV systems. Outputs include visualisation tools, accurate prediction of SOC and SOH, and integration with RESs and battery storage systems. This approach ensures efficient data utilisation, improved EV performance, and seamless connectivity for subscribers.

6.1. Enhancing AI Models Through IoT-Enabled Data Collection

IoT-enabled EV systems generate vast data through sensors embedded in batteries, powertrains, and vehicle subsystems. These data provide critical insights into battery performance, energy consumption, driving patterns, and environmental conditions. The availability of real-time and historical data enhances the performance of AI models by improving their accuracy, robustness, and ability to generalise across varying conditions [102]. ML and DL algorithms thrive on large datasets, and IoT devices facilitate continuous data collection, enabling the training of AI models for SOC and SOH predictions, thermal management, and fault diagnosis. For instance, high-resolution temperature, voltage, and current data collected via IoT sensors can improve the precision of NN models for battery thermal regulation. Similarly, vehicle-to-cloud connectivity enables AI systems to access diverse datasets from multiple vehicles, supporting the development of more generalised and scalable predictive models [103]. Despite its advantages, integrating IoT with AI models presents challenges, including data privacy, network reliability, and the computational demands of processing and analysing large datasets. Efforts to address these challenges include implementing secure data-sharing protocols, leveraging edge computing for real-time analytics, and employing federated learning to train models without centralising data [104].

