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Battery Management Systems for Next-Generation Electric Vehicles: A Comprehensive Review of Architectures, Standards, and Optimization Techniques

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ABSTRACT

Lithium-ion battery packs in contemporary electric vehicles (EVs) depend on Battery Management Systems (BMS) for long-term, safe, and effective functioning. This study summarizes the state of the art in BMS hardware and software architectures, worldwide standards, and safety laws that influence BMS testing and design, and optimization methods for key issues such as state estimation and cell balancing. We compare passive and active cell balancing techniques, examine communication, functional safety, and test/regulatory landscapes (ISO 26262, IEC 62660 series, UNECE R100, ISO 15118), and survey both conventional and sophisticated estimation algorithms, including coulomb counting, equivalent-circuit-model plus Kalman filters, particle filters, and hybrid data-driven/model-based approaches. The survey is concluded by discussing optimization approaches applied to BMS tasks, ranging from traditional parameter tuning to metaheuristics and machine learning. This study also highlights the research gaps and future goals for next-generation BMS for EVs.

Keywords: Battery Management System, State of Charge, State of Health, Cell Balancing, Active Balancing, Passive Balancing, Electric Vehicles.

1. INTRODUCTION

Lithium-ion battery (LIB) packs used in electric vehicles (EVs) are extremely sensitive to working circumstances, though, and even little variations in temperature, voltage, or current can have negative effects on performance, shorten their lifespan, or pose safety risks. Because of this, an intelligent system that can keep an eye on, safeguard, and manage battery packs over the course of their lifetime is required. The EVs industry has grown as a result of notable advancements in LIB technology that have increased energy density and decreased prices. Nevertheless, issues with battery technology and consumer concerns continue to prevent EVs from being widely adopted [1]. In the context of global decarbonization, raw minerals such as lithium, cobalt, nickel, and graphite are in high demand due to the growth of the EVs and renewable energy sectors. In order to guarantee a sustainable supply and achieve net-zero goals, this study looks at the strategies and difficulties adopted by different stakeholders along the EV battery value chain [2]. Battery technology related issues including high prices and short driving range are major obstacles to the broad use of battery EVs. In order to assist stakeholders such as academics and policymakers in achieving sustainable EV transportation, this paper examines these technological and financial challenges and offers possible solutions [3]. From procuring raw materials to disposing of LIBs at the end of their useful lives, the sustainability of the LIB lifecycle poses serious issues as electric mobility grows. In order to facilitate a circular economy for batteries, this paper examines these concerns, including material demands, economic hazards, and legislative gaps, and suggests that further study and cooperation are required [4]. Despite being essential for the energy transition and decarbonizing transportation, a number of obstacles currently prevent EVs from being widely adopted. The effects of EV grid integration, their potential contributions to energy management, and the significance of the best possible charging infrastructure are all examined in this research [5]. The feasibility of such business models is hampered by the major obstacles faced by second-life uses for retired EV batteries. The battery life cycle, application needs, and the absence of standards for exchanging battery data are the main topics of this study's analysis of these challenges. The development of multi-life battery systems is complicated by the key problems, which include the expensive repurposing stages, the challenges of determining the remaining battery life, and the lack of open standards for data interchange [6]. Research on improving battery performance has become crucial as the use of electric cars grows. In order to control important battery parameters such as State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL), this research investigates the application of predictive machine learning algorithms [7]. The quick growth of electric cars and the decarbonization of transportation are seriously hampered by the opaqueness of the LIB supply chain. This study highlights important obstacles and critical criteria like greenhouse gas emissions and human rights that need cross-tier cooperation to solve the existing absence of a thorough framework for sustainability evaluation [8]. The dominance of LIB is highlighted in this paper's summary of developments in EV battery technology, covering various battery chemistries and charging standards. Additionally, it investigates how artificial intelligence (AI) may be used to manage issues like recycling and material shortages as well as optimize battery performance [9]. Lithium metal batteries are a viable technology for future electric cars with greater range and cheaper costs since they have a considerable cost and energy density advantage over LIB. To satisfy the demanding requirements of the automobile sector, there are still significant obstacles to overcome at the cell and system levels, such as enhancing cycle life, safety, and fast-charging capabilities [10].

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Accurately estimating crucial metrics like SOC and SOH, which are essential for dependable energy management, is one of the main issues in battery use. Furthermore, there are major safety problems related to overcharging, overheating, over discharging, and cell-to-cell irregularities result in imbalances that lower available capacity. Advanced sensing, estimation, and control methods that are incorporated into the BMS are needed to address these problems. Reliable monitoring of LIB degradation is crucial for the safety and reliability of electric vehicles. A study proposes a robust and accurate model using instantaneous voltage and its drop to simultaneously estimate both the SOC and SOH of batteries [11]. Given the widespread use of LIB in various applications, the accurate estimation SOH is crucial for safety and performance. Accurate SOH estimation of LIB in EVs remains challenging, and a presented work compares data-driven methods to assess their practical applicability [12]. A hybrid machine learning model was created in a joint estimate framework for battery systems in order to increase the precision of capacity a stand-in for SOH and SOC predictions. By employing Fiber Bragg Grating sensors to record comprehensive temperature and strain data, the framework automatically extracted valuable characteristics from the enhanced readings, resulting in notable reductions in error and standard deviation [13]. An equivalent circuit model (ECM) and a deep learning network are used in a novel approach to evaluating the SOH of LIB. The method employs an enhanced Vision Transformer network to predict SOH with excellent accuracy and a fractional-order model to detect important health characteristics [14]. Initial state errors are a common problem with model based techniques for estimating battery state, which can cause instability and jeopardize battery safety. This work introduces a novel approach that essentially removes the need on initial state settings by co-estimating the SOC and SOH using two radial basis function auto-regressive models [15]. This study suggests employing impedance measurements and differential capacity (dQ/dU) as immediate indicators for the SOC and SOH of lithium-ion cells for battery diagnostics. According to the research, key signals from these techniques can represent the available charge and forecast future heat events, negating the need for complete charge-discharge cycles [16]. A novel physics-enhanced online joint estimating framework is suggested to increase the accuracy of SOH and SOC estimations for LIB under the high C-rate discharge circumstances of eVTOL aircraft. With a root mean square error of less than 0.5% for SOH estimate and 0.78% for SOC estimation, the technique employs a unique auto encoder-Mamba network to increase long-term accuracy and stability [17]. A combined estimating methodology is presented to handle the impact of battery health changes on SOC and voltage estimations. To enhance SOC estimation using an Extended Kalman Filter (EKF), the framework employs a Bi-directional Long Short-Term Memory network tuned with Particle Swarm Optimization (PSO) to precisely estimate the terminal voltage and SOH [18]. A novel approach of tracking the SOH and estimating the SOC of LIBs is put forth in order to guarantee their longevity and safety. The technique employs a bank of three neural network models normal, caution, and fault to estimate SOC and a multilayer neural network for SOH diagnosis. The use of a long short-term memory model inside this framework yields better performance, as demonstrated by experimental data [19]. For a LIB to operate safely, it is essential to estimate its SOC and SOH accurately. A novel SOC-SOH Estimation Framework is put forth in order to overcome the drawbacks of conventional techniques. This system improves efficiency and accuracy across the battery's whole lifespan by achieving a unified, combined calculation of SOC and SOH using a unique charging encoder [20].

