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Review

Advances in Battery Modeling and Management Systems: A Comprehensive Review of Techniques, Challenges, and Future Perspectives

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Abstract

Energy storage systems (ESSs) and electric vehicle (EV) batteries depend on battery management systems (BMSs) for their longevity, safety, and effectiveness. Battery modeling is crucial to the operation of BMSs, as it enhances temperature control, fault detection, and state estimation, thereby maximizing efficiency and preventing malfunctions. This paper thoroughly examines the most recent advancements in battery and BMS modeling, including data-driven, thermal, and electrochemical methods. Advanced modeling approaches are explored, including physics-based models that incorporate mechanical stress and aging effects, as well as artificial intelligence (AI)-driven state estimation. New technologies that facilitate data-driven decision-making, real-time monitoring, and simplified systems include digital twins (DTs), cloud computing, and wireless BMSs. Nonetheless, there are still issues with cost optimization, cybersecurity, and computing efficiency. This study presents key advancements in battery modeling and BMS applications, including defect diagnostics, temperature management, and state-of-health (SOH) prediction. A comparison of machine learning (ML) methods for SOH prediction is given, emphasizing how well neural networks (NNs) and transfer learning function with real-world datasets. Additionally, future research objectives are described, with an emphasis on next-generation sensor technologies, cloud-based BMSs, and hybrid algorithms. Distinct from existing reviews, this paper integrates academic modeling with industrial benchmarking and highlights the convergence of hybrid physics-informed and data-driven techniques, multi-physics simulations, and intelligent architecture. For high-performance EV applications, this analysis offers insight into creating more intelligent, adaptable, and secure BMSs by addressing current constraints and utilizing state-of-the-art technologies.

Keywords: battery management systems; artificial intelligence; machine learning; digital twins; energy storage systems; cloud and IoT integration; lithium-ion batteries

1. Introduction

1.1. Importance of Battery Management Systems in Modern Energy Storage Systems

Integrating battery energy storage systems (BESSs) with advanced battery management systems (BMSs) enhances power quality, reduces energy losses, and optimizes energy usage in electrical networks by improving battery performance, safety, and lifespan through precise control and modeling [1]. Accurate state-of-charge estimation and enhanced charging efficiency in electric vehicles (EVs) can be achieved by combining real-time capacity estimation with optimal charging algorithms and advanced modeling techniques, all while relying on non-invasive measurements and streamlined open-circuit voltage (OCV) modeling [2].

1.2. Evolution of Battery Management System Technologies

In order to improve the performance, lifespan, and safety of batteries in EVs, it is crucial to accurately estimate the battery's state of charge (SOC). Jose et al. [3] conducted a literature review and thematic analysis to perform a thorough analysis based on 210 scientific articles. The study highlights important subjects and difficulties for further research in the field of BMSs in addition to pointing out current shortcomings and knowledge gaps. The simulation of OCV, which is used to estimate the battery SOC, is one of the important topics that is looked at. According to the findings, using a normalization method in OCV modeling eliminates the need for multiple measurements at various temperatures; instead, a single measurement at room temperature is sufficient. The precision and dependability of the measurements are improved by this optimization. Additionally, through online parameter identification, equivalent battery models that simulate battery behavior under varied load and temperature conditions offer high accuracy and flexibility in model changes. The study also looks at optimized charging algorithms and real-time battery capacity estimation. When two distinct approaches to battery capacity estimation are combined, the SOC estimation becomes more accurate [3–5].

1.3. Role of Artificial Intelligence, Cloud Computing, and Digital Twins in Battery Management Systems

The application of AI and distributed computing technologies significantly enhances the capabilities of BMSs. These advancements enable real-time monitoring, adaptive control, and predictive functions, supporting more accurate state estimation, fault detection, thermal regulation, and cell balancing. The ability to process and analyze large datasets across different system levels enhances operational efficiency, improves battery safety, and extends lifespan. Key characteristics, such as low cost, lightweight design, and durability, can be more easily achieved through the integration of advanced data analytics and control strategies. These developments collectively represent a major step toward more intelligent, efficient, and reliable energy storage solutions for future transportation systems [6–8].

1.4. Research Gaps and Motivation for This Review

BMSs play a critical role in ensuring the safety, effectiveness, and overall success of both large-scale ESSs and electric transportation. Enhancing performance requires focused attention on structural design, operational parameters, system integration, and installation procedures. Clear and comprehensive technical standards are crucial for guiding safe and efficient deployment. A thorough evaluation of these standards and practices is necessary to support compatibility, reliability, and long-term functionality across applications [9].

1.5. Objectives and Contributions of This Paper

Advancements in BMSs are increasingly driven by the integration of intelligent technologies, such as AI, cloud computing, and data analytics. These developments improve diagnostic capabilities, enhance battery performance, and extend operational life while addressing safety and operational challenges. Integrating traditional methods with emerging innovations supports more efficient, reliable, and future-ready battery management solutions.

BMSs and various modeling techniques are presented in detail throughout this survey paper. Section 2 provides an overview of BMSs, including their purpose, key components, and various architectural design types. To ensure smooth operations, relevant communication protocols are in place. Section 3 discusses current battery chemistries and technologies, including lithium-ion and next-generation choices, as well as aging and degradation processes that affect battery performance and lifespan. From equivalent-circuit models to more complex data-driven and multi-physics models, Section 4 explores the many battery modeling techniques used in BMSs and emphasizes how each technique helps to optimize battery systems. The methods for determining a battery's condition, such as SOC, state of health (SOH), and remaining usable life (RUL) forecasts, are discussed in Section 5, along with how AI might improve the accuracy of these projections. Battery thermal management techniques are covered in Section 6, ranging from passive cooling methods to complex AI-based systems intended to keep batteries within acceptable temperature ranges. Section 7 discusses battery safety and fault detection. In addition to providing information regarding prognostic health management (PHM) systems, this section provides an overview of common failure mechanisms and diagnostic methods. Section 8 of this paper discusses advanced energy management and charging strategies, with a focus on AI-driven and grid integration solutions. Section 9 examines how AI and ML, including reinforcement learning, fuzzy logic systems, and predictive models, are changing BMSs. Section 10 discusses the importance of cloud computing, edge computing, and the internet of things (IoT) in BMSs and how these technologies enable real-time control and monitoring. A detailed examination of the expanding possibilities of DT technologies, particularly AI-enhanced systems for defect detection and predictive analysis, is given in Section 11. Section 12 discusses the issues facing BMSs in the future, including the impact of AI and quantum computing (QC), as well as the need for industry-wide standards. Sections 13 and 14 concludes the report with a summary of the knowledge collected, an appraisal of research gaps, and a possible future agenda for BMS technology. This paper distinguishes itself from existing reviews by offering a comprehensive and integrative perspective that bridges academic modeling approaches with practical, real-world applications. It emphasizes the convergence of physics-based and data-driven models, the incorporation of mechanical and thermal degradation effects, and the role of intelligent systems in predictive diagnostics and control. The review also highlights the growing importance of scalable, cloud-enabled, and edge-deployed BMS architectures, which are essential for meeting the demands of modern electric mobility and grid-connected storage systems. By synthesizing recent advancements across multiple domains and identifying emerging trends and challenges, this work provides a forward-looking roadmap for the development of next-generation BMS technologies that are intelligent, adaptive, and resilient.

1.6. Industrial Benchmarking and Technical Innovations

Given the rapid evolution of battery technologies, it is essential to align academic insights with industrial innovations. Prominent corporations such as CATL, BYD, and Tesla have significantly shaped the landscape of battery management systems through proprietary designs and technical breakthroughs. CATL has introduced multi-layer battery cell structures that enhance thermal regulation and safety, as well as sodium-ion battery architectures optimized for energy density and cost efficiency [10–12]. BYD's Blade Battery features a flat-cell configuration that improves crash resistance and thermal stability, along with modular designs that incorporate integrated cooling systems [13,14]. Tesla's advancements include tables electrode designs that reduce internal resistance and improve energy density, as well as battery packs with embedded cooling channels for enhanced thermal performance [15,16]. These industrial benchmarks reflect the state-of-the-art techniques currently deployed in commercial EVs and energy storage systems. By referencing these developments, this paper situates its review within the broader context of real-world applications and highlights the convergence between academic modeling and corporate engineering practices

2. Overview of Battery Management Systems

By controlling voltage, current, temperature, and charge balancing, a BMS monitors, safeguards, and maximizes battery performance. Monitoring units, cell balancers, protective circuits, thermal management systems, and communication modules are some of its essential components.

2.1. Definition and Role of Battery Management Systems

2.1.1. Basic Functions of a Battery Management System

High-voltage BMSs are essential for ensuring the safety, reliability, and optimal operation of EV batteries. Accurate monitoring of key parameters such as voltage, current, and temperature is vital for preventing failures and extending battery life. Addressing current limitations, particularly under extreme conditions, requires the adoption of distributed architectures, real-time processing, and advanced thermal management strategies. Future improvements will include the use of sophisticated algorithms, simulations, and cloud-based systems to enhance data handling, performance, and fault detection [17].

2.1.2. Benefits of a Well-Designed Battery Management System

BMSs are vital for ensuring the performance, safety, and longevity of EV batteries. Accurate status estimation, effective thermal management, and reliable communication are essential to preventing hazardous failures. The integration of cloud-based and IoT-enabled technologies, along with the strategic use of distributed, modular, or centralized architectures, can enhance real-time monitoring and control. Future improvements will focus on advanced cell balancing, efficient cooling methods, and the implementation of cloud-supported distributed systems to meet growing demands for safety and performance [18].

2.2. Key Components of a Battery Management System

High-voltage BMSs are essential for the efficient, accurate, and safe operation of EV batteries. Meeting specific requirements for data communication, thermal control, and real-time information processing is critical to their effectiveness. Among various architectures, distributed systems offer superior performance by enabling localized decision-making and faster response times in complex conditions. Addressing challenges such as thermal risks and measurement inaccuracies requires advanced algorithms for temperature regulation and cell balancing, which support safer and more reliable battery operation in evolving electric mobility systems [19].

2.2.1. Microcontrollers and Embedded Systems

Embedded systems serve as the foundation for integrating hardware and software in robotic applications, enabling real-time control and interaction between microcontrollers, sensors, and actuators. Mastery of C/C++ programming, circuit design, and hardware communication protocols is essential for fully leveraging microcontroller capabilities and ensuring precise, efficient system operation [20].

2.2.2. Power Management Circuits

Fast and efficient cell balancing in lithium-ion batteries (LIBs) can be achieved by enabling direct energy transfer between high- and low-voltage cells through a DC-DC converter. Using relays for dynamic cell pair selection enhances switching efficiency and reduces implementation costs. A control system that incorporates real-time monitoring and predictive load management ensures stable voltage distribution, prevents overcharging or undercharging, and significantly shortens balancing time. High balancing efficiency under various operating conditions, along with stable final voltage across cells, contributes to improved battery performance, reduced degradation, and extended service life [21].

2.2.3. Communication Interfaces (CAN, SPI, I2C, etc.)

Overcoming the limitations of battery-EVs requires improvements in infrastructure, communication, and system coordination. Integrating hybrid electric vehicles (HEVs) and advancing vehicle-to-grid (V2G) connectivity can enhance energy efficiency and reduce charging time. Effective management of route planning, network load, and SOC depends on reliable communication protocols. Implementing wireless technologies such as WiFi, Zigbee, CAN, and LIN enables real-time coordination between vehicles and charging systems, supporting tasks like battery management and charging optimization. Addressing current challenges such as insufficient charging stations, inaccurate SOC estimation, and lack of coordinated control is essential for the large-scale deployment of EVs [22].

2.2.4. Cloud Integration and Remote Monitoring

Cloud-based BMSs enable the creation of a DT that enhances monitoring, diagnostics, and performance optimization of battery systems. Continuous data acquisition from sensors allows for accurate, real-time assessment of SOC and SOH, even under noisy and dynamic conditions. Advanced algorithms provide highly precise estimations of charge levels and degradation trends, ensuring effective tracking of battery performance, temperature, and voltage. However, real-time performance may be affected by inherent limitations of cloud platforms, including data storage latency and transmission bandwidth constraints [23]. These factors can introduce delays in data synchronization and processing, which may impact the responsiveness of SOC/SOH estimation and fault detection. To mitigate these issues, hybrid cloud–edge architectures are increasingly being explored, allowing critical computations to occur closer to the data source while leveraging cloud resources for long-term analytics and system-wide optimization. This approach supports improved decision-making, predictive maintenance, and long-term reliability of battery systems [24].

2.3. Classification of Battery Management System Architectures

2.3.1. Centralized Battery Management Systems

A BMS with integrated PLC control and Modbus TCP/IP communication enables real-time monitoring and precise adjustment of active power, reactive power, and SOC across multiple battery units. By assigning unique communication channels through the TIA Portal, data exchange is reliably executed in short cycles, allowing both individual and collective battery management. The system supports user-friendly interaction through an HMI interface, providing flexibility for control and data visualization. This configuration ensures accurate performance tuning and monitoring, contributing to the effective operation and coordination of battery storage units in real-time applications [25].

2.3.2. Distributed Battery Management Systems

A modular simulation model of battery networks enables detailed analysis of system behavior across process, gateway, and remote management levels. By replicating the interactions between nodes, gateways, and storage layers, the model provides a comprehensive framework for evaluating monitoring, control, and communication processes. Accurate simulation of data flow, including sensing, charge control, and CAN-based messaging, enables realistic performance assessment and optimization. The approach supports scalable modeling of battery networks with distributed data handling, enabling effective analysis of delays, data integrity, and network coordination in real-world battery system configurations [26].

2.3.3. Modular Battery Management Systems

Active cell balancing circuits are crucial for maintaining voltage and state-of-charge uniformity across battery cells, directly contributing to improved safety, extended lifespan, and enhanced performance of ESSs. These circuits consistently achieve high efficiency, often exceeding 90%, making them significantly more effective than passive balancing methods. The choice of circuit depends on the specific application, as different designs offer varying trade-offs in terms of component count and performance. As the demand for EVs grows, the role of efficient active balancing technologies becomes increasingly vital for ensuring reliable and energy-efficient battery operation [27].

2.4. Communication and Networking in Battery Management Systems

2.4.1. Wireless vs. Wired Communication

Efficient and reliable monitoring of high-voltage battery packs in EVs requires an advanced BMS architecture capable of handling complex configurations and harsh operating conditions. Distributed systems, whether wired or wireless, offer scalability and precision by allowing independent monitoring of individual cells or modules. Wired systems offer robust noise resistance through isolation techniques, while wireless systems provide flexibility and simplified installation via low-energy communication protocols. High-speed, low-latency data transfer is critical for ensuring accurate performance tracking and safe operation. The ability to support both wired and wireless configurations enhances adaptability across different vehicle designs and operating environments [28].

2.4.2. Controller Area Network Protocols

Signal delays in voltage and current measurements can significantly reduce the accuracy of fault detection and internal resistance estimation in EV BMSs. Addressing this challenge requires precise synchronization across all cells in large battery packs. Implementing a global clock-based synchronization technique enables accurate timing alignment, reducing discrepancies caused by desynchronized signals. Optimizing compensation timing through model-based analysis further enhances measurement accuracy and system stability. This approach ensures more reliable monitoring, improves diagnostic precision, and simplifies scheduling and synchronization in complex battery systems [29]. Figure 1 indicates the role of Controller Area Networks (CANs) within the BMS architectures.

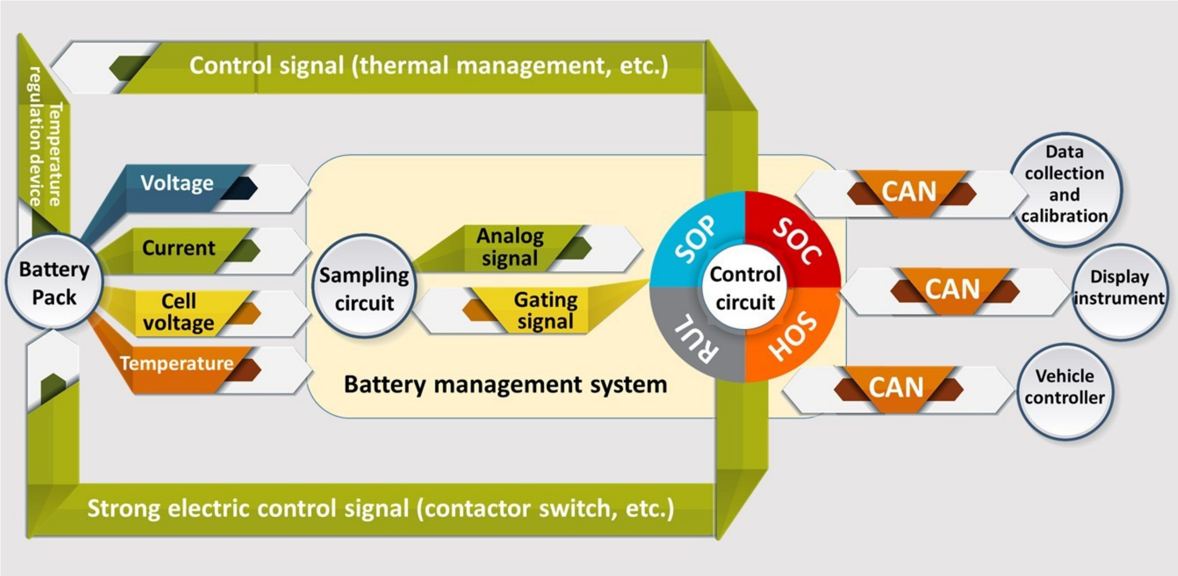

Figure 1. Controller Area Networks in the BMS architecture.

2.4.3. IoT-Based Battery Management Systems Communication Frameworks

Integrating IoT technologies with LoRa networks enhances the real-time monitoring and management of LIB systems, especially in renewable energy storage applications. Collecting detailed battery data through IoT gateways supports performance optimization and health tracking. Variations in node energy consumption highlight the importance of load balancing and network design. Identifying high-consumption nodes enables the development of targeted routing and energy management strategies, thereby improving overall efficiency and extending the system's lifespan. The use of LoRa technology offers additional advantages in large-scale deployments by reducing operational costs and improving scalability and energy efficiency [30]. Figures 2 and 3 provide a comprehensive outline of the BMS and the associated components that play a major role in its functionality. Table 1 provides an overview of key components and architectures in BMSs.

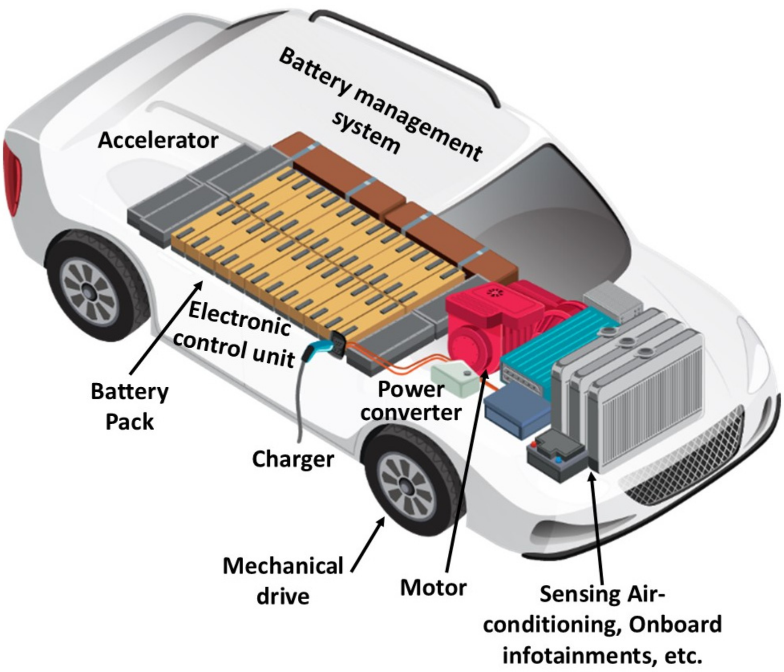

Figure 2. Battery Management System in an Electric Vehicle.

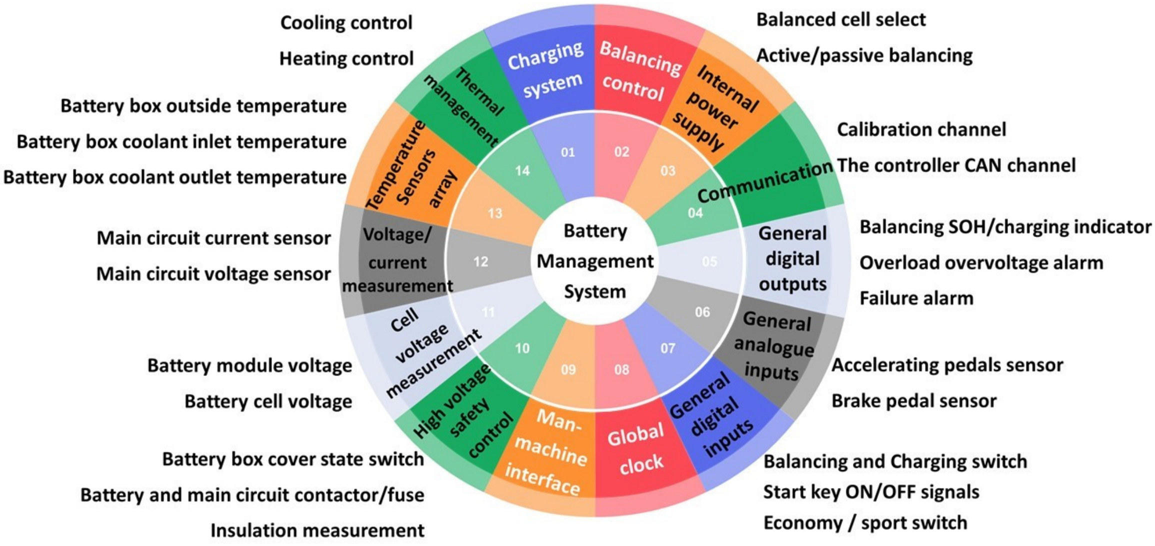

Figure 3. Key Components of Battery Management Systems.

Table 1. Overview of Key Components and Architectures in BMSs.