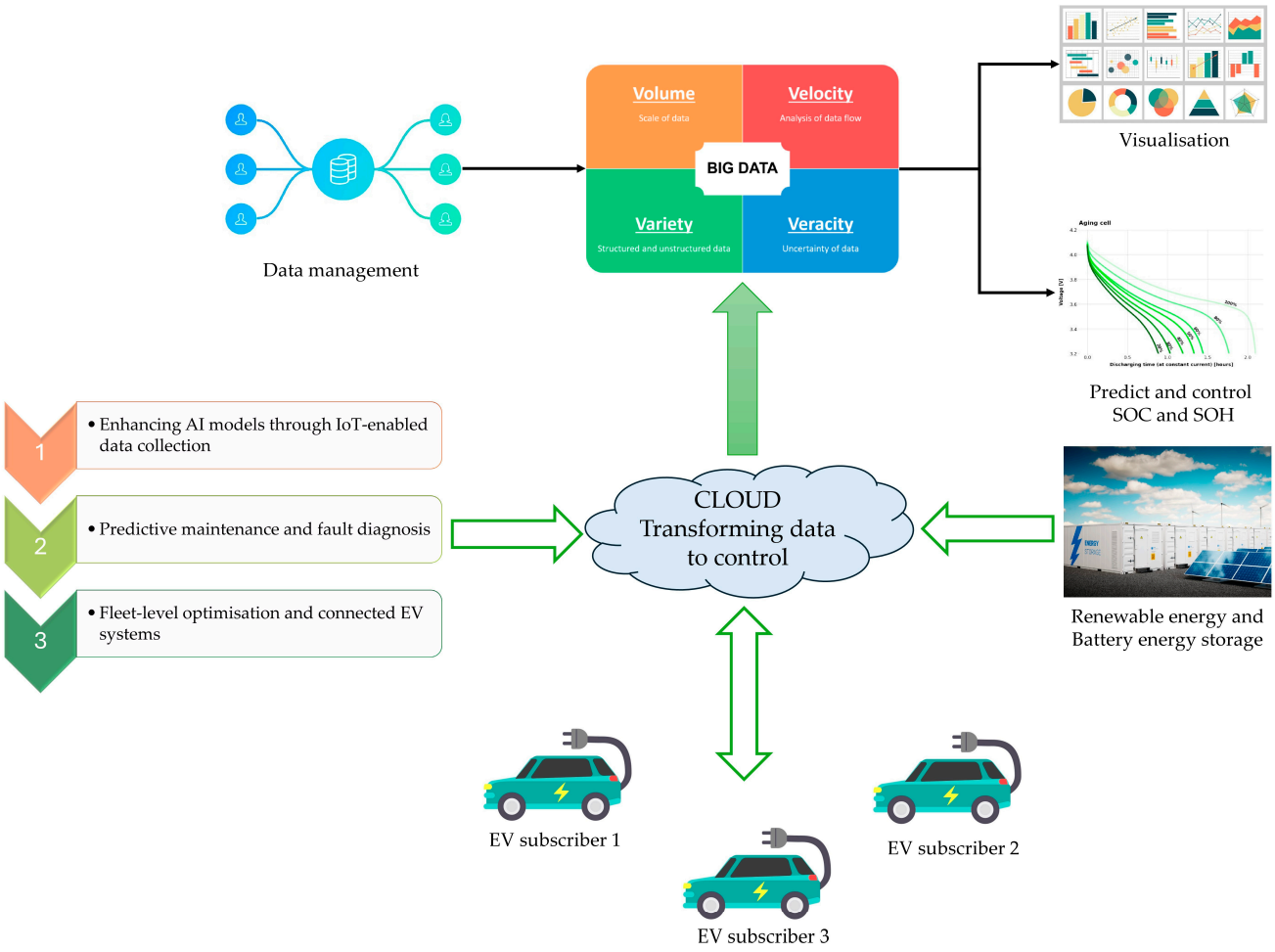


Figure 9. Cloud-based big data management for EVs in this study.

6.2. Big Data Analytics for Predictive Maintenance and Fault Detection

Predictive maintenance, enabled by IoT and AI, is transforming EV maintenance strategies by shifting from reactive to proactive approaches. IoT devices continuously monitor key parameters such as battery health, motor performance, and system temperatures, providing early warnings of potential faults or degradation. AI algorithms analyse these data to predict when and where maintenance is needed, minimising unplanned downtime and reducing operational costs [105]. For example, ML models trained on IoT-collected data can identify patterns associated with battery degradation, such as increasing internal resistance or declining capacity, and predict the battery's RUL. Similarly, anomaly detection algorithms leverage IoT sensor data to detect early signs of overheating, electrical faults, or mechanical wear in drivetrain components [106]. Predictive maintenance challenges include ensuring predictions' reliability, managing data from heterogeneous IoT devices, and integrating these systems with existing vehicle maintenance frameworks. Advances in standardisation, interoperability, and AI explainability are helping to address these issues [107].

6.3. Fleet-Level Optimisation and Connected EV Systems

IoT and big data play a pivotal role in fleet-level optimisation by enabling connected EV systems to operate more efficiently and sustainably. Fleet managers can leverage IoT-enabled connectivity to monitor the performance of multiple vehicles in real time, track energy consumption, and optimise routes based on traffic, terrain, and charging infrastructure availability [108]. AI models trained on fleet-wide data can identify usage patterns and

recommend strategies for optimising energy distribution, charging schedules, and maintenance plans. For instance, predictive analytics can prioritise charging for vehicles with the most urgent energy needs while minimising wait times at charging stations. AI-driven fleet management systems also facilitate energy balancing by dynamically allocating resources across the fleet to maximise overall efficiency and reduce costs [109].

Connected EV systems benefit from vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) communication, which enable cooperative driving and energy sharing. For example, platooning strategies supported by IoT and AI can reduce aerodynamic drag and energy consumption for vehicles travelling together. Moreover, fleet-level insights can inform long-term planning, such as optimising charging station placement and evaluating the economic feasibility of adopting RESs for fleet operations [110]. While fleet-level optimisation offers significant benefits, challenges include ensuring cybersecurity in connected systems, managing data transmission across diverse networks, and addressing the computational demands of large-scale analytics. Emerging technologies such as blockchain for secure data sharing, 5G networks for high-speed connectivity, and distributed computing frameworks are addressing these challenges [111].