A range of BMS topologies and algorithms have been offered by industry and researchers to address these issues. BMS topologies that are distributed, modular, and centralized have been created to handle packs that are getting bigger and more complicated. To increase the accuracy of SOC and SOH estimates, a variety of algorithmic techniques have been used, from basic coulomb counting to sophisticated model-based observers including Kalman filters, particle filters, and data driven neural networks. A techno economic comparison of distributed (DBMS) and centralized (CBMS) battery management systems for light electric cars is carried out in this article. A DBMS is more cost effective, adaptable, and has better fault tolerance and charge equalization, according to the research, even if a CBMS is easier to install and interact with [21]. For commercial electric cars, a new modular BMS was created to better control a high-voltage battery pack. The suggested architecture greatly reduces the complexity, weight, and volume of the wire harness by using separate cell monitoring units within each battery module that interact with a master controller via an isolated Serial Peripheral Interface [22]. For electric car batteries to operate safely and sustainably, a BMS is necessary. For high voltage system startup and shutdown, this research looks at several BMS topologies and suggests a 3S2R2 topology, which is determined to be the best in terms of component count, safety, and cost [23]. To overcome the drawbacks of traditional systems and improve the effectiveness, security, and dependability of batteries in energy storage and electric cars, an intelligent battery management system (IBMS) is suggested. Complex sensing, sophisticated control, and reliable communication protocols are made possible by the IBMS's multilayer design, which combines technologies like cloud computing, digital twins, and the Internet of Things [24]. This study presents a novel technique for rapidly balancing LIBs that transfers energy across cells utilizing a relay-based switching network and a single DC-DC converter. Its advantage over other approaches in terms of speed and cost was proved by a prototype that showed a balancing time of 48 minutes with an efficiency of 89.85%. Additionally, the paper offers a summary of the hardware architecture of BMS, including balancing strategies and methods for measuring important variables [25]. A modular BMS with a centralized topology is proposed for industrial IoT applications. The system features multiple local management units connected to a central unit, which enhances fault tolerance and deployment flexibility while maintaining high voltage monitoring accuracy even with multiple units at fault [26]. To reuse electric car batteries with various specifications and usage histories, a DBMS is suggested. Because of its scalability and flexibility, this design is perfect for integrating different battery packs without requiring complete reassembly, which is expensive and time-consuming [27]. This paper looks at the upcoming generation of BMS, emphasizing significant developments including decentralized designs, better temperature management, and the use of artificial intelligence for accurate condition prediction. New cybersecurity issues and developing battery chemistries, such as solid-state batteries, are also covered [28]. This thorough assessment examines the present status of electronic and electrical (E/E) designs in light of the growing complexity of E/E systems in contemporary automobiles. In addition to discussing the difficulties of integrating new technologies like autonomous driving, the article covers important developments like service oriented and software defined architectures and offers suggestions for further study and development [29]. BMS are essential for guaranteeing the longevity and safety of battery packs in energy storage systems (ESS) because of the rising demand for electricity. With an emphasis on the master slave topology for real world use in stationary energy storage, this work examines many BMS topologies and talks about the significance of precise battery models for performance forecasts [30].