Summary	Comparison	Ref.
Core Functions of a BMS: Discusses BMS roles in managing battery conditions and thermal control.	Distributed systems vs. centralized control.	[6]
Advantages of an Optimized BMS: Explores the impact of BMS on performance and safety, with IoT focus.	IoT/cloud-based vs. traditional systems.	[9]
BMS Applications in Key Industries: Highlights BMS use in various industries for real-time monitoring.	Real-time data in multiple industries.	[17]
Voltage, Current, and Temperature Sensing in BMS: Covers roles of BMSs in safety and monitoring.	Safety and communication vs. other monitoring systems.	[18]
Microcontroller Integration in BMS: Describes microcontrollers for real-time control and data processing.	Microcontrollers vs. traditional embedded systems.	[18]
Power Management Strategies in BMS: Describes methods for balancing lithium-ion batteries.	Active vs. passive balancing methods.	[19]
BMS Communication Protocols: Examines communication protocols to enhance BMS functionality.	Wireless vs. wired communication protocols.	[20]
Cloud Integration and Monitoring in BMS: Focuses on cloud-based BMSs and digital twins for monitoring.	Cloud-based vs. non-cloud systems for real-time data.	[21]
Centralized BMS Architectures: Discusses centralized BMS for battery storage with real-time data.	Centralized BMS with PLC vs. distributed systems.	[22]
Distributed BMS Networks: Introduces a distributed BMS model with network layers.	Distributed vs. centralized BMS architectures.	[24]
Modular BMS Designs: Focuses on active cell balancing for better performance.	Active vs. passive balancing in modular systems.	[25]
IoT-Enabled BMS Architectures: Describes IoT-based BMS architecture for energy optimization.	Comparison of IoT-based BMS optimization architectures.	[26]
Wireless vs. Wired Communication for BMS: Compares BLE and twisted pair protocols for BMS data transfer.	BLE vs. twisted pair protocols in EVs.	[27]

Table 1. *Cont.*

Summary	Comparison	Ref.
Signal Synchronization in CAN Protocols: Focuses on CAN signal synchronization for better fault detection.	Improved signal synchronization with CAN vs. traditional methods.	[31]
IoT Frameworks for BMS Communication: Discusses IoT frameworks like LoRa for lithium-ion battery management.	LoRa-based vs. other IoT communication frameworks.	[28]

3. Battery Technologies and Chemistry for Battery Management Systems

3.1. Lithium-Ion Battery Chemistry and Performance

3.1.1. Anode and Cathode Material Developments

LIBs offer high energy density and portability, making them ideal for various applications, but challenges remain in improving their efficiency, safety, and material performance. Achieving high ionic conductivity and electrochemical stability in both liquid and polymer electrolytes is critical, yet difficult. Safety concerns, including thermal instability, chemical leakage, and ignition risks, highlight the need for robust protective measures and fault management. Advancements in materials science, particularly through nanomaterials and innovations such as silicon anodes, hold significant potential in enhancing capacity, reducing weight, and supporting the future evolution of safer, more efficient LIB technologies [32].

3.1.2. Electrolytes and Separators

Non-conductive components such as electrolytes, binders, and separators, which are electronically non-conductive but critical for ionic transport and structural integrity, play a vital role in the overall performance, safety, and longevity of LIBs. Innovations in solid-state and IL electrolytes are improving conductivity and reducing flammability, while the development of water-based and environmentally friendly formulations enhances safety and sustainability. Advances in polymer binders and the use of conductive polymers help mitigate performance limitations at the electrode interface. Separators with high porosity and mechanical strength are essential for safe and efficient ionic transport. The use of green materials and supramolecular chemistry offers promising directions for future improvement [33].

3.1.3. Thermal and Safety Characteristics

Effective thermal management is essential for maintaining the safety, performance, and longevity of LIBs. Temperature increases during charging and discharging can lead to structural damage and thermal runaway if not properly controlled. Accurate thermal modeling facilitates an understanding of heat generation, both irreversible and reversible, and its impact on battery efficiency, capacity, and power output. Monitoring and regulating temperature with precision ensures optimal battery operation, while detailed analysis of heat generation and distribution support the design of more efficient and reliable thermal control systems [34].

3.2. Solid-State and Next-Generation Batteries

Emerging battery technologies such as solid-state and next-generation chemistries offer transformative potential for energy storage [35]. While the following subsections explore promising developments in solid-state and next-generation battery technologies, it is important to note that many of these systems are still in early research or pre-commercial stages. As such, their integration with BMSs is not yet a critical concern. The discussion focuses on technological pathways and bottlenecks, with the understanding that BMS applicability will become more relevant as these technologies mature and move toward industrial deployment.

3.2.1. Lithium-Sulfur Batteries

Lithium-sulfur batteries offer great promise for high-energy storage applications due to their low cost, lightweight design, and high energy density. However, challenges such as limited cycle life, safety risks, and electrolyte instability hinder widespread adoption. Transitioning to solid-state designs can address many of these issues, offering improved safety and energy performance. Advances in solid and polymer electrolyte development are critical, but further improvements in ionic conductivity, chemical stability, and resistance to degradation, such as mitigating lithium polysulfide shuttling, are necessary for practical and commercial deployment [36,37].

3.2.2. Sodium-Ion Batteries

All-solid-state sodium-ion batteries represent a promising alternative to lithium-based systems due to their cost-effectiveness, resource availability, and improved safety. The development of solid electrolytes such as ceramic, polymer, and composite types, has advanced their thermal stability, mechanical strength, and ionic conductivity. Incorporating ceramic fillers into polymer matrices enhances ion transport by reducing crystallinity, although excessive loading can hinder conductivity. While solid-state electrolytes (SSEs) still lag behind liquid counterparts in room-temperature conductivity, they offer superior durability, non-flammability, and high-temperature stability. Continued research is needed to optimize material compatibility and ensure long-term chemical stability, particularly with sodium metal interfaces [38,39].

3.2.3. Flow Batteries

Redox flow batteries (RFBs) hold strong potential for large-scale, sustainable energy storage due to their scalability and long-duration capabilities. However, challenges related to high costs and low energy density must be addressed to enable broader adoption. Advancements in organic redox species, membrane technologies, and computational modeling are crucial for enhancing performance and simplifying system complexity. High-solubility, stable redox compounds and optimized membrane materials can enhance efficiency and lower costs. Computational tools support precise material selection and system design, especially at the micro-scale. Overcoming limitations in solubility and stability of organic materials remains key to advancing next-generation RFBs [40–42].

3.2.4. Hybrid Energy Storage Systems

Solid-state sodium-air batteries offer a promising path toward efficient, cost-effective energy storage, but their advancement is hindered by issues such as dendritic growth, oxygen diffusion instability, and electrolyte degradation. Improving electrolyte materials and protecting the sodium cathode are critical to overcoming these challenges. Hybrid SSEs that blend ceramic and polymeric components offer a balanced solution by combining mechanical flexibility with high ionic conductivity and chemical stability. These composite systems enhance electrode–electrolyte contact, suppress dendrite formation, and stabilize the solid–electrolyte interface (SEI). Addressing these key factors is essential for extending battery lifespan, ensuring safety, and achieving reliable long-term performance [43,44]. Table 2 provides a comparison of different battery chemistries relevant to BMS applications.

Table 2. Comparative characteristics of battery chemistries relevant to BMS applications.

Battery Type	Energy Density (Wh/kg)	Cycle Life (Cycles)	Safety Characteristics	Operating Temp. Range (°C)	Reference
Lithium-Ion (LIB)	100–265	600–3000	Moderate; risk of thermal runaway	−20 to 60	[45]
Lithium-Sulfur (Li–S)	400–500	300–1500	Improved with solid-state; still volatile	−10 to 55	[46,47]
Sodium-Ion (Na-ion)	100–150	1000–3000	Safer than LIB; non-flammable	−30 to 60	[48]
Flow Battery (RFB)	10–50 (system-level)	10,000+	Very safe; no thermal runaway	0 to 50	[49,50]
Solid-state sodium-air batteries (Na-O_2)	~1600	1000–3000+	Safer; dendrite suppression possible	−20 to 45	[51,52]

3.3. Aging and Degradation Mechanisms of Batteries

SEI growth, lithium plating, electrolyte breakdown, and electrode deterioration are the primary causes of battery aging, resulting in resistance increasing and capacity decreasing [53]. These effects are accelerated by high temperatures and cycle stress, both of which affect safety and performance. Table 3 presents a summary of recent developments and challenges in battery technologies, electrochemistry, and degradation mechanisms.

Table 3. Summary of Recent Developments and Challenges in Battery Technologies, Electrochemistry, and Degradation Mechanisms.

Topic	Summary	Ref.
Anode and Cathode Material Developments	Focus on improving material efficiency and stability.	[29]
Electrolytes and Separators	Development of safer, environmentally friendly materials.	[30]
Thermal and Safety Characteristics	High temperatures affect performance; thermal modeling is essential.	[32]
Lithium-Sulfur Batteries	High potential but need improvements in cycling and electrolyte stability.	[33]
Sodium-Ion Batteries	Cost-effective but less efficient; need better conductivity.	[34]
Flow Batteries	Ideal for long-term storage but face cost and density issues.	[36]
Hybrid Energy Storage Systems	Stable but with electrolyte issues; hybrid systems may improve performance.	[38]
Capacity Fade and Impedance Growth	Temperature and SOC ranges impact efficiency.	[40]
Electrode Degradation and SEI Layer Formation	SEI growth impacts battery life; charging methods are crucial.	[43]
Mechanical and Thermal Degradation	Optimization of catalysts improves stability and longevity.	[54]

3.3.1. Capacity Fade and Impedance Growth

Lithium-ion cell degradation is primarily driven by lithium inventory loss, with high temperatures and wide SOC ranges accelerating this process. Elevated depth of discharge (DOD) and average SOC also contribute significantly to impedance growth and structural degradation of the positive electrode, leading to capacity fade. Mechanical changes, such as electrode thickening and fracturing, further impair performance, especially under prolonged cycling at high DOD. Including impedance effects in empirical models improves capacity degradation predictions. While NMC622/natural graphite cells perform well under controlled conditions, their performance declines under aggressive cycling, highlighting the need for optimized operating conditions and improved degradation modeling [54].

3.3.2. Electrode Degradation and Solid–Electrolyte Interface Layer Formation

Capacity degradation in LIBs is strongly influenced by factors such as SEI layer growth, charging methods, DOD, and driving patterns. While regenerative braking can help extend battery life under certain conditions, it may also reduce the usable energy over time. Charging strategies that emphasize constant current phases tend to slow SEI growth and may be more cost-effective than prolonged constant voltage charging. EV batteries generally experience less degradation due to their larger capacity buffers, whereas Plug-In Hybrid Electric Vehicle (PHEV) batteries operate under deeper discharge, which increases stress and aging. Managing DOD is essential for limiting SEI expansion and preserving long-term battery health [55].

3.3.3. Mechanical and Thermal Degradation

Optimizing polymer pyrolysis requires careful control of processing parameters, including feed type, polymer size, reactor design, temperature, catalysts, and carrier gases. Additives such as metal stearates and antioxidants can help stabilize polymers and reduce waste during processing. Efficient pyrolysis occurs at temperatures ranging from 400 to 500 °C for liquid product yield and above 800 °C for gas production, with reactor geometry and mixing systems playing a critical role in product quality. The use of metal-supported zeolite catalysts enhances the formation of valuable aromatic compounds, while hydrogen as a carrier gas promotes paraffin production. A well-coordinated approach involving precise temperature control, catalyst selection, and feed system design significantly improves the efficiency and quality of pyrolysis outcomes [56]. Figure 4 indicates the different degradation pathways associated with LIBs.

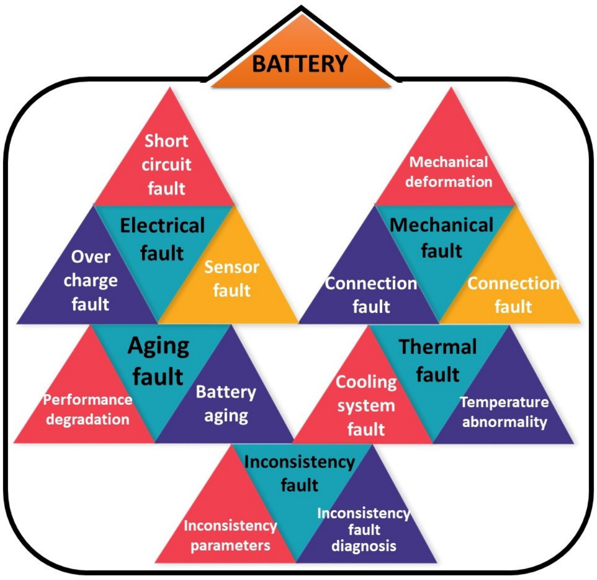

Figure 4. Different Degradation Pathways of Lithium-ion Batteries.

4. Battery Modeling Techniques for Battery Management Systems

For BMSs to forecast performance, estimate SOC and SOH, and improve safety, battery modeling approaches are essential. Common models that balance accuracy and computing efficiency for real-time applications include ML-based, electrochemical, and equivalent circuit techniques. Table 4 provides a summary of battery modeling techniques and their applications in BMSs, and Table 5 outlines the comparative trade-offs in Battery Modeling Approaches for BMSs.

Table 4. Summary of Battery Modeling Techniques and Their Applications in BMSs.

Focus of Study	Key Findings	Ref.
Equivalent Circuit Model (ECM) for battery heat generation and cooling	ECM predicts cell voltage accurately, reducing cooling system power consumption by 14%	[55]
Estimation of SOP in lithium-ion batteries using ECM	Combining offline and online methods improves SOP estimation accuracy and reliability	[56]
SOC estimation using (EKF) and ECM	Hybrid method provides accurate SOC estimation with errors between 2.5% and 4.5%	[57]
ROMs for electrochemical dynamics in BMS	Different algorithms (DRA, CRA, HRA, LRA) offer trade-offs in speed, memory usage, and accuracy	[58]
Galerkin projection method for reduced-order electrochemical model	Reduced-order model accurately predicts voltage and simulates faster than real-time	[59]
Data-driven methods for battery state estimation	Machine learning methods (ANN, SVM, RF) improve SOC estimation accuracy in BMS	[60]
Adaptive UKF for SOC estimation using Thevenin model	UKF with RLS estimates SOC with high accuracy	[61]
RC models for simulating lithium-ion batteries	Second-order RC model provides more accurate simulations, suitable for industrial use	[62]
Hybrid high-order ECM for SOC estimation under real-world driving	Hybrid model outperforms previous models, offering more accurate SOC estimation	[63]
Model reduction techniques for P2D models	Reducing variables cuts simulation time, especially at low discharge rates	[64]
Electrochemical modeling using Newman's model	Newman's model accurately simulates battery behavior using hierarchical equivalent circuits	[65]
ROEM for terminal voltage prediction	ROEM achieves high accuracy with much faster simulation times than P2D model	[66]
Machine learning and deep learning for battery fault detection	Machine learning-based techniques improve fault detection, but require further development	[67]
Hybrid physics-informed data-driven model for battery degradation	Ensemble model improves long-term prediction accuracy and adapts to varying load conditions	[68]
Multi-Physics model for electrochemical–thermal–mechanical degradation	High/low temperatures and C-rates significantly affect lithium-ion battery degradation	[69]

Using equivalent circuit models (ECMs) to estimate internal heat generation enables the accurate prediction of battery thermal behavior, supporting the development of energy-efficient cooling strategies. By dynamically adjusting coolant flow based on predicted heat output, cell temperatures can be maintained within safe limits while reducing the energy consumption of the cooling system. Experimental validation shows strong agreement between theoretical and actual voltage and thermal responses, confirming the model's reliability. This approach enhances thermal management efficiency, reduces pump power consumption, and improv overall battery pack performance, particularly under varying load conditions [57].

Table 5. Comparative Trade-offs in Battery Modeling Approaches for BMSs.

Model Type	**Accuracy**	**Computational Complexity**	**Deployment Readiness**
Equivalent Circuit Models (ECMs)	Moderate to High (with advanced RC or hybrid models)	Low—Suitable for real-time applications	High—Widely used in commercial BMSs
Electrochemical Models (EMs)	High—Captures internal electrochemical behavior	High—Complex and requires model reduction	Medium—Requires simplification for real-time use
Machine Learning (ML)	High—Excellent with complex nonlinear patterns	Variable—Depends on model architecture and training	Medium—Promising, but limited by data availability and generalization issues

Accurate state of power (SOP) estimation in LIBs requires addressing nonlinear behavior, aging effects, and thermal dynamics. Enhanced modeling approaches, such as fractional-order and multi-stage ECMs, improve estimation under complex conditions. A hybrid strategy that combines offline and online parameter identification offers both wide-range adaptability and real-time responsiveness. Simultaneous estimation of multiple battery states such as SOC, SOH, and temperature, is essential for improving SOP prediction accuracy. Integrating ML further enhances model performance by capturing complex interactions. However, the lack of standardized validation methods remains a significant barrier to effectively evaluating and comparing SOP estimation techniques [58].

Accurate and reliable state-of-charge estimation across varying temperatures can be achieved by combining a second-order (EKF) with a temperature- and SOC-dependent equivalent circuit model. This hybrid method maintains strong performance under both dynamic loading and wide temperature ranges, including extreme cold conditions. By incorporating a two-dimensional polynomial to capture parameter sensitivity, the approach effectively accounts for thermal effects on battery behavior. Its low computational cost and consistent accuracy make it suitable for real-time implementation in BMSs, ensuring robust SOC estimation even in challenging operational environments [59].

Reducing the computational complexity of physics-based battery models is essential for their practical integration into real-time BMSs. By generating reduced-order models (ROMs), different algorithms offer trade-offs between speed, memory efficiency, and accuracy. The selection of an appropriate algorithm, such as CRA for speed, HRA for memory efficiency, LRA for high accuracy, or DRA for specific conditions, should be based on the operational context, including temperature and charge dynamics. These optimized models enable faster simulation and accurate representation of internal battery behavior, supporting more effective and responsive system-level control [60].

Reducing electrochemical battery models using the Galerkin projection method enables accurate and efficient simulation while preserving key physical behaviors. By converting diffusion-based partial differential equations (PDEs) into lower-order ordinary differential equations, the model achieves fast computation with minimal loss of accuracy. Verified across different battery chemistries and dynamic operating profiles, the model maintains voltage prediction errors within ± 30 mV. Its ability to simulate much faster than real-time makes it highly suitable for real-world applications such as battery state estimation and control, with careful selection of basis functions ensuring high fidelity in both frequency and time domains [61].

Accurate SOC estimation is crucial for optimizing the performance and lifespan of LIBs. Both data-driven and equivalent circuit modeling approaches offer valuable tools for capturing battery behavior. ML techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, and Decision Trees, excel in processing complex, high-dimensional data and modeling nonlinear dynamics, enabling real-time and precise SOC predictions. Electrical circuit models, particularly the 2RC model, provide a physically interpretable framework for simulating battery dynamics under varying conditions. Combining these approaches enhances SOC estimation accuracy and supports more intelligent, adaptive BMSs [62]. Figure 5 represents the classification of battery modeling techniques applied in BMSs.

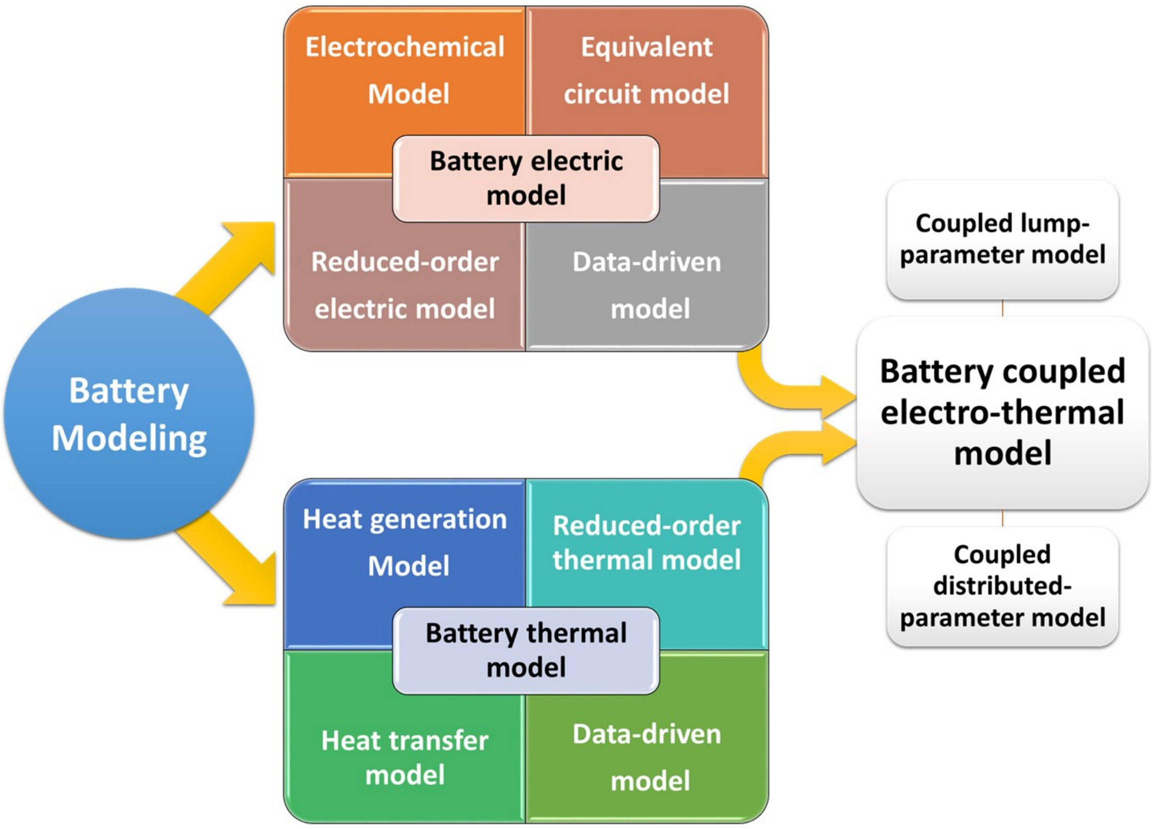

Figure 5. Classification of battery modeling techniques in BMSs.