7. Challenges and Limitations of AI Applications in EVs

While AI offers transformative potential for EV technology, its application has challenges and limitations. These obstacles include data privacy and security concerns, the computational constraints and costs associated with AI integration, and the need for interpretable AI models that ensure transparent and reliable decision-making. This section explores these issues and discusses potential strategies for overcoming them.

7.1. Addressing Data Privacy and Security in AI-Driven EV Systems

AI applications in EVs often rely on extensive data collection from various sources, including battery systems, vehicle sensors, and connected infrastructure. This dependence on data raises critical concerns about data privacy and security, particularly as EVs become increasingly interconnected through IoT and cloud-based systems [112]. Figure 10 outlines the key challenges and limitations of integrating AI into EVs. These challenges are grouped into three main areas. The Addressing Data Privacy and Security Section includes tackling data privacy challenges and cybersecurity risks and implementing effective mitigation strategies. The Computational Constraints and Cost of AI Integration Section highlights hardware and resource demands, economic and operational impacts, and the trade-offs between cloud and edge computing solutions. Lastly, the Interpretable AI Models for Transparent Decision-Making Section focuses on overcoming transparency challenges, managing stakeholder trust and accountability, and advancing research and development initiatives to create more interpretable AI systems. These factors are critical in ensuring the effective, safe, and widespread adoption of AI in EV technologies.

- Data Privacy: Many AI frameworks require detailed user data, such as driving behaviour, location, and charging habits, to enhance their predictive capabilities. However, collecting and processing such data can infringe on user privacy, especially without clear consent or anonymisation. Regulatory frameworks like the General Data Protection Regulation in Europe mandate stringent data protection measures, but compliance across global markets remains inconsistent [112].
- Cybersecurity Risks: The interconnected nature of AI-driven EV systems makes them vulnerable to cyberattacks, including data breaches, ransomware attacks, and system takeovers. Hackers could exploit vulnerabilities in V2X communication networks or cloud-based AI systems, potentially jeopardising safety and user trust [113].

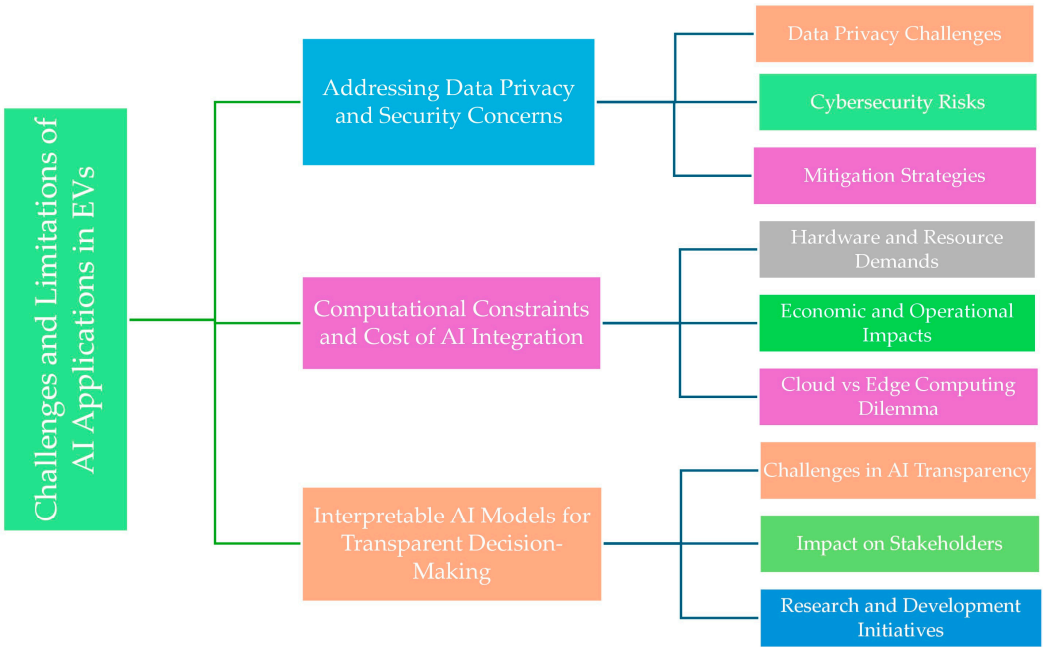


Figure 10. Challenges and limitations of AI applications in EVs.