International safety regulations and communication protocols have a significant impact on BMS design in addition to technical performance. While ISO 15118 enables safe vehicle-to-grid (V2G) communication, standards like ISO 26262, UNECE R100, and IEC 62660 provide functional safety and testing criteria. Interoperability, safety certification, and widespread acceptance in automotive applications are guaranteed by adherence to these guidelines. If LIBs in electric cars operate outside of a safe range, they present a serious safety concern from thermal runaway, which is becoming more and more prevalent. A BMS keeps an eye on voltage, current, and temperature to prevent this and keep the battery in a safe condition. To address these hazards, this study uses the ISO 26262 functional safety standard. In order to guarantee that the functional safety purpose is fulfilled, the standard offers a framework for automotive electrical and electronic systems, including crucial procedures such as hazard analysis, risk assessment, and the creation of safety criteria [31]. To reduce the inherent risks of LIBs, an automobile BMS must be developed with functional safety. From the first hazard and risk assessment to the last verification, the design process presented in this article adheres to the ISO 26262 standard. The result of the effort is a BMS slave that satisfies the exacting standards of Automotive Safety Integrity Level (ASIL) C [32]. A novel functional safety architecture is put forth that separates hardware and software safety requirements, simplifying and speeding up the design process in light of the safety hazards associated with LIBs in electric cars. In order to increase overall vehicle safety and economy, the design may be implemented into both current and future BMS and complies with ISO 26262 [33]. This thesis suggests a novel hardware design for an electric motorcycle BMS in response to new safety regulations for electric mobility. The design's robustness is confirmed by failure mode and effect analysis and fault tree analysis, and it is evaluated using a technique that conforms with ISO 26262 standard. According to the findings, the BMS satisfies important criteria for random hardware failures and attains acceptable safety standards, offering a helpful manual for upcoming safety critical electrical systems [34]. A battery monitoring integrated circuit (IC) has been developed to satisfy the exacting safety and accuracy requirements of electric cars. The circuit has a ±10 mV cell voltage detection accuracy and can monitor and balance up to 128 cells. It conforms to the ISO 26262 functional safety standard and includes fault detection and recovery procedures to improve dependability. The design's high level of safety for automotive applications is demonstrated by the hardware architecture metrics that satisfy the strict ASIL-D criteria [35]. UN ECE R100 requirements, which demand battery safety during accelerations, must be followed while converting a diesel bus to an electric one. This work used transient structural modeling to establish a useful technique for evaluating the battery integrity of a converted bus. The examination of S235 steel battery frames revealed that plastic deformation resulted from accelerations of 10 g and 12 g, which raised the stress levels (364.89 MPa and 439.08 MPa, respectively) over the steel's tensile strength. Despite being high, the highest deformation values of 63.04 mm in the 12 g mode were nonetheless within the manufacturer's permitted range. Without changing the bus body, the technique gives engineers a means to assess the safety and viability of certification for such adaptations [36]. To satisfy UNECE R100 criteria, a prototype system was created to identify thermal propagation (TP) in an electric passenger vehicle's BMS, with an emphasis on high-reactivity chemistries like NMC-811. The system's potential for an accurate and fast alarm system was demonstrated in simulated testing where it detected TP in 171 seconds using a modular software design [37]. Communication between the EV, Electric car Supply Equipment (EVSE), and a Central Management System (CMS) is crucial for a dependable and seamless electric car charging process. In order to provide a useful tool for study and teaching, this work describes the creation of a software-based simulator that simulates this connection by implementing the Open Charge Point Protocol (OCPP) for the EVSE-to-CMS link and the ISO 15118 protocol for the EV-to-EVSE link [38]. Electric cars are susceptible to assaults that might harm the vehicle or the electrical grid since the most recent version of the charging standards, ISO 15118-20, still does not provide a way to confirm the integrity of the charger. Firmware integrity verification is added via remote attestation in a proposed standard addition, which may be implemented with little resource cost and without sacrificing backward compatibility with devices that do not support it [39]. This article presents a novel method for utilizing Wireshark and a V2G sniffer system to monitor ISO 15118 communication between electric cars and charging stations. Insights into message exchanges between the EVCC and SECC are provided by the system, which records and transmits communication data in real-time, exposing trends and possible areas for improvement [40]. The performance of EV batteries is thoroughly examined in this study using both simulation based and experimental methods. The simulation model was verified against the experimental data to demonstrate its correctness, and it was tested using the IEC 62660-1 standard to guarantee real-world relevance [41]. Battery safety remains a critical barrier for large scale EV deployment due to the high energy density of active materials and the flammability of electrolytes. Recent studies highlight that while multiple global standards and regulations exist for abuse testing, they often fail to replicate real-life crash scenarios, leaving manufacturers uncertain about which framework ensures maximum safety. Scholars suggest that a harmonized international standard is necessary to eliminate this dilemma and enhance EV consumer protection [42].

The main goals of this study are listed below:

- Determine and evaluate the essential BMS operations needed to guarantee EVs batteries operate safely, dependably, and effectively.
- Examine several BMS designs and design methodologies, emphasizing their benefits, drawbacks, and applicability to contemporary EV applications.
- Verify compliance and interoperability by reviewing the regulatory frameworks and industry standards that control BMS integration in EV charging infrastructure.
- Discuss state estimate methods for precisely determining a battery's SOC, SOH, and RUL.
- Examine optimization strategies used in BMS, including as control based, AI-driven, and heuristic approaches, to increase battery life and efficiency.
- Present a conceptual road plan for the future of BMS, with a focus on cybersecurity, IoT, AI, and sustainable energy systems.

A graphical abstract summarizing the key components and flow of the study is presented in Figure 1 for a clearer overview of the manuscript.

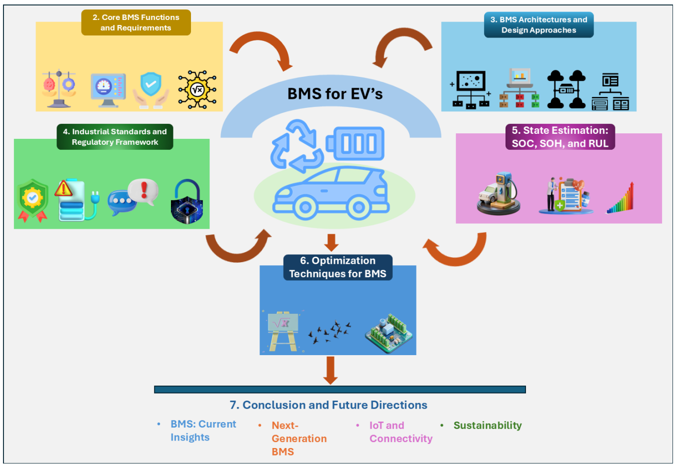


Fig. 1 **Graphical abstract illustrating the key sections and workflow of the proposed BMS review for next-generation EVs.**

The core functions and requirements of BMS are discussed in Section 2. The architectures and design approaches of BMS are presented in Section 3. The industrial standards and regulatory frameworks relevant to BMS in EV charging systems are covered in Section 4. The discussion on state estimation methods, including SOC, SOH, and RUL, is provided in Section 5. Advanced optimization techniques for enhancing BMS performance are explored in Section 6. Finally, the conclusions and future research directions are summarized in Section 7.