4.1. Equivalent-Circuit Models

4.1.1. Thevenin-Based Models

Reliable state-of-charge and health estimation is critical for effective battery management and vehicle performance. Adaptive Unscented Kalman Filters (KFs), when combined with recursive parameter tuning and a Thevenin-based equivalent circuit model, offer a practical balance between computational efficiency and estimation accuracy. High-quality input data, particularly a precise OCV-SOC curve and accurate initial SOC estimates, significantly enhance performance. However, sensor limitations, especially current measurement inaccuracies, can impact overall system precision. Improving sensor accuracy and further refining the algorithm in controlled environments are key steps toward achieving more accurate and robust SOC estimation in real-world applications [63].

4.1.2. Resistance-Capacitance Models

First- and second-order RC models offer a practical balance between accuracy and computational efficiency for simulating LIB behavior in real-time applications. The second-order RC model provides superior accuracy across a range of discharge profiles, including complex driving cycles, making it suitable for high-precision applications such as EVs and aerospace systems. With relative errors of less than 2%, both models meet industrial accuracy requirements; however, the second-order RC model consistently outperforms the first-order model in capturing dynamic behavior. Due to their fast simulation speeds, RC models are preferable over more complex electrochemical models (EMs) for applications requiring rapid response and reliable real-time battery management [64].

4.1.3. Advanced High-Order Equivalent-Circuit Models

A hybrid modeling approach enhances SOC estimation accuracy under complex and dynamic operating conditions, such as those found in real-world driving and stress tests. The model maintains strong performance even when initial SOC estimates are inaccurate, demonstrating robustness against typical uncertainties. Compared to other filtering methods, it offers superior accuracy, particularly in nonlinear and congested load profiles. While performance may decline near zero SOC or under extreme temperature variations, the method remains effective in most real-world scenarios. This makes it a reliable solution for applications requiring precise SOC tracking under challenging conditions [65].

4.2. Electrochemical Models

4.2.1. Pseudo-Two-Dimensional Models

Model reduction techniques significantly improve simulation efficiency for LIBs, particularly under low discharge conditions. By simplifying thermal and electrochemical dynamics, such as treating temperature as a global variable or assuming a uniform solid-phase potential, simulation time can be significantly reduced with minimal loss of accuracy at low currents. Among the strategies, φ-reduction offers a good balance of speed and accuracy across various conditions, while the combined reduction model is ideal for applications prioritizing fast computation over high accuracy. However, reduced models become less reliable at high discharge rates due to increased estimation errors. Overall, model reduction is an effective strategy for accelerating simulations in scenarios with low to moderate current demands [66].

4.2.2. Newman's Battery Model

Reformulating the Poisson–Nernst–Planck (PNP) equations using electrochemical potentials and volume averaging enables the development of large-scale models that closely align with the Newman model while offering improved clarity in charge carrier dynamics. By incorporating chemical capacitance and transport properties into a hierarchical equivalent circuit framework, the behavior of porous electrodes is accurately captured in both solid and liquid phases. This approach enhances the precision of modeling charge transport and reveals fundamental connections between kinetic and thermodynamic properties, providing a more detailed and efficient representation of battery electrode behavior for advanced electrochemical modeling [67]. Hierarchical equivalent-circuit models have been experimentally validated in several research-grade BMS prototypes developed for electric-vehicle and stationary-storage applications. One study demonstrated a multi-node equivalent circuit framework capable of capturing temperature- and state-of-health-dependent parameter variations across parallel cells, achieving voltage prediction errors below 2% during dynamic drive-cycle testing. Another research work introduced a hierarchical balancing and estimation architecture that integrates cell-level RC sub models with pack-level supervisory control, achieving efficient computation and scalable implementation suitable for modular BMS configurations. Collectively, these investigations confirm that hierarchical ECMs act as effective intermediates between high-fidelity electrochemical models and simplified single-cell circuits, providing both real-time compatibility and modular scalability for next-generation EV systems and ESSs [70,71].

With recent advances in embedded computation, the real-time feasibility of P2D-based models has significantly improved. Modern BMS controllers equipped with high-performance microprocessors or FPGA acceleration can execute extended-order P2D solvers using adaptive meshing and reduced-order parameterization without violating real-time constraints. Consequently, the limitation associated with classical P2D formulations is primarily historical; current implementations demonstrate that physics-resolved modeling and fast numerical solvers can now coexist in practical, on-board BMS environments.

4.2.3. Reduced-Order Electrochemical Models

Reduced-Order Electrochemical Models (ROEMs) offer a strong balance between computational speed and predictive accuracy, making them ideal for real-time battery management in EVs. With terminal voltage errors generally under 20 mV and significantly faster simulation times compared to full-order models, ROEMs accurately capture battery behavior under dynamic conditions such as FUDS and UDDS profiles. Their ability to model key electrochemical dynamics, such as electrolyte concentration and diffusion potential, while maintaining low computational demand, enables efficient integration into BMSs. Future enhancements focusing on parameter adaptation for temperature and aging effects will further strengthen their applicability in real-world scenarios [68].

4.3. Data-Driven Models for Battery Prediction

4.3.1. Machine Learning and Deep Learning-Based Models

Effective fault detection and prediction in LIBs remain challenging due to limited understanding of failure mechanisms, scarce fault data, and the complexity of real-world operating conditions. Advancements in flexible thresholding, real-time monitoring, and fault detection during stress scenarios, such as fast charging or degradation, are critical for ensuring safety and reliability. Accurate load estimation and optimized cell balancing are essential for system stability. While ML offers promising capabilities for predictive fault diagnosis, further research is needed to overcome challenges related to data availability, algorithm complexity, and computational efficiency for practical deployment in large-scale battery systems [69,72,73].

4.3.2. Hybrid Physics-Informed Data-Driven Models

Based on data on energy consumption, the suggested battery degradation model forecasts variations in internal resistance and battery capacity using multi-layer perceptron variational networks. The findings show that this model can accurately forecast future capacity and battery voltage changes, including discharge endpoints, even with sparse data. The study demonstrates increases in prediction accuracy and decreased errors, especially for long-term forecasts, by employing an ensemble model and integrating data from older batteries. The suggested model's ability to adapt to different load conditions is one of its main advantages. The model accurately forecasts capacity loss in various scenarios by utilizing data from batteries exposed to comparable degradation conditions. Furthermore, adding variational layers to the neural network (NN) reduces prediction uncertainty and yields more accurate forecasts of battery status. The study, however, acknowledges certain limitations that could impact the findings, such as the use of homogeneous battery data and identical load conditions for all tests. All things considered, the hybrid model is a strong instrument for predicting remaining useful life and maximizing battery performance, especially in Unmanned Aerial Vehicle (UAV) systems. To improve prediction accuracy and fault detection, future work will test the model under actual load conditions and extend it to additional powertrain system components [74].

4.4. Multi-Physics and Digital Twin Models

4.4.1. Coupled Electrochemical–Thermal–Mechanical Modeling

Battery degradation is strongly influenced by operating conditions, with both temperature and C-rate playing critical roles through distinct mechanisms. High C-rates accelerate the loss of active cathode material due to increased diffusion-induced stress, while high temperatures intensify the formation of SEI. Conversely, low temperatures promote lithium plating by slowing reaction kinetics. The degradation initially progresses linearly but can rapidly escalate after prolonged cycling. A detailed electrochemical–thermal mesoscopic model effectively captures these dynamics, enabling accurate prediction of capacity loss and offering deeper insight into degradation behavior across varying operational conditions. This makes it a valuable tool for assessing and managing long-term battery performance [75].

4.4.2. Digital Twins for Battery System Optimization

Cloud-based BMSs, enhanced by IoT and DT technology, provide a powerful framework for real-time monitoring, diagnostics, and predictive analytics. By continuously collecting and analyzing battery data in the cloud, the system enables accurate estimation of SOC and SOH, even in the presence of early faults. Advanced algorithms, such as H-infinity filters and particle swarm optimization (PSO), support the long-term tracking of degradation. Experimental validation confirms the system's reliability and stability across various conditions, demonstrating its effectiveness for precise battery state assessment and intelligent management in both stationary and dynamic applications [24].

4.4.3. Modeling Trade-Offs and Deployment Guidance

Battery modeling approaches can be contrasted along several key dimensions: real-time suitability (latency and computational requirements), data and calibration demand, stability of training and estimation, interpretability and verifiability, generalization and robustness across temperature, aging, and usage conditions, uncertainty quantification (UQ), and long-term maintenance and portability across chemistries and pack designs [23,76].

ECMs, such as Thevenin or RC networks, are widely adopted in embedded BMSs due to their excellent real-time suitability, often achieving kilohertz update rates on microcontrollers [77]. They require relatively modest data for calibration, the OCV-SOC curve and a small set of RC parameters identified from drive cycles [78]. ECMs are stable, well-conditioned for parameter identification, and highly interpretable, as their elements map directly to ohmic resistance, polarization, and diffusion processes. Their generalization is good within local operating conditions but requires re-identification across temperature and SOH variations unless parameters are explicitly modeled against these factors [79]. Uncertainty quantification is naturally incorporated through KF, and maintenance is light, usually limited to periodic re-identification. These models are most appropriate when fast, explainable estimation is required under resource constraints [76].

Electrochemical models, including DFN or pseudo-two-dimensional formulations, provide the highest level of physical fidelity. They capture electrochemical and transport phenomena in detail, making them valuable for safety analysis, fast-charging studies, and cell design [80]. However, their computational cost precludes direct real-time deployment without model reduction [81]. They also require extensive parameterization, including kinetic and thermophysical properties, which are often difficult to obtain. Parameter identifiability can be challenging, and model calibration may require regularization or constraints. Nevertheless, when properly parameterized, EMs generalize strongly across operating conditions, though aging-induced drifts necessitate recalibration. While UQ can be incorporated via ensemble or filtering methods, this is computationally expensive. These models are best used when physical insight and predictive accuracy are prioritized over real-time feasibility [81]. Reduced-order electrochemical models, such as single-particle models, offer a compromise between ECMs and full EMs [80]. After reduction, they can operate in real time at 10–100 Hz on automotive ECUs. They require fewer parameters than DFN but still depend on accurate OCV and kinetic characterizations. Compared to DFN, their reduced state dimension improves numerical stability and identifiability while retaining physical interpretability. Their generalization is good, though parameter adaptation with temperature and SOH improves robustness. UQ is readily incorporated with filtering approaches. Maintenance involves light periodic refitting, making ROEMs well-cited to applications requiring both real-time performance and a physics-based backbone [76].

Purely data-driven machine learning (ML/DL) models rely on extensive training datasets covering diverse drive cycles and operating conditions. Once trained, inference is computationally efficient, but training is sensitive to optimizer settings, normalization, and data leakage [76]. These models can achieve high accuracy under complex, nonlinear usage, but suffer from limited interpretability and potential distribution shifts under new chemistries or unseen conditions [81]. UQ requires specialized techniques such as ensembles, Monte Carlo dropout, or evidential layers. Maintenance is moderate to high, involving periodic retraining as fleet data evolve. Such models are most effective when large-scale telemetry is available and accuracy is prioritized over physical interpretability [82,83].

Hybrid physics-informed models—for example, coupling SPMs with neural networks—mitigate the limitations of both pure physics and data-driven approaches. Embedding physical priors improves training stability, reduces data requirements, and constrains predictions to physically plausible ranges [84,85]. These models retain partial interpretability through their physics components, generalize better out of distribution than pure DL, and combine traditional filter covariances with ML-based UQ. Maintenance typically involves refreshing the neural component or re-identifying a limited parameter set. They are attractive for safety-critical applications requiring both accuracy and guardrails.

Finally, digital twins integrate physical or reduced-order models with data assimilation, often deployed in edge–cloud architectures. They demand continuous sensor streams (voltage, current, temperature, and impedance, when available), and their robustness depends on the assimilation method used. When physics-based, DTs remain interpretable and provide strong generalization by continuously recalibrating against real-world measurements, although this depends on the reliability of the sensors. UQ is naturally supported by Bayesian filtering and ensemble methods. While setup is resource-intensive, ongoing maintenance is moderate once deployed. DTs are particularly suited for fleet-level monitoring, predictive maintenance, and lifecycle optimization [23,83,86].

To conclude, ECMs are most suitable for cell-level BMSs with stringent real-time constraints. Reduced-order EMs balance physical fidelity and real-time deployment, making them valuable for fast-charging and safety applications. Pure ML/DL approaches are advantageous when large-scale telemetry is available; however, hybrid physics-informed models offer a safer and more robust alternative for critical deployments. At the fleet scale, DTs provide a pathway for continuous health monitoring and predictive maintenance. Table 6 summarizes the trade-offs across model families in terms of real-time suitability, data requirements, stability, interpretability, and maintainability.

Table 6. Comparative evaluation of battery modeling approaches based on deployment trade-offs.

Model Family	Real-Time Suitability	Data Needs	Training/ID Stability	Interpretability	Generalization (T/Aging/Usage)	Uncertainty	Maintenance
ECM (RC/Thevenin)	High * (MCU)	Low-Med *	High	High	Med (needs re-ID)	Good (KF cov.)	Low
EM (DFN/P2D)	Low (full); Med with reduction	Med-High	Med (ID sensitive)	Very high	High (with correct params)	Med-High (costly)	Med
SPM/ROEM	Med-High	Med	Med-High	High	High (with adaptation)	Good	Med
ML/DL (pure)	Med (inference)	High	Train: Med-Low	Low-Med	Med (OOD risk)	Med (ensembles)	Med-High
Hybrid physics-informed	High	Med	High	Med-High	High	Good	Med
Digital Twin	Med-High (edge/cloud)	High	Med-High	High (physics-led)	High (continuous calibration)	High	Med-High

* All High/Med/Low are relative within BMS contexts. "Training/ID" = training (ML) or identification (physics).

5. Battery State Estimation in Battery Management Systems

In BMSs, battery state estimation refers to methods for precisely assessing the SOC, SOH, and forecasting future battery performance. To track battery health and calculate RUL, techniques including KF, EKF, particle filtering, and ML algorithms are frequently employed. In practical applications, these methods allow for improved performance optimization, early degradation detection, and increased LIB dependability. Table 7 describes a summary of SOC estimation algorithms and their performance.

Table 7. A summary of SOC estimation algorithms and their performance.

Response	Typical Accuracy/Error	Response Time	Remarks
Coulomb Counting	Accuracy is influenced by current and time drift	Fast	Cumulative errors from current sensor noise and capacity uncertainty
Open-Circuit Voltage (OCV)	Error: $\pm 5\%$ (with dual EKF and temperature compensation)	Slow	Requires rest conditions; sensitive to temperature and model fit
Extended Kalman Filter (EKF)	SOC error $< 5\%$, OCV error < 0.1 V	Real-time	High precision across full SOC range; adapts to dynamic conditions
Dual EKF + LSTM	High robustness under full cycles	Real-time	Tracks SOC and SOH jointly; noise-resistant
AI-based (e.g., NARX)	Accuracy depends on sensor precision and input variability	Moderate	Sensitive to measurement uncertainty; confidence intervals overlap observed

5.1. State of Charge Estimation Methods

Selecting an appropriate OCV-SOC model requires balancing accuracy, computational load, and implementation complexity. While linear models offer simplicity and closed-form solutions, more complex models may provide better accuracy at the cost of increased processing demands. Evaluation criteria, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as well as numerical stability and modeling error, help determine model quality. Priority is given to accuracy in applications that require high reliability. The study highlights that model selection should consider system constraints and recommends using multi-criteria decision-making methods, such as the Borda count, or more informed choices, especially in resource-limited environments [87].

KF-based algorithms ($x_{k|k-1}$, $P_{k|k-1}$, K_k), including the EKF, offer high-precision estimation of battery parameters and SOC, making them well-suited for real-time battery management applications. Simulation and experimental results confirm that the method accurately captures the nonlinear behavior of the SOC-OCV relationship, particularly at low and high SOC levels. With SOC estimation errors consistently below 5% and OCV errors under 0.1 V, the approach ensures reliable decision-making during charging and discharging. Its rapid parameter convergence and ability to adapt to varying operating conditions highlight its effectiveness for dynamic battery monitoring and control [88].

Accurate and reliable modeling is essential for effective battery management in lithium-ion systems used across EVs and smart grids. Data-driven, equivalent circuit, and EMS each offer unique advantages, and their selection should be tailored to specific application needs. State estimation techniques, particularly for SOC and SOH, have demonstrated strong accuracy and stability across various studies. Real-time integration of sensor data with estimation algorithms is crucial for monitoring battery condition and ensuring safe and efficient operation. A comprehensive understanding of available modeling approaches enables the design of more adaptive and robust BMS solutions [89].

Accurate SOC estimation is vital for ensuring the reliability, safety, and performance of LIBs in both mobile and stationary energy systems. Advanced modeling approaches, such as enhanced EKF techniques, improve estimation precision by capturing dynamic battery behavior under varying operating conditions. A comparative analysis of parameter identification methods underscores the importance of selecting robust techniques to minimize residual effects on OCV and enhance estimation accuracy. Integrating SOC estimation into real-time BMSs using microcontroller-based systems enables efficient monitoring and control, supporting fault detection, optimal charging strategies, and overall system stability across diverse applications [90].

Accurate estimation of SOC and SOH under real-world driving conditions is achievable through advanced methods combining DEKF and Long Short-Term Memory (LSTM) algorithms. The approach demonstrates high robustness to sensor noise and effectively tracks battery capacity and health, even during full charge–discharge cycles. Resetting the BMS operational history enhances estimation precision, supporting better range prediction and lifecycle assessment. The findings underscore the importance of incorporating diverse environmental factors into estimation strategies and highlight the need for standardized evaluation methods to ensure consistency and reliability across BMSs [91].

Real-time estimation of SOH (State of Health) is critical for the effective operation of BMSs in EVs, yet it remains challenged by factors such as battery aging, thermal effects, charge imbalance, and data limitations. While DL methods like Convolutional Neural Networks (CNN), LSTM, GRU, and autoencoders offer potential for improving estimation accuracy, their implementation is often hindered by high computational costs and sensitivity to model design choices. Hybrid approaches that combine DL with traditional methods such as Kalman and particle filters show promise in enhancing performance. However, achieving reliable SOX estimation still requires addressing key issues in thermal management, data quality, and real-world validation practices [92]. Different architectures address complementary challenges in time-series estimation. CNNs are effective for extracting local features from raw signals, offering efficiency and robustness to noise. LSTMs are designed to capture long-range dependencies and are advantageous for modeling sequence evolution. CNNs therefore, excel in short, structured segments, while LSTMs are preferred when a longer temporal context is required [93,94].

5.1.1. Open-Circuit Voltage Method

Simultaneous estimation of SOC and capacity in LIBs can be achieved with high accuracy using a dual EKF combined with a modified OCV–SOC relationship ($V_{OCV} = f(SOC,T)$, where T = Temperature). By addressing measurement noise and adapting the OCV-SOC curve to specific battery types, the method enhances reliability across various operating conditions. Decoupling filter weights and state sequences simplifies computation while maintaining estimation precision, with errors consistently within ±5% of actual values. The approach demonstrates strong convergence even with initial inaccuracies, making it a practical and robust solution for real-time battery monitoring and management [95,96].

5.1.2. Coulomb Counting Method

Coulomb counting is a practical method for estimating the SOC in rechargeable batteries, but its accuracy is influenced by cumulative errors over time. Key error sources such as current measurement, integration drift, oscillator instability, and capacity uncertainty can significantly impact estimation reliability, especially across full-discharge cycles. These errors evolve differently, with some scaling with time and others with accumulated charge. To improve estimation accuracy, both the estimated SOC and the associated error variance should be considered. Incorporating error models and correction strategies can enhance the effectiveness of Coulomb counting, particularly when combined with advanced methods such Kalman filtering [97].

$$SOC(t) = SOC(0) - \frac{1}{Q}\int_0^t I(\tau)d\tau \tag{1}$$

$$V_{OCV} = f(SOC, T) \tag{2}$$

where $SOC(t)$ represents the SOC at time $SOC(t)$, while $SOC(0)$ is the initial SOC. Q denotes the nominal capacity of the battery, V_{OCV} is the open circuit voltage, T represents temperature, and $I(\tau)$ refers to the current at a given time τ [98].

5.1.3. Model-Based Kalman Filters (EKF, UKF, PF)

Accurate and efficient SOC estimation in EVs can be achieved using KF algorithms combined with simplified yet effective battery models like the EECM. While KFs offer real-time estimation with low computational load and self-correction features, challenges remain in model selection, initial SOC determination, and parameter tuning. Improving estimation accuracy requires advanced battery models that capture electrochemical behavior under dynamic conditions, including aging, hysteresis, and temperature effects. Enhancing filter adaptability and testing across diverse scenarios are essential for robustness, and integrating KFs with complementary methods may further reduce computational demands while maintaining precision [99].

5.1.4. AI-Driven State of Charge Estimation

Accurate SOC estimation using AI models such as NARX depends heavily on understanding and accounting for measurement uncertainty. Evaluating these models from a metrological perspective reveals that sensor precision and input variability significantly affect estimation accuracy and confidence. As uncertainty increases, overlap between estimated and reference confidence intervals also rises, highlighting the need for careful sensor selection in BMS design. This approach provides a reliable framework for assessing AI-based SOC estimation methods and supports more informed decisions regarding the integration of ML with real-world measurement systems. While both the EKF and UKF extend the Kalman filter framework to nonlinear systems, their technical treatments differ. The EKF relies on local linearization of the nonlinear state equations using Jacobians, which can introduce approximation errors and reduce stability under highly nonlinear dynamics. In contrast, the UKF employs the unscented transform to propagate a set of deterministically chosen sigma points through the nonlinear dynamics, capturing mean and covariance up to the second order without requiring Jacobian calculations. This makes the UKF more accurate for strongly nonlinear models and easier to implement when analytic derivatives are difficult to obtain, at the cost of higher computational demand [100]. Beyond sensitivity to sensor precision and data variability, the adaptability of AI models varies significantly across battery aging stages. While traditional architectures such as NARX perform reliably during early cycles with stable signals, their accuracy declines as batteries age due to cumulative nonlinear degradation effects. In contrast, recurrent and hybrid models such as LSTM and PI-LSTM demonstrate stronger adaptability by learning temporal dependencies and incorporating physical aging factors, including temperature and cycle depth. Consequently, model selection for BMS applications should consider not only initial accuracy but also the long-term adaptability required to maintain predictive reliability throughout the battery's lifecycle [101–103].