Strategies to mitigate these concerns include the following:

1. Data Encryption: Employing end-to-end encryption for data transmission and storage.
2. Federated Learning: This involves training AI models locally on vehicles and aggregating insights without transmitting raw data, thereby preserving privacy.
3. Anomaly Detection: Using AI to detect and respond to suspicious activities or security breaches in real time [113].

7.2. Computational Constraints and Cost of AI Integration

The deployment of AI in EV systems requires significant computational resources, particularly for tasks such as real-time state estimation, predictive maintenance, and dynamic control. These demands present challenges related to both hardware and operational costs [113].

- Hardware Limitations: Real-time AI applications often require specialised hardware, such as GPUs or Tensor Processing Units (TPUs), to perform complex computations. However, integrating these components into EVs can increase vehicle costs and energy consumption, potentially negating some efficiency gains [114].
- Cloud and Edge Computing Trade-offs: While cloud-based AI systems provide scalable computational power, they depend on reliable network connectivity, which is not always available in remote areas. On the other hand, edge computing enables on-vehicle AI processing but is constrained by hardware limitations and heat dissipation challenges [114].
- Cost of Development and Deployment: Developing AI models requires extensive data collection, annotation, and training, which can be time-intensive and expensive. The cost of maintaining and updating these systems further adds to the financial burden on manufacturers [115].

Emerging solutions include the following:

1. Model Optimisation: Developing lightweight AI models that balance performance with computational efficiency.
2. Hybrid Architectures: Combining cloud and edge computing to maximise resource utilisation while ensuring reliability.

Shared Infrastructure: Leveraging shared AI and data platforms across manufacturers to reduce costs and accelerate innovation [115].

7.3. Interpretable AI Models for Transparent Decision-Making

A major limitation of AI systems in EV applications is their often opaque nature, commonly referred to as the "black box" problem. Many AI models, particularly DL algorithms, produce accurate predictions but lack explainability, making it difficult to understand how decisions are made [10]. This lack of transparency poses challenges in safety-critical applications such as battery management and autonomous driving.

- Trust and Accountability: Users and regulators may hesitate to adopt AI systems they cannot fully understand or audit. For example, if an AI-driven BMS fails to prevent a battery fire, it may be challenging to identify the root cause or assign accountability [116].
- Regulatory Compliance: As governments introduce stricter regulations for AI in transportation, manufacturers must demonstrate that their systems are both reliable and interpretable. Transparent AI models can help meet these regulatory requirements while fostering trust among stakeholders [117].
- Bias and Fairness: Opaque AI systems risk introducing biases that could affect their decision-making, such as prioritising certain energy-saving strategies at the expense of others. Ensuring fairness requires interpretable models that allow developers to detect and correct biases [116].

To address these issues, researchers are focusing on the following:

1. Explainable AI (XAI): Developing methods that make AI decisions interpretable, such as generating human-readable explanations for model outputs.
2. Hybrid Models: Combining rule-based systems with AI to balance interpretability and adaptability.
3. Simulation and Testing: Rigorous validation of AI models in diverse scenarios to identify potential flaws and improve transparency [117].

7.4. Limitations of AI-Based Methods and Hybrid AI + Model-Based Solutions

AI-driven approaches have significantly advanced BMSs by improving state estimation (SOC, SOH), fault detection, and predictive maintenance in EVs. However, despite their capabilities, AI-based methods present several critical limitations that hinder their widespread applicability and real-time deployment in energy management systems.