2. CORE BMS FUNCTIONS AND REQUIREMENTS

The BMS is the intelligent brain of an EV's ESS. Its capabilities extend well beyond simple monitoring; it assures safety, improves performance, extends battery life, and ensures compliance with international standards. For next-generation EVs, which need higher energy densities, faster charging, and more reliability, the functional requirements of a BMS rise even further. This section provides a detailed explanation of the key components and associated requirements of a modern BMS.

2.1 Measurement and Monitoring

Precise measurement and monitoring are the cornerstones of every BMS. Some of the important parameters that should be included in a BMS are described below;

2.1.1 Cell Voltage Monitoring:

To guarantee battery longevity, performance, and safety, precise cell voltage monitoring is crucial. By measuring voltage, the BMS can identify dangerous over and under voltage situations that may otherwise result in thermal runaway, electrode deterioration, or electrolyte breakdown. For accurate SOC and SOH assessment, BMS ICs attain millivolt-level precision, usually within ±2-5 mV. This is especially important in large EV battery packs where minute measurement mistakes may add up [43-44].

Differential sensing, sigma-delta ADCs, and temperature compensated calibration circuits are used in BMS designs to preserve accuracy, and filtering and oversampling reduce electromangentic interference (EMI) interference and switching noise. Algorithms for protection and balancing can also be directly integrated with voltage monitoring data. For example, they can stop charging when a cell gets close to its maximum voltage or stop discharging when a cell reaches dangerous depletion. Voltage monitoring is becoming a key component of next-generation EV BMS platforms, thanks to recent developments that expand this capability with diagnostics for wire defects, aberrant self-discharge, and predictive maintenance [45-46].

2.1.2 Pack Current Measurement:

Because it directly supports charge and discharge current tracking, coulomb counting for SOC estimation, and the detection of abnormal operating conditions like short circuits, overcurrent events, and inrush currents during startup, high-precision current measurement is a fundamental requirement in BMS design. Since modest cumulative mistakes in coulomb counting can result in large drift in long-term capacity projections, current measurement accuracy has a major impact on both SOC and SOH estimation [47-48]. In addition to guaranteeing safety and adherence to vehicle regulations, reliable current sensing allows the BMS to enforce protective limits by disconnecting the pack in the event of a problem.

Pack current sensing is dominated by two popular methods: Hall-effect sensors and low-ohmic shunt resistors with precision amplifiers. Although they result in minor power losses, shunt resistors are the industry standard for the majority of EV applications due to their high precision, quick response, and linear properties. On the other hand, Hall-effect sensors provide lower heat generation and galvanic isolation, but they are usually more expensive and more sensitive to temperature drift. In order to fulfill the exacting specifications of next-generation EVs, recent developments combine these techniques with digital calibration, sigma-delta ADCs, and temperature compensation circuits to achieve sub1% accuracy throughout broad operating ranges.

2.1.3 Temperature Monitoring:

To guarantee the lifetime, performance, and safety of EVs, battery pack temperature monitoring is essential. Temperature sensors, such as IC-based sensors, resistance temperature detectors, or Negative Temperature Coefficient thermistors, are positioned strategically at various points, such as the battery pack, module busbars, and individual cell surfaces. These sensors aid in preventing overheating and reducing the possibility of thermal runaway, a hazardous situation in which the temperature of a cell increases uncontrolled and may result in an explosion or fire [49]. To control the entire thermal environment and maximize cooling techniques, coolant and ambient temperature monitoring is crucial in addition to interior cell temperatures.

Higher-level BMS functions, such as cell balancing, defect detection, and the calculation of SOC and SOH, also depend on accurate temperature data. However, the severe working conditions in EVs make it difficult to obtain accurate readings. Despite vibration, EMI, and significant temperature swings that are common in vehicle settings, sensors must remain precise. To guarantee reliable and precise heat monitoring, which has a direct influence on the battery system's safety and efficiency, sophisticated sensor calibration, shielding, and data processing techniques are frequently used [50].

2.2 Safety and Protection

Safety is still the primary objective of any BMS. Without robust protections, a minor problem might escalate into a catastrophic battery failure. Among the defense mechanisms are:

2.2.1 Over voltage/Under voltage Protection:

A key safety feature of BMS is overvoltage and undervoltage protection, which keeps individual cells from functioning outside of their safe voltage range. This safe working range usually falls between 2.5 and 4.2 volts per cell for lithium-ion chemistries. While voltages below the lower limit might result in irreversible capacity loss, higher internal resistance, and shortened cycle life, exceeding the upper limit can induce electrolyte breakdown, gas production, and even thermal runaway [51-52]. To ensure the battery pack's lifetime and safety, the BMS continually checks cell voltages and has the ability to cut the battery off from the load or charger if specified thresholds are reached. In electric cars, where rapid voltage variations can be caused by regenerative braking, quick charging, and changing load circumstances, it is extremely important to provide accurate voltage protection.

2.2.2 Over current Protection:

An essential safety aspect of BMS for EVs is overcurrent protection. In high-demand situations like fast acceleration, regenerative braking, or external short circuits, it protects the battery cells and related electronics from excessive currents. These circumstances may cause the battery pack to overheat, perhaps experience thermal runaway, and sustain irreparable damage.

In order to identify and reduce overcurrent occurrences, contemporary BMS solutions use hardware and software techniques. Current detecting circuits and protective parts like fuses and circuit breakers are examples of hardware solutions. When certain current thresholds are surpassed, software algorithms that continually monitor the current flow might start preventative measures like unplugging the load or charger. This two-pronged strategy guarantees both predictive and immediate defense against overcurrent threats.