5.2. State-of-Health Estimation

5.2.1. Feature Extraction Methods

Accurate state-of-health (SOH) estimation can be achieved by combining a convolutional autoencoder with a self-attention mechanism, thereby eliminating the need for manual feature engineering. This approach effectively extracts and processes features, resulting in low Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) across both experimental and public datasets. The model demonstrates strong generalization and precision, making it well-suited for integration into BMSs. Future exploration of partially charged or discharged conditions will further enhance its applicability in real-world scenarios, supporting robust, data-driven battery health monitoring [104].

5.2.2. Impedance-Based State-of-Health Estimation

EISGAN offers highly accurate and reliable capacity estimation for LIBs by leveraging electrochemical impedance spectroscopy (EIS) data through a generative modeling approach. The model effectively captures capacity degradation trends and maintains low prediction errors across different battery stages and operational conditions. Its performance surpasses that of direct EIS-based methods, demonstrating strong potential for integration into battery health monitoring systems. Although interpreting the latent variables requires further analysis, this method provides a powerful data-driven tool for capacity estimation. Future research should be directed toward comparing this method with circuit-based and physics-informed models for a broader assessment of SOH [105].

5.2.3. Machine Learning and Fuzzy Logic for State-of-Health Estimation

Fuzzy logic systems provide an effective approach for evaluating the SOC and SOH of LIBs, particularly at temperatures above 0 °C. The study confirms that AC impedance measurements, influenced by factors such as temperature, DC current, and charge level, can serve as reliable indicators of battery condition. Significant differences in impedance between new and aged cells, especially under DC bias, highlight the value of impedance-based diagnostics. Fuzzy logic enables meaningful interpretation of these variations, supporting accurate health assessment and monitoring of battery aging effects under real-world conditions [106]. Table 8 provides a summary of SOC estimation algorithms and their performance.

Table 8. Summary of SOH Estimation Algorithms and Their Performance.

Response	Typical Accuracy/Error	Response Time	Remarks
Autoencoder + Self-Attention	Low RMSE and MAPE	Moderate	Strong generalization: no manual feature engineering required
EISGAN (Impedance-based GAN)	Low prediction errors	Moderate	Captures capacity degradation trends; high accuracy across conditions
Fuzzy Logic + AC Impedance	Reliable at $T > 0$ °C	Real-time	Effective for aged vs. new cell differentiation under DC bias

5.3. State-of-Energy and State-of-Power Estimation

5.3.1. Energy Availability Prediction Models

Accurate estimation of SOP and voltage can be achieved even with uncertain initial conditions, enabling the reliable prediction of battery performance in EVs. Temperature significantly impacts battery power and energy capabilities, with higher temperatures enhancing discharge potential. The method accurately tracks these variations across different thermal environments and operational states, maintaining estimation errors below 2%. It also accounts for aging effects, ensuring that power output remains within safe design limits over the battery's lifecycle. This approach provides a robust, real-time tool for evaluating battery energy and power availability under diverse and dynamic driving conditions [107].

5.3.2. Artificial Intelligence and Deep Learning-Based State-of-Power Estimation

Advanced ML architectures like CNNs and LSTMs significantly enhance SOP prediction by capturing complex patterns in battery data. However, challenges in data availability and diversity limit the effectiveness of the model. Synthetic data generation using generative adversarial networks (GANs) and Variational Autoencoders (VAEs) offers a promising solution by enriching datasets with realistic variations, reducing dependence on manual data collection. For practical deployment, improving model interpretability and incorporating multidimensional correlations, such as those in temporal, spatial, and frequency domains, is essential. These enhancements will enable more accurate, adaptable, and intelligent decision-making in real-world battery and communication systems [108]. Table 9 provides a comparison between AI methods and traditional estimators for battery state estimation.

Table 9. AI Methods vs. Traditional Estimators for Battery State Estimation.

Criteria	Traditional Estimators (EKF, PF, KF)	AI Methods (ML/DL)
Accuracy under Nonlinear Dynamics	EKF accurately captures SOC-OCV nonlinearities, especially at low/high SOC levels; errors < 5%	DL models (e.g., LSTM) enhance prediction by learning complex patterns; outperform EKF under variable conditions
Robustness to Sensor Noise	Good adaptability but sensitive to initial conditions and model parameters	DEKF + LSTM combo shows high robustness to sensor noise
Adaptability to Aging and Temperature Effects	Limited; requires careful tuning and advanced model integration	Physics-informed DL (e.g., PI-LSTM) captures real-world aging/stress factors better
Computational Complexity	Low to moderate; suitable for real-time use in embedded systems	High computational cost; less practical for low-power BMSs
Data Requirement	Lower; model-driven with fewer data dependencies	High; requires large, diverse datasets; sensitive to data quality
Real-time Capability	Well-suited for real-time applications	Real-time deployment possible but depends on model complexity and hardware support

Table 9. *Cont.*

Criteria	Traditional Estimators (EKF, PF, KF)	AI Methods (ML/DL)
Interpretability	High; based on physical models with clear assumptions	Lower; "black-box" nature of DL hinders interpretability
Best Use Case	Embedded, real-time systems with limited computation and reliable model parameters	Complex, dynamic environments where capturing degradation patterns or forecasting RUL is critical

5.4. Remaining Useful Life Prediction

5.4.1. Probabilistic Degradation Modeling

Bayesian inference combined with MCMC sampling provides a powerful framework for predicting the useful life of devices by incorporating physical aging mechanisms and updating predictions as new data becomes available. This method outperforms traditional models, especially in scenarios with limited prior knowledge, and offers high accuracy in assessing degradation behavior. However, its practical use is currently limited by high computational demands and difficulty in detecting sudden failures without prior indicators. Future improvements should focus on reducing complexity and enhancing scalability to make the approach more applicable for real-world maintenance and reliability forecasting [109].

5.4.2. Artificial Intelligence and Physics-Informed Models for Remaining Useful Life Estimation

The Physics-Informed LSTM (PI-LSTM) approach enables accurate modeling of LIB degradation and reliable prediction of RUL by integrating data-driven learning with a physics-based aging model. By incorporating key stress factors such as temperature, SOC, cycle time, and discharge rate, the method effectively captures real-world operational influences on battery aging. Combining physical insights with LSTM-based learning improves generalization and prediction accuracy across diverse conditions. Experimental results confirm superior performance compared to other DL models, making PI-LSTM a robust and precise tool for battery health forecasting and lifecycle management [110].

Development and calibration of core BMS algorithms, such as fast-charge current-limit estimation, follow a hybrid simulation-experiment workflow. The process begins with physics-based or reduced-order electrochemical modeling, where safety-constrained current limits are computed using optimization algorithms (e.g., sequential quadratic programming or genetic algorithms (GA) under predefined voltage and temperature thresholds. These theoretical limits are embedded in a digital-twin environment to perform virtual charging experiments, allowing rapid sensitivity analysis across thermal, SOC, and degradation parameters. The results are then transferred to hardware-in-the-loop (HIL) test benches, where measured current–voltage–temperature profiles are compared to simulated predictions. Deviations are used to update model coefficients through recursive least squares or Bayesian calibration. The loop continues until convergence between simulation and experiment is achieved, after which validated parameters are stored in the BMS lookup tables for real-time implementation. This closed iterative cycle accelerates validation, enhances reproducibility, and ensures that the fast-charging algorithm remains both data-driven and experimentally grounded [111]. Table 10 describes a summary of techniques for state estimation, health monitoring, and prognostics in LIBs.

Table 10. Summary of Techniques for State Estimation, Health Monitoring, and Prognostics in LIBs.

Method	Approach	Key Features/Results	Challenges	Ref.
SOC Estimation (General)	Hybrid models	Error evaluation, AIC/BIC for model quality.	Accuracy vs. computational power.	[74]
Kalman Filter (KF)/EKF	Kalman filters for SOC estimation	SOC error $\leq$ 2%, Voc error < 0.1 V, 0.03%.	Real-time accuracy, dynamic conditions.	[75]
State Estimation Models for Li-ion	Data-driven, equivalent circuit, electrochemical models	Accurate SOC, SOH estimation, real-time monitoring.	Model complexity.	[24]
EKF Advanced Method	EKF with OCV modeling	Better accuracy, real-time application.	High setup and parameter complexity.	[87]
DEKF and LSTM for SOH Estimation	DEKF and LSTM for driving conditions	High accuracy in SOC, SOH estimation.	Environmental factors, standardization.	[88]
SOX Estimation (SOC, SOE, SOH)	KF, PF, AI techniques (CNN, LSTM)	Improved SOC, SOH, and state estimation.	Data quality, computational cost.	[89]
OCV Method	Dual EKF, modified OCV-SOC	SOC and capacity estimation within ±5%.	Noise, initial errors in measurements.	[90]
Coulomb Counting	Measurement of charge/discharge cycles	Long-term errors from oscillators, capacity, measurement errors.	Error growth, needs error mitigation.	[91]
Model-Based Kalman Filters	Kalman filters with MBM for SOC estimation	Accurate, low computational demand, self-correcting.	Calibration, model adjustments.	[92]
AI-driven SOC Estimation	NARX and machine learning for SOC	Improved estimation, sensor accuracy critical.	Measurement uncertainty.	[95]
Feature Extraction for SOH	Convolutional Autoencoder for SOH estimation	High accuracy, RMSE 0.0048, MAPE 0.46%.	SOH under partial conditions.	[97]
Impedance-Based SOH Estimation	EISGAN for capacity estimation	MAE and RMSE < 2 mAh, more precise than traditional methods.	EIS data analysis required.	[99]
Machine Learning and Fuzzy Logic	Fuzzy logic and machine learning for SOH using EIS	Uses temperature, charge, and current for SOH estimation.	DC current, temperature effects on impedance.	[100]
Energy and Power Estimation	Energy models for SoP	Power error $\leq$ 2%, temperature impact.	Design constraints under extreme conditions.	[104]
AI and Deep Learning for SOP	CNN, LSTM for SOC and power estimation	Improved SOP predictions with advanced architectures.	Data expansion, model interpretability.	[104]
KF and EKF	KFs for battery parameter and SOC estimation	SOC error < 2%.	Limited to linear systems, complexity with accuracy.	[105]
Hybrid Model for SOC Estimation	Combines different SOC models	Balances accuracy and efficiency.	Integration complexity.	[106]
Nonlinear SOC Estimation	Advanced nonlinear filters	Better accuracy for specific battery types.	Complexity, noise sensitivity.	[107]

5.5. Sensitivity Analysis Discussion

The performance of battery state estimators in BMSs is inherently sensitive to temperature, battery aging, and measurement noise, all of which can compromise the stability and robustness of SOC, SOH, and RUL predictions. Understanding these sensitivities is critical for ensuring reliable battery operation in real-world applications.

5.5.1. Temperature Effects

Temperature directly influences electrochemical reactions, internal resistance, and the OCV-SOC relationship, making SOC estimation particularly sensitive under thermal variations. Methods like dual EKF with temperature-dependent OCV models have demonstrated robustness to thermal fluctuations by dynamically adapting the voltage response [95]. Similarly, SOH estimators that leverage impedance-based features or ML models must account for temperature-dependent impedance changes to avoid misinterpreting thermal effects as degradation [80,82]. For RUL prediction, temperature is a key stress factor in probabilistic degradation and physics-informed LSTM models, affecting the rate of capacity fade and cycle life [85,86]. Failure to account for thermal conditions can lead to systematic bias in estimators, resulting in underestimation of degradation or overestimation of available energy.

5.5.2. Aging Effects

Battery aging introduces nonlinearity and drift in SOC and SOH estimation. Coulomb counting accumulates integration errors over time, and even Kalman-based estimators can experience model mismatch if capacity fade and internal resistance changes are not updated [23,78]. ML and hybrid AI-physics approaches for RUL estimation are sensitive to historical degradation patterns, requiring retraining or adaptive updates to remain accurate [86]. Impedance-based SOH estimators also rely on aging-sensitive features; without calibration for cell aging, their predictions can become unstable [105]. Overall, estimator robustness improves when models incorporate aging mechanisms either explicitly (physics-informed) or implicitly (adaptive ML frameworks).

5.5.3. Measurement Noise and Operational Variability

Sensor noise in current, voltage, and temperature measurements can propagate through SOC and SOH estimators, affecting confidence intervals and convergence [74,79]. EKF and UKF approaches are inherently designed to mitigate stochastic noise, with UKF offering improved performance for highly nonlinear dynamics [100]. Deep learning models, including CNNs and LSTMs, require careful input preprocessing and noise-aware training to avoid overfitting or unstable predictions [24,84]. Noise sensitivity is especially critical for SOH and RUL prediction, where small errors in feature extraction or state evolution can result in large deviations in degradation assessment [86].

6. Battery Thermal Management Systems

Battery Thermal Management Systems (BTMS) are essential for maintaining the ideal battery temperature, preventing overheating, and ensuring effectiveness and safety. Heat pipes, phase change materials (PCMs), liquid cooling, and air cooling are examples of common cooling methods. Each approach has its own benefits and drawbacks, including cost, complexity, and temperature homogeneity. Although thermal control and system efficiency are balanced in effective BTMS designs, scaling systems for large battery packs, controlling temperature gradients, and ensuring long-term reliability under various operating conditions remain challenging tasks. presents a comparative analysis of BTMS: cooling techniques, efficiency, and challenges.

6.1. Importance of Thermal Management

Effective battery thermal management is critical for ensuring safe, efficient, and long-lasting battery operation. While various cooling technologies, such as PCM, liquid, air, nanofluid, heat pipes, and TEC, offer distinct advantages, each presents specific limitations related to design complexity, thermal conductivity, cost, or reliability. Maintaining battery temperatures within the optimal range of 15–35 °C and minimizing spatial temperature variation to under 5 °C is essential to prevent performance loss, capacity degradation, and safety risks. Optimizing BTMS design requires a careful balance between thermal efficiency, integration feasibility, and system constraints to support stable battery operation across diverse applications [112].

Combining PCM with jute fiber significantly improves the thermal performance of LIBs by reducing peak temperatures more effectively than PCM alone. This hybrid approach minimizes PCM usage, reduces system weight, and enhances energy efficiency, offering a practical and sustainable alternative to energy-intensive active cooling methods. It supports stable battery operation under varying discharge rates and environmental conditions. The findings pave the way for developing lightweight, low-power active-passive thermal management systems, with future work focusing on system integration, optimization, and validation across diverse real-world scenarios [113].

Integrating PCM and copper-PCM foam into BTMS significantly reduces temperature rise and improves temperature uniformity compared to natural cooling, particularly under high discharge rates. Copper foam enhances PCM distribution and heat dissipation due to its porous structure, helping to prevent uneven aging and extend battery life. While this passive cooling approach slightly reduces energy density compared to active systems, it offers improved energy efficiency by eliminating the need for active cooling power. Selecting materials with higher latent heat can further enhance thermal capacity, making this method a viable, low-power alternative for EVs battery cooling [114].

Software tools such as ANSYS Fluent, COMSOL, and MATLAB/Simulink play a crucial role in optimizing battery thermal management by enabling the precise design and simulation of complex cooling systems. Key challenges include maintaining temperature uniformity, managing heat during high-power operation, and mitigating thermal runaway risks. Traditional cooling methods may be inadequate for high-performance batteries, prompting the need for advanced solutions such as immersion or direct liquid cooling. Future improvements focus on hybrid cooling strategies, enhanced thermal conductivity materials, and smart active control systems to improve efficiency and battery lifespan. Optimized battery pack designs with integrated internal cooling further contribute to safer and more energy-efficient thermal management [115].

Copper-PCM foam significantly enhances thermal uniformity in battery modules by leveraging the porous structure of copper to improve PCM distribution and reduce internal temperature differentials to below 5 °C. This thermal improvement can extend battery life by minimizing uneven aging. From an energy efficiency perspective, while copper-PCM foam cooling slightly lowers volumetric and gravimetric energy density compared to active cooling systems, it eliminates the energy consumption associated with active cooling, potentially enhancing overall EV efficiency. However, its effectiveness diminishes at extremely high discharge rates, highlighting the need for further material optimization, particularly through the use of PCMs with higher latent heat capacity, to improve both thermal performance and energy density [116].

Battery temperature is significantly influenced by discharge rates and environmental conditions, with higher rates and extreme heat posing risks to battery lifespan. PCMs, particularly capric acid, effectively absorb heat and maintain safe operating temperatures, especially at lower discharge rates. A 3 mm layer of capric acid provides more efficient thermal control than a thicker paraffin layer, offering a compact and cost-effective passive thermal management solution. However, in extremely hot climates, PCM alone may be insufficient, and a hybrid system combining PCM with liquid cooling is recommended to ensure optimal battery performance and longevity [117]. This heating behavior can be expressed quantitatively using the Bernardi equation, which relates current, voltage, and entropy changes to internal heat generation as shown in Equation (3) [118],

$$\dot{Q} = I(V - U) - TI\frac{dU}{dt} \tag{3}$$

where $\dot{Q}$ represents the rate of heat generation within the battery, typically measured in W. I is the current flowing through the battery, where a positive value indicates charging and a negative value indicates discharging. V denotes the terminal voltage, while U refers to the OCV. T is the battery temperature in K, and $\frac{dU}{dt}$ describes the rate of change in OCV with temperature, accounting for the entropic heat generation.

PCM provides effective thermal control at moderate discharge rates but loses efficiency at higher rates due to its limited heat storage capacity. Optimizing PCM thickness, identified as 26 mm, enhances cooling performance, while incorporating fin structures, particularly I-shaped fins, significantly improves heat transfer and thermal uniformity. Enhancing air convection and incorporating high-conductivity materials, such as graphite, metal foam, or carbon fibers, further enhances the effectiveness of PCM, although structural stability must also be considered. For multi-cell packs, internal fins can aid in intercellular heat dissipation. Integrating PCM with optimized fin structures offers a practical and efficient solution for improving LIB thermal management [119].

6.1.1. Effects of Temperature on Battery Lifespan

Battery temperature plays a significant role in accelerating aging, particularly at elevated levels above room temperature, while the effects of SOC and C-rate vary by cell type. Significant discrepancies between ambient and actual cell temperatures, often up to 40 °C higher, can occur under high C-rates and poor cooling conditions, leading to faster degradation. Structural factors such as electrode and separator thickness, as well as cell geometry, also influence heat generation and aging. Current experimental and simulation approaches often overlook transient temperature spikes, which can critically affect cyclic aging outcomes. Accurate temperature assessment and improved thermal management are essential for preserving battery longevity, particularly in high-energy applications [120,121].

6.1.2. Thermal Runaway Prevention

Preventing thermal runaway is a critical focus of battery thermal management, with systems categorized as internal, more complex and costly but space-efficient, or external, which require more space. Effective mitigation requires predictive modeling that can estimate internal cell temperatures and identify thermal runaway risks early in the design phase and during operation. Advanced BTMS strategies are evolving to combine liquid and evaporative cooling for better thermal control. Additionally, research is progressing in identifying vulnerable battery types and developing integrated fire suppression systems to minimize damage, underscoring the need for continued investigation into more precise forecasting and protective solutions [122]. The overall cell temperature evolution can be described by a lumped energy balance, where generated heat competes with convective and conductive losses.

$$mc_p\frac{dT}{dt} = \dot{Q} - hA(T - T_\infty) + q_{cond} \tag{4}$$

where $mc_p\frac{dT}{dt}$ represents the rate of change in internal energy of the battery. Here, m is the mass of the cell, c_p is the specific heat capacity, and $\frac{dT}{dt}$ denotes the rate of temperature change with time. The term $\dot{Q}$ corresponds to the total heat generation rate within the battery, which includes both irreversible (Joule) and reversible (entropic) heat contributions.

Heat loss to the surroundings is modeled through the convective term $hA(T - T_\infty)$, where h is the convective heat transfer coefficient, A is the surface area of the battery, and $(T - T_\infty)$ is the temperature difference between the battery surface and the ambient environment. Additionally, conductive heat transfer is represented by q_{cond}, which accounts for heat exchanged through direct physical contact with neighboring components, such as a cooling plate or adjacent cells in a module [123].

6.2. Passive Thermal Management Strategies

6.2.1. Phase Change Materials

A passive thermal management strategy using PCMs and insulation effectively prevents freeze–thaw damage in PEM fuel cell stacks operating in cold environments by maintaining temperatures above freezing for extended periods up to two days. This approach offers notable advantages in compactness and energy efficiency compared to active heating systems. System performance is highly sensitive to ambient temperature but less affected by HTCs, emphasizing the importance of careful PCM selection and insulation design. Integrating automated PCM recharge systems is recommended to enhance reliability and ensure continuous protection under fluctuating conditions [124]. The cooling potential of PCMs is defined by their total heat storage capacity, combining latent and sensible heat contributions.

$$Q_{phase} = mL + mc_p\Delta T \tag{5}$$

where Q is the total heat required to change the temperature and phase of a substance. The phase-change component is given by 'mL', where m is the mass of the substance and L is the latent heat, representing the energy required to change the phase at constant temperature. The sensible heat is expressed as '$mc_p\Delta T$', where m is the mass, c_p is the specific heat capacity at constant pressure, and ΔT is the temperature change of the substance without any phase transition [125].

6.2.2. Thermal Insulation and Heat Spreading

Integrating PCMs with intercellular air cooling and liquid cooling provides an effective, energy-efficient solution for managing LIB temperatures, particularly under high discharge conditions. Hybrid BTMS designs that incorporate advanced materials, such as porous structures and nanoparticles, and utilize technologies like 3D printing, enhance both thermal performance and system adaptability. Combining passive and active methods, such as heat pipes with PCMs, further improves cooling efficiency while reducing system weight and cost. Additionally, the use of ML for design optimization and topology configuration holds great potential for advancing BTMS performance and safety across diverse environmental conditions [126].

6.3. Active Thermal Management Strategies

6.3.1. Liquid Cooling Systems

Optimizing thermal management systems through advanced modeling and energy-efficient cooling strategies significantly reduces energy consumption and environmental impact. Liquid cooling techniques, such as heat pipes, jet impingement, and pool boiling, offer high efficiency, while free cooling with natural cold sources further enhances performance. Hybrid air coolers and water-based systems, particularly those utilizing seawater or ocean water, are highly effective for large-scale applications such as data centers, delivering substantial energy and cost savings. Integrating these systems with renewable technologies, such as solar power, further boosts sustainability, making them key solutions for efficient, low-emission thermal management [127].