7.4.1. Key Limitations of AI-Based Methods in BMS

- Need for Large-Scale Experimental Data and Generalisation Issues: One of the biggest challenges of AI-based methods is their reliance on large volumes of high-quality experimental data for training. AI models, especially DL- and ML-based frameworks, require extensive datasets encompassing diverse operating conditions, battery chemistries, and environmental variations to generalise effectively [113].
    - Data Scarcity: Many AI models are trained on laboratory datasets, which may not fully represent real-world driving conditions.
    - Transferability Issues: AI models trained on one battery type may not perform accurately for different chemistries, capacities, or operating environments without additional re-training [116].
    - Cost of Data Collection: Gathering experimental data for battery degradation, thermal behaviour, and charge–discharge cycles is time-consuming and costly, limiting the scalability of AI-based solutions.

- Computational Complexity and Real-Time Constraints: Many AI algorithms, particularly NNs and RL, require significant computational resources, which on-board vehicle processors may struggle to support. Real-time applications demand low-latency predictions, yet some AI models sacrifice speed for accuracy, making them impractical for dynamic vehicle control systems [112].
- Lack of Physical Interpretability: AI models operate as black-box systems, making it difficult to physically interpret their decisions in battery management. Unlike model-based approaches derived from electrochemical, thermal, or circuit models, AI methods lack direct connections to the physical principles governing battery behaviour.

7.4.2. Hybrid AI + Model-Based Approaches: Overcoming Limitations

Hybrid AI + Model-Based approaches have emerged as a promising solution to address the weaknesses of pure AI-based methods. These methods combine AI-driven data analytics with physics-based and model-based frameworks, leveraging the strengths of both approaches to enhance accuracy, reliability, and scalability [117].

- Physics-Guided AI Models: These models integrate AI algorithms with electrochemical, circuit-based, or thermal models, reducing dependency on large experimental datasets. Instead of learning purely from data, the AI model is constrained by known physical laws, improving generalisation and interpretability [116].
- Data-Efficient Machine Learning Approaches: Hybrid AI methods use fewer training samples by incorporating synthetic data from physics-based simulations, reducing reliance on costly experimental datasets. Transfer learning and meta-learning techniques allow models to adapt across different battery types with minimal re-training.
- AI-Augmented State Estimation (SOC, SOH): Traditional Kalman filters, particle filters, and observer-based models can be enhanced with AI-driven pattern recognition, improving SOC and SOH accuracy with less computational demand. Hybrid methods allow fault-tolerant BMS, where physics-based models handle normal conditions while AI predicts anomalous behaviour and failures [116].

8. Next-Generation AI Solutions for a Sustainable EV Ecosystem

As EV adoption accelerates, AI's role in addressing critical challenges and enhancing EV performance is poised to expand further. This section explores key future directions for AI in EV technology, focusing on advancements in battery management, integration with RESs, and the development of scalable and resilient AI frameworks for global deployment.

8.1. Innovations in AI Techniques for BMS

The continuous improvement of AI techniques is essential for advancing BMSs and addressing challenges such as battery degradation, safety, and energy optimisation. Future AI innovations are likely to focus on the following areas:

1. Hybrid AI Models: Combining physics-based models with AI techniques, such as ML and NNs, can provide more robust and accurate predictions of battery SOH, SOC, and RUL under diverse conditions [118]. Hybrid approaches will bridge the gap between theoretical accuracy and real-world applicability.
2. Unsupervised and Semi-Supervised Learning: As the availability of labelled battery data is limited, unsupervised and semi-supervised learning methods will play a critical role in uncovering hidden patterns in large datasets. These techniques can identify degradation trends or anomalies without requiring extensive labelled datasets, reducing the dependency on time-intensive data collection [119].
3. Real-Time Edge AI Processing: Developing lightweight AI algorithms for edge computing will enhance real-time decision-making in BMSs. Edge AI can process sensor

data directly on the vehicle, minimising latency and dependence on external networks [119].