According to researches, overcurrent prevention helps maintain the battery's long-term health in addition to preventing harm right away. The BMS prolongs the battery's operating life and helps preserve its capacity by reducing exposure to high currents. In EVs, where battery longevity is closely related to vehicle performance and safety, this is especially crucial [53-54].

2.2.3 Short Circuit Protection:

One essential safety feature of BMS for EVs is short circuit prevention. It employs Metal-Oxide-Semiconductor Field-Effect Transistors (MOSFETs) or fast-acting electronic fuses (eFuses) to identify and isolate anomalous microsecond-scale current spikes. These parts quickly cut off the battery pack when they detect a short circuit, protecting the cells and related circuitry.

Ultra high speed circuitry is used by contemporary eFuses, including Toshiba's TCKE8 series, to cut current within 150 nanoseconds of a short circuit [55-56]. Protecting delicate components from the high currents linked to short circuits requires this quick reaction. Furthermore, following a short circuit occurrence, these eFuses have the ability to autonomously reset, enabling system recovery without the need for human involvement.

Performance is further improved by including Silicon Carbide (SiC) MOSFETs into eFuse designs. High-frequency switching capabilities provided by SiC MOSFETs allow for even quicker overcurrent fault identification and interruption. For example, under test settings at 650 A of short-circuit current in an 800 V system, a proof of concept for a high-voltage eFuse system showed a short-circuit detection reaction time of less than 160 nanoseconds.

The safety and dependability of EVs, where quick fault identification and isolation are essential to avert catastrophic failures, depend heavily on these developments in short circuit protection.

2.2.4 Over temperature Protection:

One essential safety aspect of BMS for EVs is over-temperature protection. It keeps cooling systems, busbars, and battery cells operating within acceptable thermal bounds, avoiding overheating that can cause thermal runaway or shorten battery life. Real-time temperature monitoring, thermal management techniques, and responsive control mechanisms are all used to provide this protection.

The temperature of each battery cell, busbar, and cooling system is continually monitored by BMS. The system can identify any departures from ideal temperature conditions thanks to real-time data from sensors positioned at key points. The BMS can start corrective measures, including modifying charging/discharging rates or turning on cooling mechanisms, when temperatures get close to crucial thresholds in order to maintain safe operating temperatures [57].

To avoid overheating, thermal management must be done well. Heat sinks, phase transition materials, and liquid or air cooling systems are some methods for releasing extra heat. To absorb and move heat away from the cells, for example, coolant is circulated via channels in the battery pack using liquid-cooling systems. Phase change materials also contribute to a stable thermal environment by absorbing heat during temperature spikes and releasing it during temperature drops [58].

Predictive analytics and machine learning methods for early thermal defect detection have been introduced by recent developments in BMS technology. These systems may anticipate possible overheating incidents and take preventative measures to reduce hazards by examining past temperature data and finding trends. The safety and dependability of EV battery systems are improved by this proactive strategy [59].

2.2.5 Isolation Monitoring:

Isolation monitoring is crucial in high-voltage systems, especially in EVs, to protect service workers and vehicle occupants. To ensure that the insulation between live items and the vehicle chassis satisfies required resistance values, routine insulation resistance tests are carried out in accordance with ISO 6469-1/2. These tests assist in identifying any insulation deterioration or flaws that can provide a risk of electric shock. Insulation resistance measuring equipment, such as charging socket insulation resistance and vehicle insulation resistance tests, are used to determine if the insulation resistance of the vehicle level satisfies the necessary criteria [60].

Contemporary BMS use diagnostic loops and redundant sensing channels to improve safety. These systems meet the functional safety requirements of ISO 26262 since they are made to identify errors and provide fail-operational safety. Redundancy lowers the risk of dangerous circumstances by allowing BMS to maintain operational safety even in the case of a component failure. For instance, the BMS's redundancy mechanisms guarantee precise monitoring, problem identification, and system dependability all of which are essential for EVs to operate safely [61].

2.3 Estimation Functions

Modern BMS rely on complex estimating techniques since it is impractical to directly monitor critical battery states including SOC, SOH, and RUL. Techniques including coulomb counting, open-circuit voltage (OCV) correlation, and Kalman filtering are commonly used to estimate SOC; each has advantages and disadvantages. For example, OCV-based techniques are more precise but need rest intervals, which makes them unfeasible during dynamic vehicle operation, whereas coulomb counting provides quick and continuous estimation but suffers from cumulative drift [62-63]. To increase the accuracy of SOC estimate under various load situations, sophisticated model-based techniques like EKF and Unscented Kalman Filters integrate electrical equivalent circuit models with real-time data.

Because SOH and RUL estimates entail defining capacity fading, internal resistance increase, and degradation patterns, they provide additional complexity. In order to capture nonlinear battery aging characteristics that standard models are unable to capture, data-driven approaches that make use of machine learning (ML) and neural networks are becoming more and more popular [64]. Long short-term memory (LSTM) networks and support vector machines, for instance, have demonstrated promise in accurately forecasting RUL from cycle data with LSTM models showing superior performance in capturing temporal dependencies in degradation patterns, as evidenced in applications such as jet engine prognostics [65]. Accurate assessment of battery characteristics ensures reliable vehicle range and supports predictive maintenance, warranty management, and second-life applications of EV batteries. Estimation functions are increasingly serving as the intelligence core of BMS design, enabling safe, efficient, and future-proof battery operation as electric vehicle adoption accelerates [66].

2.3.4 RUL Prediction:

Predicts the pack's useable lifespan using aging models, machine learning, or analogous circuit models based on physics. Customer confidence, warranty costs, and vehicle range prediction are all directly impacted by estimating accuracy.

Battery dependability and maintenance planning depend on accurate RUL predictions. In order to evaluate battery health indicators during charging, a recent study suggested a hybrid PSO-ELM-RVM model that combines relevance vector machines, particle swarm optimization, and extreme learning. Dependable RUL estimate for LIB is made possible by the model's precise capacity prediction and uncertainty quantification [67].