6.3.2. Air Cooling and Heat Pipes

The Spiral Heat Conduction System (SHCS) effectively reduces the temperature of LTO battery cells, significantly enhancing thermal regulation compared to natural convection. Depending on environmental conditions, SHCS achieves temperature reductions of up to 34%, helping to prevent overheating and extend battery lifespan. Fluid dynamics simulations confirm the system's performance under varying ambient temperatures and coolant outlet velocities, with increased flow rates further lowering cell temperatures. The SHCS demonstrates strong potential for maintaining safe operating conditions during high-demand scenarios, such as fast charging, thereby promoting improved battery safety, efficiency, and durability [128].

6.3.3. Immersion Cooling

Immersion cooling significantly outperforms air cooling by offering lower superheat temperatures and higher heat transfer coefficients (HTCs), particularly when enhanced with shell materials such as porous copper wool and graphite. These materials, along with microstructures such as edges and channels, increase surface area for vapor generation and improve thermal performance. Innovations like pressure regulation and inert gas injection further enhance system efficiency and reliability. However, continued research is necessary to address challenges in bubble dynamics, surface energy behavior, coating durability, and adaptive control under varying conditions, in order to fully realize the potential of two-phase immersion cooling systems [129]. Although immersion cooling achieves higher heat transfer coefficients and more uniform temperature distribution than traditional liquid cooling, its cost-effectiveness depends on application scale and lifetime operation. Initial system costs are typically 1.5–2 times higher due to specialized dielectric fluids and sealing requirements, yet operational costs can be lower over time because of reduced pump power demand, maintenance frequency, and coolant degradation. Comparative assessments indicate that when long-term energy efficiency and thermal uniformity are considered, immersion cooling can deliver up to 20–30% lifecycle cost savings compared to liquid cooling in high-performance battery systems [130].

6.4. Artificial Intelligence and Machine Learning for Thermal Management

6.4.1. Predictive Thermal Control Using Neural Networks

ML plays a growing role in enhancing LIB performance by enabling accurate temperature forecasting and optimizing thermal management strategies. While no single algorithm universally excels, models like ANNs, LSTM, and GRU have proven effective, especially for time-series prediction when combined with physical models and optimization techniques. These hybrid approaches can significantly reduce battery temperatures, improve cooling efficiency, and extend battery life. Additionally, ML enhances the analysis of key thermal parameters, supporting more precise and adaptive BTMS designs across a wide range of operating conditions [131].

6.4.2. Digital Twin-Based Thermal Optimization

The integration of advanced microchannel design and Gaussian Process Regression (GPR) has significantly improved the thermal performance of battery systems. The optimized structure reduced the maximum temperature and temperature differential by 4 °C and 5 °C, respectively. The microchannel plates enhanced heat dissipation by promoting coolant flow disturbance and separation, especially in compact modules. GPR further contributed by enabling precise simulation of parameter interactions and guiding multi-objective optimization. Parameters such as internal and external coolant flow rates were found to have a critical influence on temperature uniformity and cooling efficiency. Overall, this approach not only enhances battery thermal management but also offers a powerful virtual modeling tool for future system optimization [132].

7. Battery Safety and Fault Diagnosis in Battery Management Systems

For BMSs to reduce risks, including thermal runaway, short circuits, and overcharging, battery safety and fault diagnosis are essential. Impedance spectroscopy, voltage and current monitoring, and ML algorithms are methods for diagnosing and detecting faults to identify anomalous patterns or early warning indications of failure. To reduce risks and guarantee battery longevity, key approaches include real-time monitoring, predictive analysis, and safety procedures. The development of universal fault detection models that can account for various battery chemistries and operating conditions remains challenging, despite recent progress. Table 11 outlines the key findings and methodologies in battery safety and fault diagnosis.

Table 11. Comparative Analysis of Battery Thermal Management Systems: Cooling Techniques, Efficiency, and Challenges.

Technique	Cooling Method	Advantages	Challenges	Impact on Temperature	Efficiency and Cost	Ref.
Phase Change Materials	Passive	Low energy, effective in cold climates	Limited conductivity, needs modification	Reduces temperature, effective at low discharge	Low energy, good for cold climates	[109]
Copper-PCM Foam	Hybrid (Passive)	Improved uniformity, increases lifespan	Reduced efficiency at high discharge	Lowers temperature, enhances uniformity	Reduces power consumption, improved efficiency	[110]
Liquid Cooling	Active	High efficiency, rapid control	Complex, potential for leaks, high cost	Significant reduction in temperature	High cost, more energy-intensive	[122]
Air Cooling and Heat Pipes	Active	Low cost, easy to implement	Less efficient in heat, space issues	Reduces temperature, less effective than liquid	Low consumption, limited capacity	[124]
Immersion Cooling	Active	Superior heat transfer, better performance	High cost, research needed	More efficient than air cooling	Higher efficiency, complex and costly	[126]
AI and Machine Learning	Predictive Thermal Control	Reduces heat generation, optimizes prediction	Dependent on data quality, complex	Reduces temperature significantly	Optimizes energy use, increases efficiency	[127]

7.1. Battery Failure Modes

7.1.1. Overcharging and Over-Discharging

This study presents impedance measurement results for commercial coin-type cells and highlights the impact of SOC, overcharge, and overdischarge on their electrochemical behavior. The findings reveal that while overdischarged cells exhibit reversible changes in impedance, overcharged cells undergo irreversible alterations. Using a measurement model to extract physical parameters, the analysis showed that variations in ohmic resistance primarily drive the impedance response in overdischarged cells. The model, composed of randomly selectable linear forms compliant with waist-chronic relationships, effectively captures the underlying electrochemical dynamics. These results underscore the diagnostic value of impedance analysis in distinguishing between reversible and irreversible battery degradation [133].

7.1.2. Internal Short Circuits and Dendrite Formation

Accurately detecting and predicting internal short circuits (ISC) in LIBs is critical for ensuring safety and system reliability. Traditional modeling techniques are often inadequate in fully replicating the complex dynamics of ISC formation. To address this, advanced approaches that integrate AI, big data analytics, and multi-sensor fusion are necessary. These techniques can analyze large volumes of battery data in real-time, extract subtle fault patterns, and enhance prediction accuracy. By enhancing early warning capabilities and supporting predictive maintenance, such methods contribute significantly to the prevention of catastrophic battery failures and the development of safer BMSs [134]. Figure 6 highlights the common failure modes in LIBs.

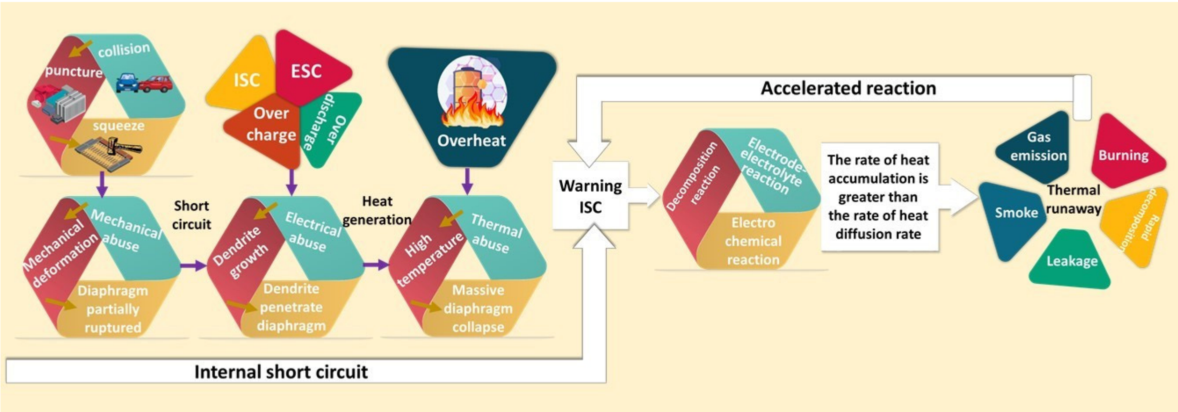

Figure 6. Common failure modes associated with Lithium-Ion Batteries.

7.2. Fault Detection and Isolation Methods

7.2.1. Model-Based Fault Detection

A model-based fault detection and isolation (FDI) approach using five nonlinear unknown input observers (NUIOs) effectively identifies and isolates faults in rudder servo systems under nonlinear dynamics and unknown disturbances. This method does not rely on prior assumptions about external conditions and uses linear matrix inequalities (LMI) for observer design. Both simulations and real-world tests confirm its accuracy and efficiency in detecting gear and sensor faults, offering reliable online monitoring and reducing manual inspection efforts [135]. Although NUIO-based diagnostic frameworks have been demonstrated primarily on electromechanical subsystems such as servo control units, their underlying methodology is applicable to battery systems exhibiting nonlinear dynamic behavior, including LIB and SIB chemistries. Both chemistries benefit from NUIO implementation due to their strong coupling between electrical and thermal states and sensitivity to disturbances. The observer's capacity to estimate system states in the presence of unknown inputs makes it particularly suitable for detecting voltage, current, or temperature anomalies in these rechargeable chemistries under uncertain operating conditions [136–138].

7.2.2. Data-Driven Fault Detection Using Artificial Intelligence

Effective fault detection and isolation (FDI) significantly enhances system safety, reliability, and efficiency, particularly in critical industries such as aerospace, automotive, energy, and manufacturing. By identifying faults early, FDI prevents severe failures, reduces downtime and maintenance costs, extends the lifespan of components, and supports regulatory compliance. Advanced FDI systems using predictive analytics and ML enable proactive maintenance and ensure smooth, dependable operations [139].

7.3. Online and Offline Fault Diagnosis

7.3.1. Prognostic and Health Management Systems

The integration of condition monitoring (CM) and AI significantly advances predictive maintenance in manufacturing by enabling real-time fault detection and RUL prediction. The application of cyber–physical systems (CPS) and the IoT facilitates efficient data acquisition and processing, enhancing the accuracy and responsiveness of PHM systems. While the current approaches show strong performance in real-world scenarios, challenges such as detection latency, sensor limitations, and dynamic feature selection remain areas for ongoing improvement [140].

7.3.2. Real-Time Battery Management System Fault Diagnosis

Adaptive threshold-based fault detection methods can effectively identify thermal faults in batteries, even under modeling uncertainties. Detection time tends to decrease as fault severity increases, and subtle thermal deviations can be detected within seconds. These methods also demonstrate consistent sensitivity to changes in cooling coefficients and excess heat generation. Integrating more detailed thermal models may further improve the accuracy and robustness of battery thermal fault diagnostics [141]. Figure 7 highlights the fault monitoring and evolution process within the BMS.

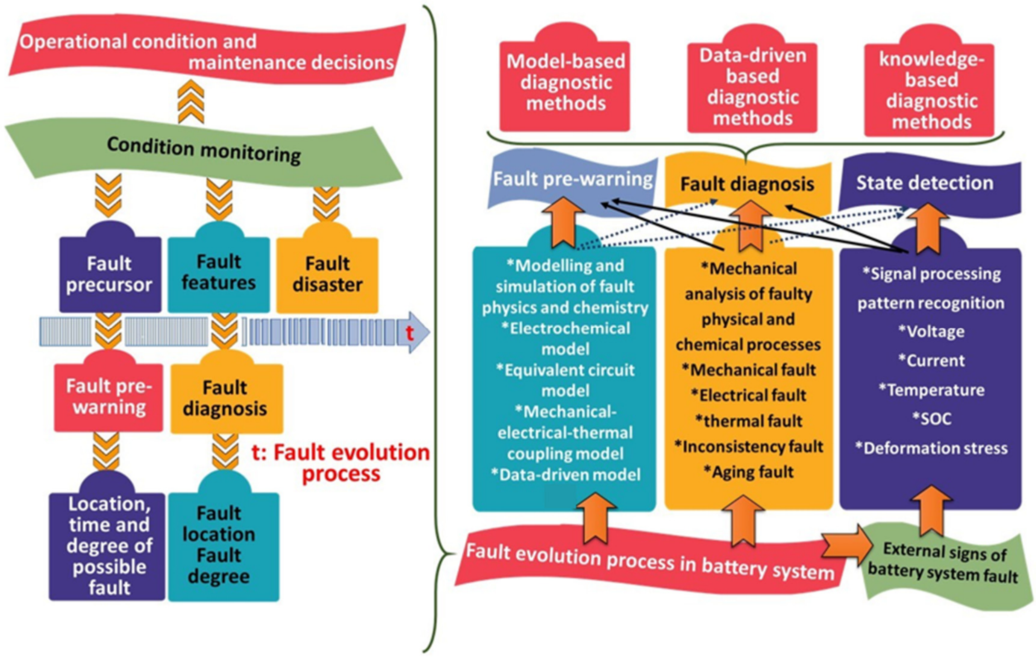

Figure 7. Fault Monitoring and Evolution Process within Battery Management Systems.

8. Advanced Charging and Energy Management Strategies

Optimizing battery life, efficiency, and performance is the goal of advanced charging and energy management techniques. Battery systems are increasingly incorporating energy-efficient power conversion, adaptive charging algorithms, and fast charging techniques to minimize degradation and reduce charging times. Overall energy management is further enhanced by tactics such as peak shaving, dynamic charge rate adjustment, and integration with renewable energy systems (RES). Future advancements might concentrate on smart grid integration and intelligent charging systems that use ML for real-time optimization, enhancing energy distribution and storage across a range of applications. Table 12 summarizes advanced charging and energy management strategies including key technologies and future outlooks.

Table 12. Key Findings and Methodologies in Battery Safety and Fault Diagnosis.

Category	Key Findings	Methodology	Observations	Ref.
Battery Failure Modes	Overcharging causes irreversible impedance changes, while over-discharging effects are reversible.	Impedance measurement and modeling.	Variations in ohmic resistance explain impedance changes in overdischarged cells.	[129]
Internal Short Circuits and Dendrite Formation	Existing ISC models are insufficient for accurate risk prediction. AI and big data can enhance detection and prediction.	ML, pattern recognition, and sensor fusion.	Joint prevention and diagnosis techniques can improve LIB safety.	[131]
Model-Based Fault Detection	FDI system for rudder servo control effectively detects and isolates faults.	NUIOs and logic rule programming.	Model is suitable for real-time FDI, reducing false alarms and improving decision-making.	[132]
Data-Driven Fault Detection Using AI	AI-driven FDI enhances reliability, reduces costs, and ensures safety across industries.	ML and advanced data analytics.	Predictive maintenance improves system efficiency and regulatory compliance.	[133]
PHM Systems	IoT and CPS enable real-time predictive maintenance with anomaly detection and RUL estimation.	Degradation modeling and real-time streaming data processing.	Effective in industrial environments but faces challenges like detection latency and dynamic feature selection.	[134]
Real-Time BMS Fault Diagnostics	Adaptive thresholds improve thermal fault detection accuracy.	Residual signal analysis and adaptive thresholding.	Detection time ranges from 8 to 168 s based on fault severity.	[135]

8.1. Charging Algorithms and Techniques

8.1.1. CC-CV, Trickle, and Pulse Charging Methods

Pulse charging strategies, especially those that alternate between fast and slow charging phases, have been shown to significantly outperform traditional constant current/constant voltage (CC/CV) methods. These strategies reduce overall charging time and limit the temperature rise within the battery, thereby minimizing thermal stress and potentially extending the battery's lifespan. Passive and active pulse charging circuits offer different operational benefits, with active systems delivering stronger high-frequency pulses. Battery simulation models provide a powerful platform for evaluating these charging methods by replicating internal electrochemical and thermal behaviors under varying conditions. This enables the optimization of charging efficiency, safety, and long-term performance without the cost and risk associated with extensive physical testing [142].

8.1.2. AI-Driven Smart Charging Algorithms

AI-based models can significantly enhance EV charging efficiency, reducing operational costs by up to 38%. For Malaysia to fully realize these benefits and accelerate EV adoption, challenges such as infrastructure mismatches, limited rural coverage, and fixed demand costs must be addressed. Key strategies include aligning EV and charging station standards, expanding renewable energy integration, updating pricing policies, and offering public incentives. Investments in AI research and standardized infrastructure, combined with public awareness initiatives, are essential to achieving a smart, low-carbon transportation ecosystem [143].

8.2. Grid Integration and V2G/G2V Technologies

8.2.1. Smart Grid-Enabled Battery Management Systems

Optimizing EV station locations and incorporating smart grid technologies can significantly enhance network efficiency and reduce long-term costs. Countries like the Netherlands, Germany, and France are leading the way in infrastructure development, leveraging advanced charging systems and energy storage solutions. Integrating renewable energy and blockchain technology enables decentralized energy trading, supports dynamic pricing, and accelerates the global transition toward low-carbon transportation networks [144].

8.2.2. Bidirectional Energy Flow and Optimization

Optimized coordination of EV charging and discharging can significantly enhance energy efficiency, reduce waste, and support the integration of RES. High convergence rates and effective control over energy flow contribute to improved system performance across a wide range of network scales. Emphasizing energy optimization, balanced load management, and resource utilization can enable more resilient and sustainable electric mobility infrastructures [145]. While optimized V2G/G2V coordination enhances grid stability and renewable integration, frequent bidirectional cycling can accelerate battery degradation due to increased charge–discharge depth and thermal stress. Studies indicate that repetitive energy exchange at partial SOC windows contributes to capacity fade and impedance growth, reducing the overall cycle life of traction batteries. To mitigate this effect, smart scheduling strategies that minimize deep cycling, apply temperature-aware control, and employ adaptive power limits are essential for maintaining both grid efficiency and battery longevity [146,147].

8.3. AI-Based Energy Optimization

Reinforcement Learning for Charge/Discharge Control

The application of transfer learning and reinforcement learning significantly improves energy forecasting, system adaptability, and decision-making accuracy in advanced energy networks. By prioritizing relevant experiences and leveraging pre-trained knowledge, these methods enhance the efficiency and responsiveness of intelligent management systems in areas such as smart grids, EVs, and power plants. This results in optimized energy consumption, reduced operational costs, and improved integration of renewable sources. These advancements form a solid foundation for future developments in decentralized, intelligent, and sustainable energy systems [148].

From a system integration standpoint, optimal EV fast-charging control depends on tight coupling between the electrochemical, algorithmic, and sensing layers of the BMS. At the core, multi-scale models (e.g., reduced-order DFN or physics-informed neural networks) predict internal states such as lithium concentration, temperature gradients, and side-reaction kinetics. These predictions feed into model-predictive control frameworks that compute optimal current and voltage trajectories in real time while ensuring voltage, SOC, and temperature remain within safe limits. Simultaneously, a sensor fusion layer aggregates voltage, current, and temperature feedback through Kalman or particle filters, continuously correcting model drift. High-speed data exchange between layers is managed via the BMS communication bus (e.g., CAN or LIN protocols), while supervisory controllers synchronize hardware responses to maintain global objectives such as charge efficiency, cell balancing, and thermal uniformity. This architecture allows the fast-charging process to operate as a coordinated feedback ecosystem rather than a sequence of isolated modules [111]. Table 13 provides a highlights some of the advanced charging and energy management strategies: key technologies and future outlooks.

Table 13. Advanced charging and energy management strategies: key technologies and future outlooks.

Category	Description	Advantages	Challenges	Technology Used	Future Outlooks	Ref.
Pulse Charging	Alternating fast/slow charging phases to improve efficiency and reduce heat	Faster than CC/CV, lower temperature rise, longer battery lifespan	Requires modeling for optimization	Passive and active pulse charging circuits, battery simulation models	Further optimization through simulations	[139]
AI-Driven Smart Charging	AI-based optimization of EV charging procedures	20–38% cost reduction, improved infrastructure, increased EV adoption	Mismatch between EVs and charging stations, infrastructure gaps, policy limitations	AI algorithms, predictive analytics, preventive maintenance	Standardized infrastructure, incentives, regulatory support	[140]
Smart Grid-Enabled BMS	Integration of smart grids with charging stations for enhanced performance	Reduced costs, better network efficiency, integration with renewable energy	Requires advanced power electronic converters and blockchain for optimization	SEPIC, Boost converters, blockchain, distributed systems	Expansion of energy storage, blockchain-based energy trading	[141]
Bidirectional Energy Flow	Optimization of charging/discharging in V2G and G2V systems	88.43% system convergence rate, optimized energy use, reduced waste	Needs real-world testing and economic feasibility studies	Optimization algorithms for V2G and G2V, RES	Real-world prototype development, economic validation	[142]
Reinforcement Learning	Application of RL for charge/discharge control and energy optimization	Improved learning accuracy, better energy policy optimization	Integration of decentralized energy resources, scalability for complex networks	Transfer learning, priority experience reinforcement learning	Enhanced decentralized energy management, intelligent policy adaptation	[143]

9. Artificial Intelligence and Machine Learning in Battery Management Systems

BMSs are undergoing a revolution due to AI and ML, which enable more precise status estimates, predictive maintenance, and improved energy efficiency. Through improved charge/discharge algorithms, defect detection, and health prognostics, methods including NNs, support vector machines (SVMs), and reinforcement learning contribute to increased battery performance. By recognizing usage and degradation patterns, AI-driven models can adjust to real-time data, improving safety, energy economy, and battery life prediction. The next generation of intelligent energy management systems will continue to rely heavily on AI and ML as BMSs becomes more data-driven. Table 14 summarizes AI and ML applications in battery management and energy optimization.

Table 14. AI and Machine Learning Applications in Battery Management and Energy Optimization.