4. Quantum Computing for Battery Optimisation: Applying quantum algorithms could unlock unprecedented computational capabilities for modelling and optimising battery behaviour, enabling breakthroughs in energy density and charging efficiency [119].

8.2. Seamlessly Integrating RESs with EV Charging Networks

Integrating RESs into EV charging infrastructure presents a significant opportunity to reduce the carbon footprint of EVs and enhance grid stability. AI will play a pivotal role in enabling this integration through advanced predictive and optimisation capabilities:

1. Predictive Analytics for Renewable Energy Availability: AI models can predict energy production from renewable sources [120], allowing EV charging stations to schedule charging operations during periods of peak energy availability [121]. This integration ensures that EVs are powered by clean energy, maximising sustainability.
2. Smart Grid Integration: AI-powered smart grids can balance energy supply and demand by dynamically allocating energy from renewable sources to EVs. These systems optimise grid operations by coordinating energy storage, V2G technology, and distributed energy resources [121].
3. Energy Arbitrage and Load Balancing: AI frameworks can enable charging stations to perform energy arbitrage by storing excess renewable energy during periods of low demand and supplying it during peak demand. This capability reduces grid strain and enhances profitability for charging providers [121].
4. Off-Grid Renewable Charging Solutions: The development of AI-driven microgrid systems for remote or off-grid areas will enable EV charging using locally generated renewable energy. These systems can dynamically manage energy storage and distribution to ensure reliability and sustainability [121].

8.3. Building Resilient and Scalable AI Frameworks for Global EV Adoption

The global deployment of AI-driven EV technologies requires frameworks that are not only scalable but also resilient to diverse environmental, economic, and regulatory challenges. Key strategies include the following:

1. Federated Learning for Scalability: Federated learning allows AI models to be trained across multiple vehicles or regions without centralising sensitive data. This approach enhances scalability while preserving data privacy and reducing the computational burden on central servers [122].
2. Adaptable AI Models for Diverse Conditions: AI frameworks must be adaptable to address the variability in driving environments, regulatory standards, and infrastructure across regions. Transfer learning and domain adaptation techniques can enable AI models trained in one region to generalise effectively to others [122].
3. Standardisation of AI and Data Protocols: Developing standardised data formats, communication protocols, and AI frameworks will facilitate interoperability across different manufacturers and regions. This standardisation will reduce the complexity and cost of deploying AI technologies at scale [123].
4. Resilience to Cyber Threats: As AI reliance grows, ensuring the resilience of these systems against cyberattacks will be crucial. AI-driven anomaly detection and self-healing mechanisms can enhance the security and robustness of EV systems [123].
5. Integration with Circular Economy Models: Scalable AI frameworks will also play a role in battery recycling and lifecycle management, ensuring that materials are reused efficiently to minimise waste and reduce environmental impact [123].

9. Conclusions and Future Perspectives

AI is revolutionising the EV industry, addressing critical challenges, and unlocking new opportunities in battery management, system control, and fleet-level optimisation. This review has explored how AI-driven innovations, including ML, NNs, and RL, transform key aspects of EV technology. From accurately predicting the SOC and SOH to dynamically optimising energy distribution, enhancing regenerative braking efficiency, and supporting predictive maintenance, AI enables higher efficiency, safety, and reliability in modern EVs. Integrating IoT devices and big data analytics further amplifies AI's potential by providing real-time insights and advanced predictive capabilities, optimising both individual vehicle performance and fleet-wide operations. However, despite these advancements, deploying AI in EVs presents several challenges that must be addressed to ensure widespread adoption and reliability. Issues such as data privacy, cybersecurity threats, computational constraints, and the interpretability of AI models remain significant barriers. Additionally, AI methods are often data-intensive, requiring large, high-quality experimental datasets to improve prediction accuracy and generalisation across diverse operating conditions. Integrating RESs into AI-driven BMSs introduces another layer of complexity, necessitating further research into hybrid AI-based control strategies that enhance the efficiency and stability of energy management within EV ecosystems.