The BMS functional architecture is shown in Figure 2, where the central BMS controller performs state estimation, balancing control, thermal management, and safety logic based on readings from per cell sensors and cell-monitor ASICs. In addition to communicating status and control messages with the vehicle control unit and external chargers, the controller activates the power stage (contactors/MOSFETs) [68].

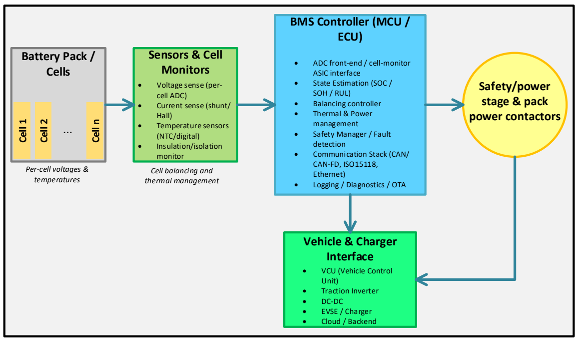


Fig. 2 Block diagram of BMS core functions and architecture.

2.4 Cell Balancing

Cell to cell variations are a normal occurrence in battery packs due to temperature gradients, uneven aging, and manufacturing tolerances. If weaker cells are ignored, the pack's useable capacity is compromised and cell balancing solves this problem of uneven cell voltages by using following two techniques;

2.4.1 Passive Balancing:

The most popular and commonly used technique for balancing the cell voltages in LIB packs is passive balancing. This method uses resistors or transistor based shunting circuits to dissipate surplus charge from higher voltage cells as heat until the cell voltages converge within a tolerable tolerance. The approach is appealing for situations where cost and design simplicity are top priorities since it is simple, inexpensive, and needs very basic circuitry.

Its low energy efficiency, however, is its main disadvantage; especially in big battery packs with frequent balancing requirements, the total system efficiency declines as the excess energy is squandered as heat. Furthermore, localized heating caused by passive balancing may cause issues with thermal management if left unchecked. Because of its dependability, simplicity of use, and compatibility with the majority of BMS topologies, passive balancing is still widely used in consumer electronics, hybrid cars, and electric vehicles despite these drawbacks [69-70].

2.4.2 Active Balancing:

To disperse energy across cells in a battery pack, active balancing uses power electronic circuits like DC-DC converters, switching capacitors, or inductive energy transfer devices. The extra charge from higher voltage cells is actively transferred to lower voltage cells rather than dissipating as heat, which saves energy and increases pack efficiency overall. Although the design of this approach is more complicated since it calls for more parts usage like capacitors, inductors, or transformers and complex control algorithms.

SOC imbalances frequently cause LIB packs in EVs to lose capacity and age more quickly. In order to improve overall pack use and drastically reduce SOC discrepancies, a recent study suggested an active balancing technique for both the charging and discharging phases. In order to provide a strong feedback loop between balance and predictive health management, the work additionally incorporated RUL prediction using machine learning, with k-Nearest Neighbors and Random Forest achieving the maximum accuracy ($R2 \geq 0.996$) [71].

Although active balancing has advantages, the increasing number of active components causes trade offs in terms of cost, circuit complexity, and possible reliability problems. In grid scale energy storage systems and next generation EVs, however, when efficiency and pack lifetime exceed the added design complexity, it is becoming more and more popular.

3. BMS ARCHITECTURES AND DESIGN APPROACHES

Since the battery delivers the entire propulsion power in EVs, the BMS plays a pivotal role in monitoring and controlling all activities associated with the battery. This review article presented in [72] provides an overview of major BMS subsystems and their influence on EV performance, with emphasis on different architectures and control strategies. It critically examines recent research in battery modeling, state estimation, cell balancing, and thermal management, highlighting the merits and limitations of various approaches. The article further discusses modern advancements such as IoT-enabled and cloud-based BMSs aimed at improving safety, reliability, and scalability. Finally, key challenges and recommendations for the future development of efficient BMSs in e-mobility applications are presented.

Depending on the vehicle type, safety requirements, battery pack size, and budgetary constraints, battery management systems can be implemented in a variety of architectural configurations. The architecture's design directly affects scalability, fault tolerance, performance, and compliance with automotive requirements. BMS designs often fit into one of three topologies: hybrid, distributed, or centralized. Each has unique benefits and drawbacks.

3.1 Centralized BMS Architecture

A single central controller is directly connected to all sensing components like temperature, voltage, and current sensors and control operations in a centralized BMS. Measurement, protection, estimate, balance, and communication are all carried out by this controller. Centralized BMS topologies are essential for battery module safety, control, and monitoring because they guarantee disconnection in the event of an emergency. According to recent studies, for both EV and stationary applications, safe operation necessitates careful management of construction, operating parameters, integration, and installation in addition to adherence to changing regulations and norms [73].

3.1.1 Advantages:

Simpler hardware structure and lower cost due to fewer controllers.

Suitable for small to medium battery packs where wiring complexity is manageable.

Easier firmware update and centralized diagnostics.

3.1.2 Challenges:

High wiring harness complexity for large packs, leading to increased weight and EMI susceptibility.

Single point of failure: If the central controller fails, the entire system is compromised.

Limited scalability, making it unsuitable for large EVs and ESS.

Figure 3 illustrates a typical centralized BMS where all cell connections terminate at one controller board.

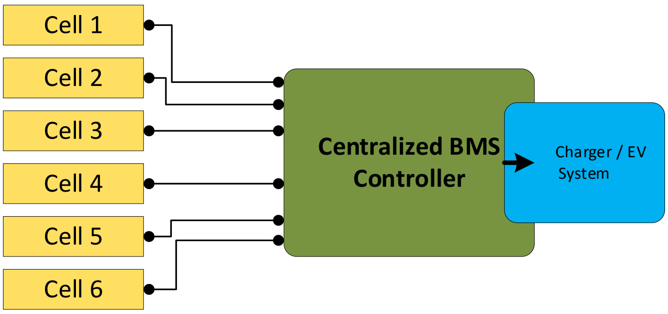


Fig. 3 Centralized BMS architecture.