Main Focus	Key Findings	Technologies/Techniques	Ref.
DNN for SOC Estimation	DNN performed well across different temperatures, improving accuracy with data augmentation and effectively handling noise.	DNN, Temperature Adaptability, Data Augmentation, Gaussian Noise	[144]
Q-learning for EV Battery Management	Q-learning improved energy efficiency by 15% and battery life by 20%, optimizing management under various driving conditions.	Q-learning, EV Battery Management, Driving Condition Adaptation	[145]
ANN and Fuzzy Logic for SOC Control	ANFIS-based system improved SOC estimation, optimized energy use, and extended battery life compared to conventional methods.	ANFIS, ANN, Fuzzy Logic, Energy Optimization	[148]
FLC and Supercapacitors for Energy Optimization	FLC with supercapacitors optimized energy use, maintained SOC, and extended battery life in different conditions.	FLC, Supercapacitors, Boost Converter, Energy Optimization	[149]
LSTM and ECM for Fault Detection	LSTM and ECM accurately detected battery faults and thermal fire risks, ensuring reliability and safety.	LSTM, ECM, Fault Detection, Thermal Fire Warning	[150]
FLC with Neural Networks in EMS	FLC combined with neural networks and optimization algorithms improved battery life and efficiency in hybrid systems.	FLC, Neural Networks, Optimization, EMS	[151]
DNN with Multiple Layers for SOC Prediction	DNN with four layers outperformed three-layer models in generalizing SOC prediction with lower errors.	DNN, SOC Estimation, Hidden Layers, Generalization	[152]
FLSMO for SOC Estimation	FLSMO algorithm showed superior performance over EKF and SMO in terms of noise stability and temperature adaptation.	FLSMO, SOC Estimation, Noise Stability, Temperature Adaptation	[153]
AI for EV Energy Management and Cybersecurity	AI optimized energy use, addressed cybersecurity challenges, and identified issues in EV systems.	AI, Machine Learning, Energy Optimization, Cybersecurity	[154]
MPPT and Fuzzy Logic for Charging Control	MPPT algorithm achieved high efficiency, and fuzzy logic-controlled battery charging/discharging, enhancing performance.	MPPT, Fuzzy Logic, Battery Charging Control, Solar PV	[155]
Machine Learning in HEV EMS	Machine learning algorithms like Q-learning and DQN optimized power distribution, reducing fuel consumption and improving efficiency.	Machine Learning, Q-learning, DQN, EMS, HEV	[156]
Machine Learning for SOC and battery efficiency	Improved SOC management with Machine Learning increasing battery efficiency across varying conditions	Machine Learning, AI Accelerators (GPUs, TPUs), Big Data, Cloud Computing	[157]
Optimization in hybrid vehicle charging and microgrid cost	MDA algorithm reduces charging error and operating costs, outperforming other optimization methods	MDA Algorithm, Microgrid, Optimization (PSO, GA, DA), Energy Storage	[158]
DNNs and Machine Learning for battery health and fault diagnosis	DNNs (LSTM-RNNs) excel in predicting battery degradation, improving health prediction and fault diagnosis	DNNs (LSTM-RNN), SVM, Particle Filters, Neural Networks, GPR	[159]
Model-based SOC estimation with Machine Learning	Kalman Filters for SOC estimation, combined with SVM and FL for enhanced accuracy	Kalman Filters (KF, UKF, EKF), Neural Networks, ANFIS, SVM, Fuzzy Logic	[160]
Machine Learning for battery charging voltage prediction	Linear Regressor outperforms Decision Tree in prediction accuracy, with improvements from LSTM	Linear Regressor, Decision Tree, LSTM, Cross-validation, Optimization	[161]

Table 14. *Cont.*

Main Focus	Key Findings	Technologies/Techniques	Ref.
Fuzzy clustering for battery health monitoring	IT2CC outperforms other clustering methods, improving accuracy and cluster identification	IT2CC, FCM, PCM, Data Clustering, Cluster Validation	[162]
AI-based control for BMS performance	FPGAs are ideal for implementing AI in BMSs, offering low power and high performance	AI, FPGA, GPUs, ASICs, Predictive Control, BMS	[163]

Deep neural networks (DNNs) demonstrate high accuracy and robustness for estimating the SOC of LIBs across varying temperatures and operating conditions. They maintain performance even under noisy or inaccurate measurement scenarios and exhibit rapid recovery from initial input errors. These capabilities make DNNs well-suited for real-world SOC estimation tasks in EV and energy storage applications, offering reliable performance in dynamic and uncertain environments [164].

Q-learning significantly enhances battery management by improving energy efficiency and extending battery life compared to traditional methods. It enables adaptive decision-making under varying driving conditions, reduces charging frequency, and supports more economical and efficient system operation. This approach holds significant potential for enhancing EV performance while delivering substantial environmental and economic benefits [150].

Adaptive discharge control using NN and fuzzy logic significantly enhances SOC estimation accuracy, improves energy efficiency, and extends battery life. Systems that integrate decentralized architecture, dynamic load balancing, and thermal protection demonstrate better performance and reliability under complex and variable operating conditions compared to conventional approaches [151].

Simulation results show that fuzzy logic controllers (FLC) outperform conventional PI controllers in dynamic performance, particularly in terms of faster decay and settling times. Integrating supercapacitors with power converters enhances system responsiveness and helps regulate battery charge levels effectively, both during active and idle vehicle conditions. Under varying driving scenarios, the coordinated operation of Boost and SEPIC converters contributes to maintaining optimal battery SOC, reducing engine load, and preserving battery life. These results highlight the importance of intelligent control strategies and hybrid energy storage integration for improving energy efficiency and battery longevity in EV applications [152].

The results indicate that integrating data-driven models with equivalent circuit modeling significantly enhances the early detection of battery faults and thermal hazards. The technique can reliably issue fault warnings well in advance of critical events, offering sufficient time for preventive action. It demonstrates both high prediction accuracy and strong robustness across various operational scenarios, with minimal false alarms. By effectively capturing abnormal behaviors such as voltage fluctuations, the method ensures safe battery operation and improves diagnostic reliability. Combining temporal modeling and electrochemical insights proves to be a promising direction for improving fault detection and thermal risk mitigation in battery systems [153].

Combining fuzzy logic control (FLC) with NN, frequency-domain techniques, and optimization algorithms significantly improves energy management system (EMS) performance. These hybrid approaches enable more efficient power distribution between energy sources, enhance fuel economy, extend battery lifespan, and reduce operational costs. Adaptive and online FLC strategies offer increased flexibility and responsiveness to dynamic driving conditions and varying load demands, making them effective for real-time energy management in hybrid electric systems [154].

The study demonstrates that DNNs with four hidden layers achieve high accuracy in SOC estimation across various driving conditions, including those not included in the training set. Increasing the number of hidden layers improves model generalization and error reduction up to a point, with four layers proving optimal. Although deeper models typically require longer training, this approach maintained training efficiency. The results confirm that appropriately designed DNNs can provide robust, accurate, and efficient SOC estimation, outperforming simpler architectures and existing techniques in various real-world scenarios [155].

The FLSMO algorithm demonstrates high accuracy and robustness in estimating the SOC of LIBs under varying conditions. It achieves an average SOC error of less than 1% and a maximum error of 2.37% during dynamic cycles, such as FUDS, while also quickly converging to within a 3% error margin, even when the initial SOC estimate is significantly incorrect. The algorithm maintains strong performance in the presence of current and voltage noise, outperforming EKF and standard SMO in terms of MAE, RMSE, and MaxE. Additionally, it exhibits superior resilience to temperature-induced disturbances and parametric uncertainties, resulting in lower estimation errors across a wide temperature range (5 °C, 25 °C, and 45 °C). These results highlight FLSMO's effectiveness and reliability for practical SOC estimation in EV and battery management applications [156].

The main conclusion is that integrating AI into EV energy management significantly enhances efficiency, reduces energy consumption, and improves system reliability through intelligent optimization, forecasting, and real-time control. However, achieving sustainable and secure implementation requires overcoming key challenges such as cybersecurity risks, communication protocol compatibility, and system interoperability. Continued research, infrastructure investment, and standardization are essential to fully realize the potential of AI-driven intelligent energy management systems [157].

The MPPT charging control algorithm effectively achieves up to 98% power tracking efficiency, ensuring batteries are charged efficiently while preventing overcharging and overdischarging under varying irradiation conditions. Fuzzy logic-based battery management further optimizes charging and discharging control based on SOC levels, enhancing system performance and maintaining precise battery characteristics. Compared to conventional methods with efficiencies ranging from 85% to 91%, this approach achieves an efficiency of around 95%. Real-time implementation and testing confirm the system's responsiveness and effective regulation of current and voltage in response to changing solar conditions [158].

ML techniques, particularly DL and reinforcement learning algorithms, have significantly advanced EMS for HEVs. These methods enable automatic, adaptive decision-making in complex driving environments without requiring detailed system models. Reinforcement learning approaches such as Q-learning, DQN, and DDPG improve fuel efficiency by optimizing power distribution between combustion and electric engines, reducing energy waste, and enhancing driving comfort. Hybrid algorithms that combine multi-objective reinforcement learning further enable simultaneous optimization of battery life, fuel economy, and vehicle performance, demonstrating substantial gains in EMS effectiveness [159].

Models enhanced through this approach demonstrate improved ability to predict battery SOC across diverse environments and dynamically adapt to changing conditions. Transfer learning enables knowledge gained in one domain to enhance performance in others, although increasing model complexity presents challenges in ensuring interpretability and user trust. Emerging technologies such as big data analytics, cloud computing, and AI hardware accelerators (e.g., GPUs and TPUs) accelerate model training and real-time deployment, facilitating remote optimization and extensive battery monitoring. These advancements, alongside innovations in battery technologies such as solid-state batteries, are poised to significantly improve EV charge management and battery efficiency across various driving and environmental conditions [160].

High accuracy in forecasting HEV charging demand can lead to significant reductions in microgrid operating costs by effectively shifting peak loads to off-peak times and incorporating market price considerations. Advanced optimization algorithms with strong search and convergence capabilities enhance solution quality, reduce computation time, and yield consistent results in complex renewable microgrid energy management problems. Optimizing energy storage scheduling, such as charging early and discharging later, further enhances cost savings and overall microgrid efficiency [161].

DNN, especially LSTM-RNNs, exhibit strong predictive capabilities for modeling battery capacity degradation over time, outperforming traditional methods such as SVM, particle filters, and standard RNNs. Optimization techniques like Dropout enhance their accuracy and reduce redundancy. ML methods, including ANN, SVM, and Gaussian process regression, have also advanced fault diagnosis by effectively detecting battery issues such as overcurrent, voltage anomalies, internal short circuits, and dendrite formation. Their data-driven nature and flexibility enable more accurate prediction of battery health and fault conditions compared to conventional model-based approaches, which often struggle to capture complex physical behaviors [165].

Model-based techniques and filtering algorithms, particularly KFs and their adaptive variants like UKF and EKF, are widely used for SOC estimation due to their ability to reduce prediction errors across diverse scenarios and battery aging conditions. Despite their high accuracy, these methods require substantial computational resources and fast controllers. ML approaches, including NN and adaptive neural fuzzy inference systems, also achieve high accuracy by effectively handling complex and variable data, though they demand extensive storage and longer training times. Methods such as SVM and fuzzy logic offer alternative SOC estimation options, but they often involve higher computational complexity and tuning requirements. Combining filter-based models with ML techniques has been shown to further improve SOC estimation accuracy by leveraging the strengths of both approaches [163].

9.1. AI-Based Battery Modeling and Prediction

Machine Learning and Deep Learning in Battery Management Systems

The study demonstrates that careful data preprocessing, feature selection, and parameter optimization can significantly improve battery charging voltage prediction models, with linear regression and LSTM models showing notably low error metrics. Enhanced cross-validation techniques have contributed to reducing overfitting and increasing prediction accuracy. The findings highlight the importance of model optimization and anomaly reduction in improving forecast performance. Future advancements are expected through further exploration of parameter tuning, data augmentation, and hybrid modeling approaches to enhance predictive capabilities [166].

9.2. Fuzzy Logic and Fuzzy Rule-Based Systems

Interval Type-2 Fuzzy Clustering

This method enhances cluster analysis by generating membership and non-membership degrees for data points and combining them through a validity measure, while considering cluster boundary effects and compactness. Utilizing a type-2 fuzzy approach, it effectively manages data validity and evaluates cluster separation based on center distances. The IT2CC model outperforms alternatives, such as FCM and PCM, by preventing discrete cluster formation for noise and outliers, and minimizing overlapping clusters. By relaxing strict membership constraints, it assigns low membership degrees to noise, improving robustness. Additionally, its use of a validity index accurately determines the correct number of clusters across various datasets, including those with noise and overlapping data [167].

9.3. Neural Networks and Reinforcement Learning in Battery Management Systems

AI-Based Predictive Control in Battery Management Systems

Hardware accelerators such as Application-Specific Integrated Circuits (ASICs), Field Programmable Gate Arrays (FPGAs), and GPUs are employed to improve the performance of AI algorithms in BMSs for electric mobility. Among these, FPGAs stand out due to their reprogrammability, low power consumption, and flexibility, making them particularly well-suited for handling the complex, nonlinear prediction tasks involved in estimating battery states, such as SOC, SOH, and RUL. In selecting FPGAs for AI-integrated BMS applications, factors such as computational throughput, memory bandwidth, hardware compatibility, and thermal efficiency are critical. Devices with high parallel processing capability and sufficient logic cells are preferred for running deep learning models (e.g., CNNs, LSTMs) used in SOC and SOH estimation. Compatibility with CAN, SPI, and I2C interfaces ensures seamless integration with BMS sensors and controllers. Additionally, power-to-performance ratio, reconfigurability, and support for real-time processing frameworks are essential criteria, especially for vehicular BMSs where low latency and reliability are paramount. These considerations enable efficient deployment of AI algorithms while maintaining compact and energy-efficient hardware design [168]. While GPUs excel in memory bandwidth and complex computations, their high-power usage limits their practicality for AI applications in BMSs. ASICs, though efficient for specific tasks, are limited by their high cost and long development cycles. Overall, FPGAs provide an optimal balance of computational power, energy efficiency, and adaptability for AI-driven battery management [169].

10. Cloud Computing, Edge Computing, and Internet-of-Things in Battery Management Systems

By bringing services and apps closer to data sources, edge computing offers benefits such as effective resource allocation and direct access to computing resources. The three-layer architecture of the system model, top-level cloud computing, middle-layer monitoring and scheduling nodes (MSRP), and bottom-level edge nodes (ERP), optimize task processing with the least amount of delay and flexibility in resource allocation.

Incorporating thermal safety into energy management enhances power recovery and slows temperature rise, resulting in reduced energy dissipation and improved system efficiency. This approach also significantly lowers battery aging costs, extending the system's lifespan while reducing energy waste. Real-time experiments confirm the method's effectiveness, with fast decision-making and superior performance compared to Q-learning and DQL algorithms. The DDPG-based strategy achieves faster convergence, greater energy savings, and better-wear cost reduction, demonstrating high efficiency in managing EV energy resources and successfully extending battery life in practical applications [170].

Energy consumption can be efficiently managed by using decision-making algorithms that prevent overloads and reduce costs. Different types of loads, such as computer, blade, and lighting, can be dynamically controlled by turning off devices when consumption limits are exceeded, ensuring usage remains within set boundaries. These algorithms adapt automatically to changing environmental conditions, such as humidity and temperature. Real-time consumption data can be collected through IoT devices and transmitted via wireless communication, enabling centralized monitoring and analysis. This information enables users and energy managers to make informed decisions, optimize electricity usage, and adjust consumption priorities. Applying big data and advanced analytics further enhances ongoing performance and energy management [171].

Tests on three different battery storage systems demonstrated the ability to establish direct, cloud-independent communication between home gateways and storage units. Effective coordination of numerous battery systems at residential and commercial scales is feasible when manufacturers provide local APIs. In cases without local APIs, the Sunspecs protocol provides a fallback; however, a unified standard for data exchange within this protocol is recommended. Overall, leveraging IoT technologies enhances device communication while reducing dependence on cloud infrastructure [172].

Wireless BMSs are vulnerable to cyber threats due to their reliance on communication protocols like MQTT. Blockchain technology enhances security and trust by preventing data manipulation through smart contracts and cryptographic methods. Implementing a blockchain network using platforms like Hyperledger Fabric can significantly reduce cyber risks by securely recording battery data and enabling real-time health monitoring. Experimental results show that data transfer times in blockchain-secured systems are around three seconds, which is suitable for battery management needs and faster than many unsecured systems. This highlights the effectiveness and scalability of blockchain protecting wireless battery systems [173].

Employing price-based demand response (DR) strategies such as time-of-use (ToU), critical peak pricing (CPP), and real-time pricing (RTP) significantly reduces energy operating costs. The integration of solar PV, ESSs and EVs further enhances these savings, with cost reductions reaching up to 58% under RTP. RTP emerges as the most cost-effective approach for both utilities and customers, outperforming ToU and CPP in minimizing expenses. Efficient utilization of renewable energy and storage during peak demand periods drives these improvements, demonstrating that real-time pricing is a superior strategy for optimizing energy costs [174].

Timely defect detection and predictive maintenance process optimization were achieved by selecting ten models with high accuracy and suitable complexity from 939 trained models. Cross-validation confirmed accuracy rates between 99% and 100% for all selected models. Deployment on four different edge AI devices with limited resources demonstrated that models based on magnetometer data outperformed those using accelerometer and gyroscope data in terms of accuracy, inference time, and resource consumption. Magnetometer-based models achieved inference times under 4 ms, power consumption between 0.15 and 0.69 mA, and memory usage below 5%. In contrast, accelerometer-based models consumed significantly more power, used up to 48% of available RAM, and exhibited longer processing times. High-performance microcontrollers, such as the STM32F746G-DISCO, provide the fastest inference times but at the cost of higher power consumption [175].

International standards such as ISO/SAE 21434 and SAE J3061 establish cybersecurity requirements for automotive systems including BMSs and CBMSs, providing frameworks for threat analysis and risk assessment. Cyberthreats targeting these systems encompass availability, confidentiality, and integrity attacks, potentially leading to rapid battery depletion, capacity damage, or loss of charging access. Vulnerabilities exist across multiple CBMS components, including ports, OBD-II interfaces, in-vehicle communications, and IoT protocols. Enhancing security involves employing cyberattack detection algorithms and advanced techniques like blockchain and cryptographic methods. The lack of comprehensive cybersecurity design guidelines for CBMSs emphasizes the need for stricter protocols throughout the system lifecycle. Established standards provide tools for threat analysis, risk assessment, and cybersecurity testing, while software platforms such as PHiL and MiL facilitate the simulation and evaluation of cyberattack impact [176].

10.1. Cloud-Based Battery Management Systems Architectures

AI, IoT, and cloud–edge integration are used in cloud-based BMS designs to improve data analytics, real-time decision-making, and battery performance monitoring. IoT sensors gather battery data, which is subsequently sent to cloud platforms for AI-powered advanced analytics and predictive insights. Through the optimization of energy management, the reduction in latency, and the distribution of jobs between local edge devices and the cloud, cloud–edge integration enables efficient processing. In addition to enhancing scalability and flexibility in large-scale ESSs, these developments allow for remote monitoring, performance optimization, and early failure identification. Table 15 demonstrates advancements in AI, IoT, and cloud–edge integration for battery management and energy optimization.

Table 15. Advancements in AI, IoT, and Cloud–Edge Integration for Battery Management and Energy Optimization.

Key Findings	Technologies Used	Results	Ref.
Thermal safety, energy efficiency, reduced aging cost; DDPG outperforms Q-learning/DQL.	DDPG, Q-learning, PiL	6.015 kJ energy reduction, $47.7 lower wear cost	[166]
Efficient energy control using IoT, data analytics.	ZigBee, Wi-Fi, IoT	Optimized energy use, real-time data	[167]
Cloud-independent communication between storage systems.	IoT, SunSpec	Direct communication, need for standard protocol	[169]
Blockchain secures WBMS, prevents data manipulation.	Blockchain, Hyperledger	Reduced cyber risks, real-time battery data	[170]
Solar PV, ESSs, EVs reduce energy costs in DR.	RTP, ToU, EVs, ESSs	55–58% cost reduction, better energy use	[171]
Smart dashboards optimize energy use, improve comfort.	Smart dashboards, weather API	Reduced energy use, no comfort sacrifice	[172]
Edge AI for predictive maintenance with low resource use.	Edge AI, magnetometer	99–100% accuracy, low power consumption	[173]
Smart meter, EMS optimize energy during peak hours.	Node-RED, fog computing	Load shifting, peak management	[174]
Cybersecurity in BMS using blockchain and cryptography.	Blockchain, cryptography	Detect vulnerabilities, prevent cyberattacks	[177]
IoT, computer vision for fleet management, safety.	OpenCV, IoT	Reduced accidents, optimized fuel use	[175]
Edge computing reduces latency, improves performance.	Edge computing, WebRTC	58.16% latency reduction, better performance	[178]
IoT platform for data analysis and visualization in EV batteries.	IoT, Grafana, ML	Enhanced decision-making, energy efficiency	[176]

10.2. Edge Artificial Intelligence for Real-Time Battery Management Systems Applications

Edge Computing for Low-Latency Control

Preprocessing data locally on edge devices and transmitting only critical features to the server significantly reduces data transfer volume. An adaptive strategy further optimizes communication by sending data only when meaningful changes occur, lowering transmitted data to as little as 3–42%. This reduction decreases network traffic and transmission times, leading to a substantial drop in system latency—up to 58% in 5G environments—compared to traditional WebRTC frameworks. The approach maintains effective control performance despite sending less frequent updates, cutting data transmission frequency by 20%. Overall, this method enhances system responsiveness, reduces communication load, and improves data transmission times. However, it faces challenges such as increased energy consumption and the limited computational capabilities of edge devices [179].

10.3. Internet-of-Things-Enabled Smart Battery Management

Sensor Networks and Data Analytics

An IoT-based analytics platform is structured into five interconnected layers to handle data collection, integration, storage, analysis, and visualization. Integrated into an automated EV battery assembly system, it systematically combines diverse information flows. Dashboards tailored to different user groups display operational and energy KPIs at multiple levels, providing insights such as energy costs, hourly consumption, forecasts, and system behavior analytics at the workstation level. ML algorithms detect anomalies and trigger alerts within these dashboards. The platform aims to provide a scalable, modular solution for big data analytics in smart factories, addressing the complexities of integrating various operational and information technologies. Future developments focus on expanding data coverage, exploring cloud or hybrid architectures, and optimizing data reduction and retention to enhance decision support and industrial process efficiency further [180]. Figure 8 outlines the interdependency between the five layers of the analytics platform.