Reflections and Open Research Challenges

While AI has demonstrated immense potential in advancing EV technologies, several critical research challenges and practical considerations remain:

- Balancing AI Complexity with Real-Time Processing Constraints: AI algorithms must be optimised for real-time energy management, particularly in on-board vehicle systems with limited computational power. The shift toward distributed AI architectures, cloud-based learning, and edge computing will be crucial in overcoming latency and processing limitations.
- Enhancing AI Interpretability and Trustworthiness: AI-based decision-making in EVs remains a black box, making it difficult to verify the reliability of predictions in safety-critical applications. XAI frameworks should be explored to enhance transparency and increase trust in AI-powered vehicle management systems.
- Developing Robust and Scalable AI Models: AI models must handle different battery chemistries, vehicle types, and environmental conditions with minimal re-training. Advancements in transfer learning, federated learning, and physics-informed AI models can significantly improve scalability and adaptability.
- Standardisation and Interoperability: Ensuring the global standardisation of AI-driven BMSs, wireless charging protocols, and V2G interactions is essential for seamless integration across diverse EV infrastructures. Collaborative efforts between automakers, AI researchers, and policymakers are necessary to develop universal frameworks.
- Strengthening AI Security and Privacy Measures: As AI-powered EVs rely on continuous data exchange, ensuring secure communication protocols, encrypted data storage, and robust AI cybersecurity measures will be essential to protect against hacking attempts and adversarial AI attacks.

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
BEV	Battery Electric Vehicle
BMS	Battery Management System
BPNN	Backpropagation Neural Network
BSA	Backtracking Search Algorithm
BSS	Battery Swapping Station
CAN	Controller Area Network
CC	Conductive Charging
CNN	Convolutional Neural Network
DAQ	Data Modelling, Acquisition System
DL	Deep Learning
DNN	Deep Neural Network
DoE	Design of Experiment
DST	Dynamic Stress Test
EA	Evolutionary Algorithm
EIS	Electrochemical Impedance Spectroscopy
ELM	Extreme Learning Machine
EOL	End-of-Life
ES	Evolutionary Strategy
EV	Electric Vehicle
FCM	Fuzzy C-Means
NFL	Neuro-Fuzzy Logic
FNN	Feedforward Neural Network
FNN	Fuzzy Neural Network
GA	Genetic Algorithm
GHG	Greenhouse Gas
GPR	Gaussian Process Regression
GRU	Gated Recurrent Unit
HEV	Hybrid Electric Vehicle
HIS	Hybrid Intelligent System
HPPC	Hybrid Pulse Power Characterisation
HVAC	Heating, Ventilation, and Air Conditioning
ICE	Internal Combustion Engine
IoT	Internet of Things
LSA	Lighting Search Algorithm
LFP	Lithium Iron Phosphate
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-layer Perceptron
MSE	Mean Squared Error
NARX	Non-Linear Autoregressive with Exogenous Inputs
NN	Neural Network
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OCV	Open-Circuit Voltage
PHM	Prognosis and Health Management
PHEV	Plug-in Hybrid Electric Vehicle
PEMFC	Proton Exchange Membrane Fuel Cell

PSO	Particle Swarm Optimisation
RBFNN	Radial Basis Function Neural Network
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RRN	Reinforcement Recurrent Network
RUL	Remaining Useful Life
SEI	Solid Electrolyte Interphase
SOC	State of Charge
SOH	State of Health
SVM	Support Vector Machine
TPU	Tensor Processing Unit
V2G	Vehicle-to-Grid
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
WOA	Whale Optimisation Algorithm
WPT	Wireless Power Transfer
XAI	Explainable Artificial Intelligence

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