3.2 Distributed BMS Architecture

A distributed battery energy architecture based on the microbank module (MBM) for DC microgrids is presented in [74]. The MBM integrates a micro bidirectional DC-DC converter, a micro-BMS, and a cell bank, offering high reliability, energy efficiency, and compactness. A self-reconfiguration discharge strategy and hybrid modulation for the DAB converter further enhance battery performance and efficiency. Experimental results demonstrate improved discharge time and a 7.1% increase in BESS efficiency under 1.5 kW operation. The battery pack is separated into several modules in a distributed or modular BMS, and each module has its own module monitoring unit (MMU). Through a communication connection like CAN or RS-485, these MMUs interact with a master controller while measuring and managing a subset of cells.

3.2.1 Advantages:

- Highly scalable for large packs, as additional modules can be integrated easily.
- Reduced wiring complexity at the pack level, improving EMI robustness.
- Enhanced fault tolerance: a failure in one module affects only part of the pack.
- Modular design facilitates easier assembly, testing, and maintenance.

3.2.2 Challenges:

- Higher cost due to multiple controllers.
- Communication latency and synchronization issues across modules.
- Requires robust protocols and fault-tolerant communication (CAN-FD, Ethernet).

Figure 4 shows a distributed BMS where MMUs report cell data to a master controller managing overall pack operation and communicates with the charger/EV system.

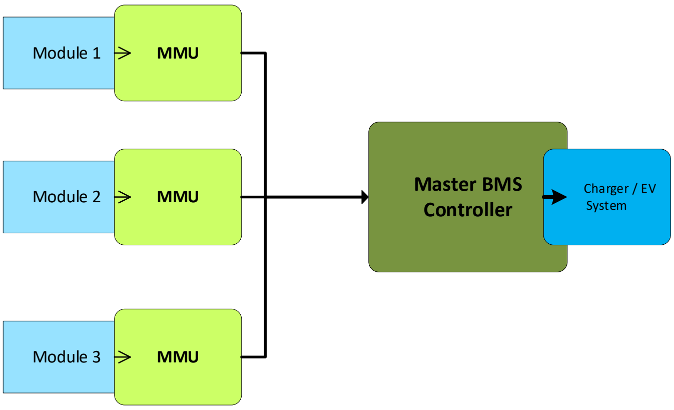


Fig. 4 Distributed BMS architecture.

3.3 Hybrid BMS Architecture

The hybrid BMS incorporates aspects of distributed and centralized methodologies. Including MMUs, smart sensing boards usually control groups of cells, but the main controller handles several essential tasks including safety algorithms, SOC/SOH estimates, and vehicle level communication.

3.3.1 Advantages:

- Optimized tradeoff between cost and scalability.
- Modular design with central intelligence for advanced algorithms like model based SOC estimation, thermal management strategies.
- Improved reliability compared to purely centralized systems.

3.3.2 Challenges:

- Higher system design complexity.
- Requires synchronization between module controllers and the central unit.
- Still dependent on a central controller for vehicle-level decisions.

Modern EVs like Tesla, BYD, and Hyundai frequently adopt this design, with a high-performance central ECU handling sophisticated calculations and diagnostics and modular sensor boards managing cell data.

3.4 Communication Interfaces in BMS Architectures

Communication plays a critical role in linking sensing modules, master controllers, and the vehicle's ECU. Commonly used interfaces include:

- CAN / CAN-FD: Industry standard for robustness, real-time performance, and error detection.
- LIN Bus: Used for low-cost communication with auxiliary components.
- Ethernet / FlexRay: Emerging in high voltage packs requiring large data throughput.
- ISO 15118 / PLC: Enables V2G communication with chargers.

The choice of communication protocol impacts latency, reliability, cybersecurity, and compliance with standards such as ISO 26262 responsible for functional safety and ISO/SAE 21434 responsible for cybersecurity.

3.5 Design Metrics and Trade offs

BMS architecture design involves trade-offs between cost, complexity, performance, and compliance which are tabulated below in Table 1.

Table 1 Architecture design comparison.

Metric	Centralized	Distributed	Hybrid
Scalability	Low	High	Moderate High
Wiring Complexity	High	Low	Moderate
Fault Tolerance	Low	High	Moderate High
Cost	Low	High	Moderate
Accuracy & Reliability	Moderate	High	High
Use Case	Small EV packs, 2-4 wheelers	Large EV packs, buses, ESS	Passenger EVs, premium systems

3.6 Industrial Trends in BMS Architectures

Recent developments in EV BMS architecture are focused on:

- Smart BMS Chips: Integrated ICs like TI BQ769x2, LTC6811, NXP MC3377x combining measurement, balancing, and diagnostics.
- Wireless BMS: Eliminates wiring harness using RF communication between modules used in GM Ultium and BMW platforms.
- Cloud Connected BMS: Remote diagnostics, predictive analytics, and OTA updates.
- Functional Safety Integration: Hardware redundancy and diagnostic coverage to achieve ASIL-D compliance.
- Cybersecurity Layers: Authentication, encryption, and intrusion detection to prevent malicious attacks.

These trends reflect the transition of BMS from a traditional protective role to an intelligent cyber-physical system, ensuring both safety and grid integration.

4. INDUSTRIAL STANDARDS AND REGULATORY FRAMEWORK FOR BMS IN EV CHARGING SYSTEMS

BMS installation in EV charging infrastructure is critical for both technological development and compliance with safety regulations and accepted global standards. Since BMS functions are crucial to ensuring safe, dependable, and efficient battery operation, international and regional standards organizations have developed extensive frameworks that govern their design, testing, and integration. These frameworks address functional dependability, safety, electromagnetic compatibility, communication interoperability, and environmental performance. This section reviews the most significant regulatory requirements and industry standards that pertain to BMS in EV charging systems.