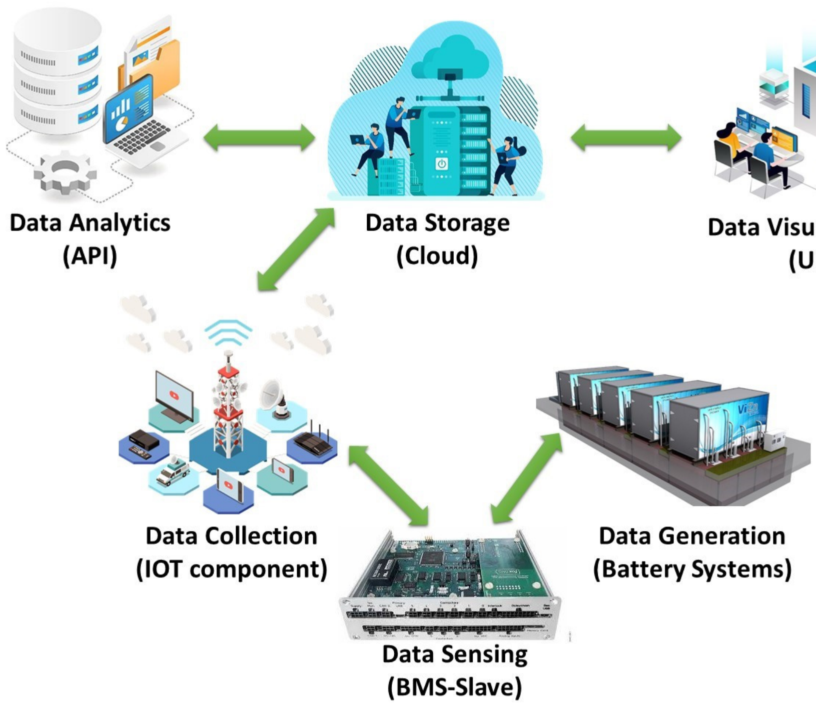

Figure 8. Dependencies between the five layers of IOT analytics.

11. Digital Twin Technologies in Battery Management Systems

BMSs use DT technologies to mimic and forecast battery behavior in real-time by building virtual versions of physical battery systems. DTs provide state-of-charge, state-of-health, and battery health insights by combining real-world sensor data to facilitate continuous monitoring, performance forecasting, and failure prediction. To improve the accuracy of these virtual models, methods such as data assimilation, physics-based modeling, and ML are employed. DTs are a crucial tool for enhancing battery performance and longevity in various applications, as they facilitate proactive maintenance, optimize energy management, and improve system design. However, practical implementation remains limited due to issues with data acquisition, integration, and the need for accurate mathematical models that can reliably simulate processes. DTs must offer real-time monitoring, anomaly detection, failure prediction, and optimization to enable timely decisions. Ensuring cybersecurity, safeguarding privacy, and seamless integration with existing systems are essential for successful adoption. Additionally, DTs should provide user-friendly interfaces for operators to access and interpret data. Despite challenges, with the right approach, including IoT devices, cloud computing, and AI, DTs can be effectively implemented to enhance process performance [177,178].

Recent advances in ML, diagnostic tools, and battery behavior modeling have significantly enhanced system performance and prediction accuracy. A key challenge remains the costly and time-consuming collection of sufficient training data, but this is being mitigated through innovative methods such as adjoint models and GANs. Combining multi-physics models with ML techniques like SVM and ANN further improves RUL forecasting and optimizes charging and control strategies. The integration of sophisticated models with real-time data from EV sensors and BMSs within a DT framework enables dynamic optimization of battery performance. This approach supports the development of advanced thermal management and fast-charging algorithms, while enhancing battery lifespan and safety. Additionally, cloud computing and dimensionality reduction techniques facilitate large-scale data aggregation and continuous performance optimization [181].

Real-time battery health can be accurately monitored by using partial data collected at key times, avoiding the need for fully discharging the battery. By organizing and synchronizing this data efficiently, the estimation becomes more precise and stable. This method enables continuous monitoring of the battery's condition, provide reliable and up-to-date information about its health over time [182].

Bayesian optimization efficiently reduces computation time for complex EMs by quickly finding optimal solutions. The Doyle–Fuller–Newman (DFN) model notably decreases lithium inventory loss during cycling, outperforming other models. Employing a parallel multi-channel optimization approach further accelerates convergence, requiring fewer evaluations when multiple channels operate simultaneously. Optimization results indicate that aging parameters and ambient temperature have a significant influence on charging protocols, with temperature and lithium deposition effects affecting charging rates. This underscores the necessity of incorporating battery aging and thermal conditions into the optimization process to enhance protocol performance [183].

DT technology enables comprehensive performance analysis, monitoring, and optimization of vehicles throughout their lifecycle by creating virtual models of complex systems. It can significantly reduce carbon dioxide emissions by up to 43% compared to diesel vehicles and supports advancements in EVs, driver assistance, autonomous control, battery management, power electronics, and health monitoring. However, challenges include the complexity of modeling diverse systems, the need for global standards and data integration, and concerns over data security and privacy due to reliance on wireless and IoT technologies. Improving communication infrastructure and data protocols is essential to ensure reliable AI predictions and decision-making. Looking ahead, DTs will evolve with Industry 5.0 and 6.0, emphasizing natural language processing and human–technology interaction for smarter vehicles [184].

The integration of DT technology with advanced DL models like LSTM and GRU significantly enhances EV performance and stability, leading to reduced emissions and improved energy efficiency. Among the tested algorithms, the LSTM model paired with the Adam optimizer at a learning rate of 0.008 achieved the highest accuracy, with a MAE of 1.432 and RMSE of 1.456. Similarly, the GRU model, using the same optimizer and a learning rate of 0.05, also delivered strong results. Additionally, an LSTM variant using the SWATS optimizer at a learning rate of 0.03 showed promising prediction precision. To further improve model training, high-quality synthetic data was generated using TS-GAN, which produced data nearly indistinguishable from real datasets after 95 epochs, as validated by the FID metric. This combination of DT, LSTM, and TS-GAN demonstrates powerful potential for optimizing battery charge level monitoring and forecasting in EVs [185].

This framework utilizes a backpropagation neural network (BPNN) to accurately complete partial discharge voltage curves of batteries with an accuracy of over 99.6%. Meanwhile, a CNN-LSTM-Attention model leverages full discharge voltage curves and the cycle's SOC to predict battery capacity, achieving accuracy above 99%. Experiments demonstrate that the system can reliably predict battery capacity in real-time under varying conditions, with the CNN-LSTM-Attention model forecasting maximum capacity with an error of less than 3 mAh, reflecting high stability and precision. BPNN excels in completing discharge voltage curves, outperforming other methods and serving as the primary model for this task. Compared to alternatives such as LSTM and SDAE, the CNN-LSTM-Attention model offers notable improvements in analyzing battery degradation to its superior capacity prediction and degradation assessment accuracy [186].

The creation of a DT for a large-scale battery system helps reduce inter-cell variations and extend battery life. Modeling such extensive systems is complex due to the sheer number of cells and the impact of individual cell degradation on overall behavior. While detailed EMs provide accuracy, they are computationally intensive; simpler models sacrifice precision, limiting insights into cell-to-cell differences. Current operational data mainly covers general parameters like temperature and voltage, which is insufficient to fully capture inter-cell variability. Enhanced data collection combined with AI integrated with physical modeling is essential to develop more precise DTs. This integrated approach enhances safety, optimizes performance, and facilitates the early detection of degradation patterns [187].

DTs for BESSs combine geometric, behavioral, and data-driven models to create an accurate representation of the physical system, enhancing energy efficiency and management. Data-driven models use ML to predict performance patterns, behavioral models capture dynamic relationships among operating parameters, and geometric models replicate the system's physical components. Integrating these models improves accuracy and reliability, enabling precise forecasting and control of BESS performance. The network layer facilitates real-time data exchange between the physical system and digital model through standard protocols, supporting continuous monitoring, analysis, and proactive interventions to prevent failures. This integration extends battery life, reduces failure rates, increases output, and lowers operational costs [188].

Integration of physical and cyber models with real-world data enables advanced power system modeling and implementation on cloud platforms. Two types of DTs, high-bandwidth and low-bandwidth, achieve high accuracy in voltage reconstruction while balancing data requirements. Embedded computing and distributed communication protocols facilitate rapid, broker-free data exchange between controllers in microgrids. Cloud services support real-time data processing, model updating, and decentralized control through consensus algorithms. Optimization of system performance is achieved via parallel computations and efficient event monitoring, enhancing microgrid control and power management capabilities [189].

Leading platforms for developing battery DTs, include Siemens Simcenter Amesim, ANSYS Twin Builder, and COMSOL Multiphysics, which enable detailed modeling and simulation of mechanical, thermal, and electrical battery components. These tools are essential for designing thermal management systems and simulating the dynamic performance of batteries. Despite technological advancements, challenges such as a lack of standardized frameworks, cybersecurity risks, implementation complexity, high costs, and managing large volumes of sensor data have limited widespread adoption. Strategic application of DTs in high-value areas is necessary to maximize benefits and avoid resource inefficiency. Interest in battery DT technology has surged recently, with significant growth in research focused on advanced monitoring, design optimization, and state-of-health estimation. Future efforts should prioritize comprehensive studies and practical evaluations, especially toward developing industry standards and exploring novel applications [190].

11.1. AI-Enhanced Digital Twin Systems: Predictive Analytics for Fault Diagnosis

Advances in technology have significantly enhanced fault tolerance and control in hand-built robots. Key challenges include managing increasing robot complexity, processing large volumes of sensor and DT data, ensuring accurate modeling, and integrating diverse technologies. Cybersecurity risks linked to the use of DT and AI also pose significant concerns. Addressing these challenges involves leveraging advanced data analytics, improved sensor technologies, refined modeling methods, standardized processes, and specialized engineering training. Emerging trends such as explainable AI, edge and QC, human–machine collaboration, adaptive learning, and reinforcement learning further strengthen fault tolerance. Additionally, future efforts will emphasize energy efficiency and sustainability in fault-tolerant control. Collectively, AI, ML, and DT technologies are driving improvements in safety, cost reduction, and quality in robotic systems, positioning fault-tolerant control as a pivotal factor in advancing robot performance and ensuring sustainable operation [191,192]. Table 16 summarizes key techniques and findings in DT technologies for BMSs. DT technology holds promises for enhancing efficiency and performance in the process industry, addressing challenges such as shorter production cycles, increased output, and improved quality assessment.

Table 16. Key Techniques and Findings in DT Technologies for BMSs.

Main Focus	Key Techniques/Models	Key Findings	Ref.
DT in BMS	GANs, SVM, ANN, multi-physics models	Enhances battery RUL prediction and system optimization	[192]
SOH Estimation	LSTM, cyclic synchronization	Provides real-time, accurate SOH estimation with partial data	[179]
Charging Protocol Optimization	BO, DFN model, multi-channel optimization	Optimizes fast charging, reducing lithium loss and considering aging	[180]
DT in Automotive	DT systems	Reduces CO_2 emissions, improves vehicle performance and safety	[181]
Battery Charge Prediction	LSTM, GRU, TS-GAN	Improves charge level prediction using synthetic data	[182]
Battery Discharge Prediction	BPNN, CNN-LSTM-Attention	Accurately predicts battery capacity and degradation	[183]
Large-Scale Battery Systems	Single-particle model, DT	AI needed for better accuracy in large-scale battery systems	[184]
DT in BESS	Geometric, behavioral, data-driven models	Enhances BESS energy efficiency and real-time monitoring	[185]
Power System Management	AWS platform, DT	Optimizes microgrid performance and power management	[186]
Battery DT Platforms	Siemens, ANSYS, COMSOL	Optimizes battery systems but faces data handling challenges	[187]
AI in Robotics	AI, ML, DT, XAI, edge computing	Enhances robot performance and fault tolerance	[189]

11.2. Case Deployments and Validation Metrics (EV/Fleet/UAV)

Recent benchmarks illustrate how advanced modeling and estimation approaches perform under real-world operating conditions in EVs and UAVs. A study by Mannapperuma et al. [193] evaluated electro-thermal and data-driven estimators using on-road EV data, highlighting the strong sensitivity of SOC/SOH pipelines to thermal coupling and reporting practical error bounds for field-measured current, voltage, and temperature signals. This demonstrated the training and validation of ML-based SOC estimators on real-world driving datasets, comparing regression models and feature sets derived from voltage-current profiles and drive cycles, and highlighting limitations in model generalization across various operating scenarios. To address nonlinearities in the OCV-SOC relation, Jafari et al. [194] proposed a three-stage EKF pipeline, validated on dynamic driving profiles, which shows improved convergence and robustness compared to conventional EKF methods [195]. In parallel, validation studies of digital-twin approaches are emerging, confirming close agreement between DT-estimated SOC and coulomb counting in a LIB module subjected to varied driving conditions, while another study detailed a cloud-based DT framework for EVs, discussing architecture, latency, and accuracy trade-offs in fleet contexts [185,196]. More recently, a study by Kiran et al. reported that a DT-based charge-time predictor reduced error to below 2% and improved scheduling accuracy by ~7% compared to a baseline approach. Beyond EVs, UAV studies also provide important insights, presenting a fast-OCV method tailored for in-flight SOC estimation in hybrid-power UAVs, which shows feasibility relative to laboratory OCV procedures. Another report mapped UAV BMS challenges and cross-referenced field-data-driven SOH/SOC forecasting examples from the literature [197]. Together, these cases highlight the importance of grounding model development in validated field data and illustrate the trade-offs between accuracy, computational demands, and deployment readiness across various platforms [198,199]. Representative benchmarks of DT and related estimation approaches in EV fleets and UAVs are summarized in Table 17, highlighting deployment contexts and reported performance metrics for recent real-world benchmarks of battery modeling and estimation methods in EV and UAV platforms.

Table 17. Recent real-world benchmarks of battery modeling and estimation methods in EV and UAV platforms.

Platform	Task/Model	Setting	Headline Result	Ref.
EV	SOC/SOH (electro-thermal + data-driven)	On-road EV signals	Practical SOC/SOH error bounds; thermal coupling critical	[193]
EV	SOC (ML regressors)	Real driving data	Model ranking and generalization analysis across cycles	[195]
EV	SOC (3-stage EKF)	Dynamic drive cycles	Faster convergence; robust to OCV nonlinearity	[185]
EV	SOC via DT (validated to CCM)	Real module, varied driving	Close SOC tracking vs. ground truth CCM	[196,197]
EV fleet	DT (cloud)	Deployed system	Architecture + latency/accuracy trade-offs	[194]
EV fleet	DT charge-time prediction	Real session	**<2%** charge-time error; **~7%** improvement	[198]
UAV	SOC (fast-OCV)	Hybrid-power UAV	In-flight feasible; reduced waiting vs. lab OCV	[199]

12. Future Challenges and Research Directions in Battery Management Systems

Real-time DT integration for predictive maintenance, AI-driven state estimation, and better battery modeling are the primary areas of future research and difficulties in the BMS field. Innovations in cybersecurity, fault diagnosis, and battery safety are essential for averting malfunctions. It remains crucial to optimize thermal management, especially for rapid charging and extreme environments. To effectively capture mechanical, thermal, and electrochemical interactions, multi-scale and multi-physics modeling is required. For scalable monitoring, AI-driven methods must utilize cloud–edge computing and IoT, while also adapting to new battery chemistries. Furthermore, standardization, regulatory compliance, and sustainable second-life battery management are necessary for the broad implementation of next-generation BMSs.

Expanding Energy Digital Twin (EDT) technology to macro scales is essential for integrating diverse energy sources, such as solar, wind, and hydro, with industrial and residential demands. This expansion requires the ability to manage the full system lifecycle, from design and processing to services, through forecasting and optimization to improve cost and energy efficiency. EDT systems must automatically detect and adapt to changes in operating environments and processes. Data security and governance are critical challenges, as energy infrastructures are vulnerable to cyberattacks and involve commercially sensitive information, demanding robust management frameworks. Additionally, EDT requires advancements in computing and software to maximize performance while minimizing costs and energy consumption. The integration of AI and ML significantly enhances the prediction and optimization of energy system performance within EDT frameworks [200].

A CNN-LSTM model combined with an advanced data preprocessing technique achieved battery State-of-Health (SOH) estimation errors below 5% across three different batteries. Trained using TensorFlow with the Adam optimizer on a GPU, the model was evaluated under four scenarios involving variations in preprocessing, training data size, sliding window size, and dropout application. Results consistently showed SOH estimation errors under 1%, demonstrating the model's strong ability to accurately predict battery capacity degradation trends. A key advantage of this approach is its automated feature extraction from voltage data, eliminating the need for manual feature engineering and enabling faster, fully automated SOH estimation. The high accuracy and robustness across various batteries highlight the model's reliability and effectiveness in battery health monitoring [201].

Advancements in digital technologies including IoT, blockchain, edge and cloud computing, AI, and DTs, are transforming real-time BMS monitoring and control, aligning with Industry 4.0 principles. The integration of these technologies enhances BMS capabilities in data analysis, monitoring, and charging management. DTs serve as precise virtual replicas of batteries, enabling continuous interaction with physical systems for improved battery life monitoring, dynamic charging, temperature regulation, and real-time health estimation. Cloud platforms support the extensive data processing and storage needs of these models, enabling the detailed management of individual battery cells, which improves overall system performance and extends battery longevity. Blockchain technology also plays a role, especially in battery swapping and EV applications, by providing secure tracking and control over battery life and usage [202].

Research on EVs is rapidly expanding, with projections indicating over 20,000 publications by the end of 2024. A significant focus is on vehicle-to-everything (V2X technology, which facilitates communication among vehicles, pedestrians (V2P), infrastructure (V2I), networks (V2N), and other vehicles (V2V). These technologies are essential not only for advancing autonomous driving but also for improving road safety and traffic efficiency. Since the early 1990s, research on V2X has surged, especially after 2016. Chinese researchers lead the field, supported by prominent companies and universities such as Huawei and Beijing University of Posts and Telecommunications. Renowned organizations, such as IEEE, have contributed extensively, reflecting a strong scientific commitment. The development of V2X spans multiple disciplines, including physics, computer science, engineering, and mathematics, underscoring its interdisciplinary nature and broad impact [203].

Reusing spent EV batteries in less demanding applications, such as energy storage, can significantly reduce their environmental impact. Ensuring battery health, capacity, and safety relies on standardized testing protocols that include electrical, mechanical, and environmental evaluations. However, global discrepancies in regulations, particularly among China, Europe, and the United States, pose challenges due to inconsistent policies and a lack of unified guidelines for battery recycling and reuse. China's centralized system, Europe's stringent regulations, and the U.S.'s more flexible approach exemplify these differences, which can impede the development of a circular economy and complicate international standardization. Comprehensive and advanced testing procedures are essential to ensure second-life batteries maintain safety and functionality across varied conditions. Key evaluations include capacity measurement, internal resistance, SOC, and self-discharge characteristics [204].

BESSs possess unique characteristics that challenge their classification as either generators or loads within power systems, as they can simultaneously act as both. This dual functionality requires clear definitions and tailored legal frameworks. Leading countries such as the US, Australia, and several European nations have developed regulatory approaches through interagency collaboration, demonstrating the importance of stakeholder cooperation. Financial incentives, such as government subsidies and tax credits, significantly support the adoption of BESSs, especially in developed regions. BESSs provide valuable services including energy arbitrage in electricity markets, frequency regulation, peak load shaving, and renewable energy integration, which help stabilize the grid and reduce revenue volatility. These capabilities have enabled pioneering nations to develop innovative business models and increase flexibility in energy management [205].

Multi-objective quantum optimization techniques, such as the Quantum Bee Colony Algorithm (QABC) and the Quantum Particle Swarm Optimization Algorithm (QPSO), significantly improve energy management by simultaneously addressing multiple constraints. Applied to ship energy systems, these algorithms enhance efficiency, reduce operating costs, fuel consumption, and emissions, while complying with Energy Efficiency and Oceans Obligations (EEOI). They optimize the utilization of clean energy by transferring excess power to electrolyzers once storage modules are full, effectively balancing energy storage between batteries and fuel cells and reducing diesel engine output. This approach not only extends battery lifespan but also enhances hydrogen production, thereby increasing overall system efficiency and reducing dependence on fossil fuels [206].

The facility-allocation (FLA) problem involves determining the optimal number and placement of facilities and is a key challenge in this field. QC, particularly using the D-Wave quantum computer, has demonstrated significant speed advantages, solving such problems up to 42 times faster than classical methods for moderate problem sizes. Despite this progress, QC faces limitations in scalability, noise sensitivity, and hardware constraints, which hinder its application to large-scale power grid optimization tasks. Algorithms like HHL, designed for solving linear systems, struggle with these challenges, preventing a definitive demonstration of quantum advantage in operational power system problems. Nevertheless, QC holds strong promise for advancing areas such as energy grid state prediction and battery development by improving computational models for material discovery and energy storage system design, crucial for addressing renewable energy integration [207].

The stacking strategy demonstrated superior prediction accuracy, achieving low error metrics (MAE: 0.0164, MAPE: 0.0217, RMSE: 0.018) and a high coefficient of determination (R^2: 0.9994) even before optimization. By applying the Variational Quantum Algorithm (VQA) for hyperparameter tuning of the random forest and XGBoost models, prediction accuracy improved substantially, reducing errors by over 60–77% across key metrics (MAE, MAPE, RMSE). The optimized stacking model consistently outperformed traditional approaches, including RNN, LSTM, and DBN, across multiple battery groups. These results demonstrate that advanced ensemble methods, combined with quantum-inspired optimization, an significantly enhance battery state-of-health prediction by better capturing complex degradation trends and reducing estimation errors [208].

QC leverages unique quantum phenomena to address complex problems in power systems, such as optimization, simulation, and ML, with enhanced efficiency. Advances in quantum hardware, software, and algorithms have increased the feasibility of applying QC in smart grid applications. Algorithms like HHL reduce computational demands during fault analysis and state estimation, while techniques such as Quantum Amplitude Estimation (QAE) accelerate contingency analysis and dynamic event simulation. Additionally, hybrid optimization algorithms such as the Quantum Approximate Optimization Algorithm (QAOA) and the Variational Quantum Eigensolver (VQE) effectively solve complex energy management and market optimization challenges. QC also plays a crucial role in power service restoration by enabling robust resource allocation and management during critical network conditions [209].

QC harnesses principles such as entanglement and superposition to solve certain problems more efficiently than classical computers. Grover's algorithm, in particular, accelerates search tasks within large, complex spaces. Implementations using 12 qubits demonstrated that the probability of finding the correct solution approaches 100% after about 50 iterations. In energy and power systems, Grover's algorithm can address difficult challenges such as system control, optimization, and reliability enhancement by efficiently searching for optimal solutions. However, its practical application faces limitations, including the need for quantum computers with larger numbers of qubits to tackle complex problems, the sensitivity of qubits to environmental noise, and the requirement to design specific oracles tailored to each problem. Overcoming these issues demands advances in noise mitigation and qubit isolation to preserve computational accuracy [210].

12.1. Emerging Battery Management Systems Technologies

Quantum Computing for Battery Management Systems Optimization

QC demonstrates significant potential for addressing complex, interdisciplinary problems in the energy sector, particularly in areas such as network optimization and expansion. Its application in ML-based energy system optimization and convex optimization is still in early stages, leaving substantial opportunities for future development. Quantum techniques could enable breakthroughs in OPF and DER management. However, challenges remain in designing effective algorithms, improving simulation tools, and creating specialized hardware capable of supporting large-scale industrial deployment, all of which currently limit the full realization of QC benefits in this field [211]. Although QC exhibits high potential for optimization and control tasks in BMSs, its practical implementation remains at a laboratory research stage. Current studies are primarily limited to small-scale, proof-of-concept demonstrations using fewer than 20 qubits, focusing on model validation and algorithmic feasibility rather than real-time deployment. Industrial applications of QC in BMSs have not yet progressed beyond simulation environments, as hardware scalability, qubit coherence, and cost remain major constraints. Consequently, the maturity of QC-based BMSs can be categorized as pre-commercial and exploratory, requiring continued advancements in both quantum hardware and hybrid algorithm integration before large-scale implementation becomes viable.

12.2. Standardization and Regulations for Battery Management Systems

Global Safety Regulations

Evaluation of LIB safety involves various tests addressing fire resistance, chemical hazards, and toxic gas emissions. Fire tests assess battery behavior under extreme fire conditions using methods such as grating body testing, projectile testing, and radiant heat exposure to determine heat resistance and explosion risk. Specialized tests measure the release of hazardous gases, such as hydrogen, carbon monoxide, and carbon dioxide, using sensors to evaluate concentrations and assess risks to humans and rescuers. Automotive battery safety is governed by international standards (ISO, IEC, SAE, UL), which specify parameters and procedures for assessing flammability, toxic gas emissions, and thermal stability. These comprehensive evaluations ensure LIBs meet safety requirements across different scenarios [212].

12.3. Future Artificial Intelligence and Digital Twin Advancements

Next-Generation AI-Driven Battery Management Systems

Wireless Battery Management Systems (wBMSs) utilize various communication technologies, including cellular networks, BLE, Zigbee, NFC, and Wi-Fi, each differing in terms of security, scalability, efficiency, and reliability. While wBMSs offer benefits such as weight reduction and a simpler design, challenges remain, including signal interference, data security risks, and a lack of standardization. The technology's early stage limits widespread adoption due to cyber threats and the absence of global protocols. Addressing these challenges requires advancements in encryption, authentication, signal processing, shielding, and international standard development. Additionally, innovations in battery pack packaging and integration, such as cell-to-pack (CTP) and cell-to-case (CTC) designs, influence wBMS performance. Overcoming these obstacles demands focused research to adapt wBMS technologies alongside evolving battery architectures [213].

13. Summary

13.1. Summary of Key Insights

The BMS plays a vital role in accurately estimating the SOC, monitoring battery condition, controlling charge and discharge, and managing thermal and safety aspects. Despite significant advancements, challenges persist in SOC estimation and BMS development, particularly in alignment with the Sustainable Development Goals. BMSs are critical components across various applications, including EVs, renewable energy systems, and portable electronics, with solar PV–battery systems being a key example where they regulate charging cycles and extend battery life. The integration of intelligent monitoring methods, such as NNs for SOC estimation and maximum power point tracking (MPPT), further optimizes system performance. However, issues such as fast charging, cell balancing, temperature management, accurate SOH prediction, and battery recycling continue to pose significant challenges affecting battery longevity and reliability [214].

13.2. Research Gaps and Recommendations

Battery aging is studied through empirical methods, primarily performed in laboratories, which provide theoretical foundations based on technical parameters. Model-based approaches simulate battery behavior using mathematical and physical equations to identify aging-related parameters. Simplified models like P2D and Single Particle Models (SPM) are favored for online SOH estimation. Electrochemical model-based techniques employ adaptive observers such as the EKF and multi-scale observers to estimate internal parameters like resistance and capacity, which correlate directly with battery health indicators such as cyclable lithium ions. Despite their accuracy, these methods are computationally intensive, limiting their use in real-time applications. Efforts to reduce computational demands include simplifying EMs and applying optimization algorithms. In contrast, data-driven approaches bypass detailed physical modeling by relying exclusively on data gathered from the battery aging process [215]. One persistent challenge for data-driven BMS frameworks is the scarcity of fault-related or abnormal operating data, which constrains the robustness of diagnostic and prognostic models. Several studies have addressed this limitation through synthetic data generation and data augmentation. For instance, GANs and VAEs have been applied to create realistic battery charge–discharge and degradation patterns, enhancing model generalization and reliability in limited-data environments. Similarly, hybrid architecture such as TS-GAN have demonstrated improved accuracy in charge-level prediction by enriching training datasets with synthetic sequences. Complementary strategies, including transfer learning and domain adaptation, further enable models trained on laboratory data to adapt to real-world field conditions with minimal retraining. Integrating these approaches within data-driven BMSs can substantially enhance fault tolerance, predictive performance, and cross-chemistry applicability [181,192].

Insufficient safety measures and monitoring can lead to serious problems, including abnormal heating, cell imbalance, overcharging, overdischarging, and increased fire risks. Intelligent control systems and algorithms play a crucial role in managing battery safety, balancing cells, and regulating temperature. A key challenge lies in the limitations of current sensing devices, which often suffer from noise and lack sufficient precision. Enhancing the accuracy of battery health estimation requires advanced battery testing equipment with improved noise reduction and more precise sensing technologies. While much research focuses on individual battery health, EVs rely on packs containing hundreds of cells, making cell imbalance after repeated charge–discharge cycles a significant concern that can degrade prediction accuracy. Combining multiple intelligent algorithms with optimization techniques, hybridization, has proven effective in improving health prediction and control performance. However, implementing such intelligent algorithms, especially DL models, faces hurdles due to long training times, though recent progress has improved accuracy while reducing training duration under varying conditions [216].

EV technologies encompass various ESS and BMS functions, including state estimation, cell balancing, fault diagnosis, and temperature control. Charging methods, such as AC, DC, and wireless charging, each offer distinct advantages but face significant challenges that hinder their broader adoption. DC charging provides faster energy transfer without the need for power converters, whereas AC charging offers multiple levels, suitable for both everyday and rapid charging needs. Wireless charging presents a promising alternative by enabling energy transfer without large batteries, whether stationary or in motion, although safety and health concerns have delayed its commercial deployment. Major obstacles to EV proliferation include high upfront costs, lengthy charging durations, limited driving range, weather-related performance degradation, and uneven development of charging infrastructure across public and private sectors. These factors collectively impact vehicle performance and slow the transition to widespread electric mobility [217].

Managing LIBs is complicated by safety challenges such as overheating and aging, making BMSs critical for monitoring and maintaining battery health. Key tasks for BMSs include predicting the battery's SOH, SOC, and remaining useful life (RUL), with fault detection being vital for ensuring efficiency and safety. ANNs have gained increasing attention for accurately estimating these parameters. Various ANN architectures, such as feed-forward neural networks (FFNNs), DNNs, CNNs, and recurrent neural networks (RNNs), are utilized for this purpose. CNNs excel at analyzing sensor data and detecting anomalies, while RNNs effectively capture temporal patterns to forecast future battery states. DNNs leverage the strengths of FFNNs, CNNs, and RNNs to improve prediction accuracy and anomaly detection. Employing ANN-based methods enhances battery performance and longevity by enabling precise state estimation and timely fault identification [218].

Efficient battery management in EVs relies heavily on the BMS, which monitors battery health and charge levels while preventing overheating and cell failures through effective thermal management. Various BMS architectures, including distributed, modular, decentralized, and centralized designs, are developed to enhance vehicle safety and efficiency. These systems are further classified into low-voltage and high-voltage types based on battery voltage, each offering distinct advantages that impact battery lifespan and performance. The BMS extends battery life, optimizes energy consumption, and improves overall vehicle performance by detecting and managing performance fluctuations and faults. They also ensure stable and reliable battery operation, contributing to higher EV efficiency and reduced fossil fuel dependency by intelligently regulating charging and discharging according to battery capacity. Despite these benefits, challenges remain, such as longer charging times, the need for specialized and not universally available charging infrastructure, and battery size constraints in heavier vehicles. Nonetheless, LIBs remain the preferred choice for EVs due to their high energy density and favorable performance characteristics [219].

The design of a BMS requires careful consideration of application-specific needs alongside battery pack topologies, physical variable measurements, and cell balancing strategies. Monitoring insulation in high-voltage systems is crucial, utilizing techniques that involve simulating various voltage conditions using switches and resistors. Effective cell charge balancing and voltage management are vital to prevent issues caused by charge imbalances, employing both passive and active balancing methods. Safety is a central focus, addressing risks related to high-voltage failures, insulation faults, and potential hazards during battery shutdowns. Standards specify minimum insulation resistance values to ensure safety, with at least 100 megaohms required for DC systems and 500 megaohms for AC systems, reflecting the stringent requirements for insulation performance [220].

Accurately estimating battery capacity remains challenging under varying conditions, such as temperature fluctuations and changing loads, leading to gaps between laboratory results and real-world BMS performance that affect user trust. Addressing these challenges requires advanced BMS designs featuring sophisticated hardware and software capable of adapting to dynamic operational and environmental factors. Improved cell balancing methods and advanced modeling techniques enable more precise condition forecasting and tailored charge–discharge control based on sensor data. Enhanced communication among BMS components, such as sensors and charging modules, using wireless technologies and standardized protocols further improves control and monitoring. Additionally, accurately determining and predicting maximum battery capacity is difficult, as batteries rarely operate under consistent discharge currents or uniform conditions [221].

BMSs play a critical role in protecting batteries from harmful conditions such as deep charging and deep discharging, while providing accurate measurements of SOC and SOH. To meet the demands of smart grid and EV applications, batteries require high energy and power densities. Smart grids rely on advanced communication and control technologies to enhance energy distribution reliability and efficiency, with energy storage, such as LIBs, flywheels, and sodium-sulfur batteries, being essential to stabilize renewable energy and meet consumer needs. EVs are gaining popularity due to their reduced emissions and lower fossil fuel dependence yet challenges like battery weight and long charging times persist, driving the need for ongoing technological improvements. Within these contexts, BMSs ensure battery safety, longevity, and performance by continuously monitoring conditions and providing precise SOC and SOH estimations to prevent damaging operational scenario [222].

Various techniques are used for SOC estimation, including adaptive filters, ML, algorithm-based models, and direct measurements. Simple methods, such as direct measurement and Coulomb counting, are commonly applied due to their ease of use but tend to lose accuracy under conditions like temperature variations or external disturbances. More complex mathematical models can provide precise results but often involve intricate computations and may lack robustness in real-world applications. Adaptive filter methods strike a balance by offering high accuracy but require precise control, which can be challenging in practice. ML approaches have gained significant attention for their flexibility and strong performance, especially in challenging scenarios such as battery aging and temperature fluctuations, although they require higher processing power and fast controllers. Ongoing advances in sensor technology, nanoelectronics, and ML are expected to further enhance SOC estimation accuracy, improving model robustness and reducing existing limitations across a range of operating conditions [223].

Battery modeling encompasses electrical, thermal, and combined electro-thermal approaches, providing a comprehensive understanding of battery state and behavior under various conditions. Accurate estimation and control of key parameters, such as internal temperature, SOH, and SOC, are essential for assessing battery condition. These estimates inform the design of optimal charging strategies that balance charging speed, capacity efficiency, and battery longevity. Common charging methods for LIBs in EVs include constant current (CC) and constant voltage (CV) charging, as well as hybrid CC-CV charging, where a constant current phase is followed by a constant voltage phase. The CC-CV approach effectively balances fast charging with battery health preservation but requires careful optimization of current and voltage settings. Additionally, multi-stage charging (MCC) techniques further enhance charging efficiency and protect against battery damage, underscoring the importance of optimizing charging protocols to improve overall battery performance [224].

LIBs have driven a significant shift in industries such as automotive, renewable energy, manufacturing, construction, and mining, reducing dependence on fossil fuels and transforming the energy storage landscape. Ensuring functional safety in BMSs is critical to meet rigorous standards of safety, reliability, and quality across electric transportation and stationary energy storage applications. Malfunctions or design flaws that fail to satisfy safety requirements can pose serious risks to the environment, people, and property. BMS plays a vital role in monitoring and protecting batteries by using sensors to track parameters such as temperature, voltage, and current, and by automatically disconnecting batteries when faults are detected. The design of these systems must minimize risks from various failure modes, with particular attention to selecting and configuring voting mechanisms [225].

13.3. Final Thoughts on Battery Management Systems Advancements

BMSs are essential for monitoring and optimizing battery performance by tracking key attributes such as temperature, state of function (SOF), health, and charge. A significant challenge in BMS design is accurately modeling and estimating the state of temperature (SOT) of the battery. While thermal EMs offer high accuracy, their complexity and computational demands limit their use in real-time applications. To address this, alternative approaches, such as impedance-based and semi-empirical models, have been developed to estimate core battery temperature and prevent issues caused by temperature rises of up to 100 °C. Future BMS designs are expected to become more accurate and robust by integrating advanced parameter identification algorithms and optimal modeling techniques. As energy storage demands grow and battery sizes increase, precise assessment of battery condition across different scales, from cells to complete systems, will become increasingly critical [226].

14. Conclusions

This paper presents a comprehensive review of battery management systems (BMSs) and battery modeling techniques, including thermal, electrochemical, and data-driven approaches. BMSs are essential in electric vehicles (EVs), renewable energy systems (RESs), and aerospace applications, where they enhance battery lifespan, optimize energy storage, and ensure operational safety. Key components such as monitoring units, cell balancers, thermal management systems, and communication modules support critical functions like voltage, current, temperature monitoring, and charge balancing. The performance of centralized, modular, and distributed BMS architectures varies in terms of efficiency, fault detection, and real-time monitoring capabilities.

Recent advancements emphasize wireless connectivity, cloud integration, and intelligent algorithms that enable adaptive control and predictive diagnostics. IoT and cloud-based platforms facilitate remote monitoring and real-time data analysis, while innovations in silicon anodes and solid-state electrolytes (SSEs) have improved energy density and safety in lithium-ion batteries. However, challenges remain in lithium-sulfur technologies, particularly regarding safety and cycle performance. Battery degradation mechanisms such as solid–electrolyte interface (SEI) formation, capacity fade, impedance growth, and thermal instability continue to be key research areas.

Accurate modeling is essential for estimating state-of-charge (SOC), state-of-health (SOH), and remaining useful life (RUL), which are vital for safe and efficient BMS operation. Common modeling frameworks include equivalent circuit models (ECMs), electrochemical models (EMs), and multi-physics simulations. ECMs such as resistance-capacitance and Thevenin-based models balance computational efficiency with real-time applicability. More advanced models integrate electrochemical, thermal, and mechanical interactions, including digital twins (DTs) and hybrid physics-informed approaches. These models enhance fault detection, degradation forecasting, and predictive maintenance.

Artificial intelligence (AI) and machine learning (ML) techniques further improve SOC, SOH, and RUL estimation. Kalman filtering, particle filtering, convolutional autoencoders, and impedance-based methods offer high precision in dynamic environments. Long short-term memory (LSTM) networks and transfer learning models support robust health monitoring and deterioration prediction. Effective thermal management remains critical for safety and performance, with techniques such as heat pipes, liquid and air cooling, phase change materials (PCMs), and immersion cooling. AI-driven predictive control and DT-based optimization help maintain temperature homogeneity and prevent uneven aging.

Battery safety and fault diagnosis are addressed through voltage/current monitoring, impedance spectroscopy, and ML-based detection. Internal short circuits, dendrite formation, and irreversible impedance changes are key concerns. Online fault diagnosis and prognostic health management (PHM) systems enable real-time problem isolation and predictive maintenance, though universal fault models across chemistries remain a challenge. Advanced charging and energy management strategies aim to improve performance and longevity. AI-driven algorithms, pulse charging, and smart grid integration support efficient energy distribution and reduced heat generation.

AI and ML technologies are revolutionizing BMSs through reinforcement learning, fuzzy logic, and predictive control. Hardware accelerators such as field-programmable gate arrays (FPGAs) enhance power efficiency in complex systems. Edge computing reduces latency and improves decision-making by processing data closer to the source, while cloud–edge integration supports scalable monitoring and diagnostics. IoT sensors provide essential data for cloud-based analysis, improving energy management and extending battery life. DTs combine ML with sensor data to forecast SOC and SOH, optimize charging, and enable proactive maintenance.

Looking ahead, BMS development will focus on predictive maintenance, real-time integration, and enhanced safety. Research will explore multi-physics modeling, cloud-edge computing, novel battery chemistries, and AI-driven estimation techniques. Key challenges include improving thermal management, fault diagnosis, and cybersecurity. Quantum computing (QC) offers potential for more efficient energy system optimization, while DTs will play a central role in performance forecasting and system design.

Overcoming these challenges is essential for building safer, longer-lasting, and more efficient battery systems. BMSs will continue to evolve by incorporating technologies such as DTs, AI, and wireless charging to support the sustainable advancement of EVs and energy storage. Electrical models (EMs) that include aging and mechanical stress will be key to future developments. This review highlights critical BMS applications such as condition estimation, thermal management, and diagnostic accuracy, while identifying the need for new standards and scalable architectures.

With a focus on EV applications, this study examined battery storage technologies, performance metrics, and wireless charging techniques. It also addressed implementation challenges and proposed improvements through cloud computing and blockchain integration. SOH estimation techniques were reviewed and categorized into clustering methods (CM), neural networks (NN), Gaussian process regression (GPR), empirical learning (EL), and transfer learning (TL). NN-based models perform well with small datasets, while TL-based models are more effective with large datasets from sources such as Sandia, Toyota, and Stanford-MIT. Real-world SOH monitoring challenges include spatiotemporal variability, computational load, and reliance on laboratory data.

This review concludes by emphasizing the importance of reliable, adaptable, and secure BMSs, particularly for high-capacity EV battery packs. Wireless BMSs (WBMSs) are presented as a promising alternative to conventional wired systems, despite ongoing concerns around cost, cybersecurity, and communication reliability. By integrating hybrid algorithms, advanced sensing technologies, and scalable architectures, future BMSs can achieve greater precision, resilience, and sustainability across diverse energy applications.

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Abbreviations

AIC	Akaike Information Criterion
AC	Alternating Current
AWS	Amazon Web Services
ASICs	Application-Specific Integrated Circuits
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANFIS	Adaptive Neural Network-Based Control System
BPNN	Backpropagation Neural Network
BESS	Battery Energy Storage System
BMS	Battery Management System
BTMS	Battery Thermal Management System
BIC	Bayesian Information Criterion
CM	Condition Monitoring
CNN	Convolutional Neural Network
CPS	Cyber–Physical System
CAN	Controller Area Network
DL	Deep Learning
DNN	Deep Neural Network
DR	Demand Response
DOD	Depth of Discharge
DT	Digital Twin
DC	Direct Current
DER	Distributed Energy Resource
DFN	Doyle–Fuller–Newman
EV	Electric Vehicle
EIS	Electrochemical Impedance Spectroscopy
EM	Electrochemical Model
EEOI	Energy Efficiency and Oceans Obligations
ESS	Energy Storage System
ECM	Equivalent Circuit Model
EKF	Extended Kalman Filter
FLA	Facility-Allocation
FDI	Fault Identification and Isolation
FUDS	Federal Urban Drive Cycle
FPGA	Field Programmable Gate Array
GPR	Gaussian Process Regression
GA	Genetic Algorithm
GAN	Generative Adversarial Network
HTC	Heat Transfer Coefficient
HEV	Hybrid Electric Vehicle
IoT	Internet of Things
IT2CC	Interval Type-2 Fuzzy Clustering
KF	Kalman Filter

LMI	Linear Matrix Inequality
LIB	Lithium-Ion Battery
LSTM	Long Short-Term Memory
BLE	Low-Energy Bluetooth
ML	Machine Learning
MCMC	Markov Chain Monte Carlo
MAPE	Mean Absolute Percentage Error
MCU	Microcontroller
MPPT	Maximum Power Point Tracking
NN	Neural Network
NARX	Nonlinear AutoRegressive with eXogenous Inputs
NUIO	Nonlinear Unknown Input Observer
OCV	Open-Circuit Voltage
OPF	Optimal Power Flow
PDE	Partial Differential Equation
PSO	Particle Swarm Optimization
PI-LSTM	Physics-Informed Machine Learning
PCMs	Phase Change Materials
PHEV	Plug-In Hybrid Electric Vehicle
PNP	Poisson–Nernst–Planck
PEM	Polymer Electrolyte Membrane
OPF	Power Flow Optimization
PiL	Processor-in-the-Loop
P2D	Pseudo-Two-Dimensional
QABC	Quantum Bee Colony Algorithm
QC	Quantum Computing
QPSO	Quantum Particle Swarm Optimization Algorithm
RLS	Recursive Least Squares
RFBs	Redox Flow Batteries
ROEM	Reduced-Order Electrochemical Model
ROM	Reduced-Order Model
RES	Renewable Energy System
RC	Resistance-Capacitance
RUL	Remaining Usable Life
RMSE	Root Mean Square Error
SPM	Single Particle Model
SEI	Solid–Electrolyte Interface
SSE	Solid-State Electrolyte
SOC	State of Charge
SOH	State of Health
SOP	State of Power
SOT	State of Temperature
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
UKF	Unscented Kalman Filter
UDDS	Urban Dynamometer Driving Schedule
VAE	Variational Autoencoder
V2P	Vehicle-to-Automobiles and Pedestrians
V2X	Vehicle-to-Everything
V2G	Vehicle-to-Grid
V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Networks
V2V	Vehicle-to-Vehicles
WBMS	Wireless Battery Management System

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