4.1 Functional Safety Standards

Because BMS failures might result in catastrophic dangers including thermal runaway, fire, or explosion, functional safety is a crucial need for EV design. Road vehicles functional safety ISO 26262, is the most well known standard, outlining the lifecycle requirements for electrical and electronic systems in automobiles. Hazard analysis, risk assessment, fault detection, redundancy plans, and the assignment of ASIL A to D are all mandated by ISO 26262 for BMS.

4.1.1 ASIL Determination for BMS:

While less important monitoring tasks could be given lower levels (A or B), functions like over voltage and over current protection usually come under higher ASIL levels (C or D).

4.1.2 Impact on Charging Systems:

Compliance with ISO 26262 guarantees consistent safety performance for both onboard and offboard charging activities, particularly when integrating with EVSE.

4.2 Electrical Safety and Battery Specific Standards

In addition to functional safety, a number of standards focus on the safe design, operation, and testing of rechargeable batteries;

- IEC 62619 specifies safety requirements for secondary lithium cells and batteries for industrial applications, including overcharge, over discharge, short circuit, and thermal abuse tests.
- IEC 62133-2 sets safety standards for lithium-ion portable applications, influencing EV battery pack component testing.
- UL 2580 (North America) covers safety standards for batteries in electric vehicles, including mechanical integrity, fire resistance, and crash testing.
- UN 38.3 regulates transportation safety of lithium batteries, requiring altitude simulation, thermal test, vibration, shock, and external short circuit testing.

Adherence to these guidelines ensures that BMS managed EV batteries are safe in real world charging and operation scenarios, especially while fast charging, when hazards are higher.

4.3 Communication and Interoperability Standards

Effective communication between the BMS, EVSE, and vehicle's Energy Management System (EMS) is essential for reliable charging. Several standards and protocols govern this interoperability:

- ISO 15118: Defines V2G communication for plug and charge, authentication, billing, and smart charging. It allows the BMS to negotiate charging rates with the charging station based on SOC, SOH, and thermal limits.
- IEC 61851: Governs conductive charging systems, including charging modes, pilot signaling, and power flow coordination.
- SAE J1772 / GB/T 20234: Define connector types and charging interface protocols in North America and China, respectively. The BMS must comply with these to ensure compatibility with global charging infrastructure.
- CAN/CAN-FD and LIN: Widely used for in vehicle communication. The BMS exchanges real time battery data including voltages, currents, and faults with the vehicle control unit and charger controller.

4.4 Cybersecurity Standards for BMS in Charging Systems

Cybersecurity becomes crucial when EVs are integrated with cloud based management platforms and smart grids. According to standards like ISO/SAE 21434 and ISO 15118, BMS communication interfaces must be protected from unauthorized access, data spoofing, and denial-of-service attacks, particularly over CAN. Cybersecurity protects charging systems from malicious assaults and guarantees grid reliability and billing integrity.

4.5 Environmental and Reliability Standards

EV batteries must perform reliably under diverse climatic and operational conditions. Standards ensure that BMS can detect environmental stress and maintain protection:

- IEC 60068 series: Specifies environmental testing including temperature cycling, humidity, vibration, mechanical shock for EV electronic components.
- ISO 16750: Focuses on road vehicles environmental conditions and electrical loads.
- Automotive EMC Standards (CISPR 25, ISO 11452): Ensure BMS electronics do not emit excessive electromagnetic noise and remain immune to disturbances from nearby systems, including high-power chargers.

4.6 Certification and Testing Practices

Strict certification processes are used to verify adherence to standards. Functional safety audits, EMC testing, and battery abuse testing are carried out by testing organizations like TUV, UL, and Intertek. Hardware in the Loop and Model in the Loop simulations are frequently used in EV development to validate BMS software against defined failure situations like short circuit while charging. These procedures guarantee that BMS implementations are evaluated in real-world settings in addition to being theoretically compatible.

4.7 Regional Regulatory Frameworks

- European Union (EU): EV BMS must comply with the EU Battery Regulation (2023), which enforces requirements for battery sustainability, labeling, and second-life use.
- United States: The national highway traffic safety administration mandates compliance with FMVSS regulations, in combination with UL 2580.
- China: GB/T standards dominate EV charging and BMS testing, requiring compatibility with local fast charging protocols.
- Japan and Korea: JARI and KS standards govern BMS testing and communication for EV batteries.

4.8 Summary of Standards Landscape

Table 2 summarizes key international standards relevant to BMS in EV charging systems.

Table 2 Key Standards Governing BMS in EV Charging Systems

Standard / Regulation	Domain	Relevance to BMS in EV Charging Systems
ISO 26262	Functional Safety	Hazard analysis, ASIL classification, fault handling
IEC 62619 / UL 2580	Battery Safety	Overcharge, short circuit, mechanical and thermal abuse testing
UN 38.3	Transport Safety	Testing for shipping and logistics of lithium batteries
ISO 15118	Communication	V2G, smart charging, plug-and-charge authentication
IEC 61851	Charging Interface	Conductive charging protocols, power coordination
SAE J1772 / GB/T 20234	Connectors & Protocols	Physical and electrical interface for charging
ISO/SAE 21434	Cybersecurity	Protection against cyberattacks on BMS communication
IEC 60068 / ISO 16750	Environmental & Reliability	Temperature, vibration, humidity, and electrical load testing
CISPR 25 / ISO 11452	EMC Standards	Emissions and immunity of BMS electronic components

4.9 Implications for BMS Development

Following these guidelines is both required by law and beneficial to the market for producers. Compliance increases customer confidence in EV safety, guarantees compatibility across various charging infrastructures, and obtains certification for international markets. From a research standpoint, these standards also direct innovation in BMS architecture, impacting choices on communication protocols, redundancy, and sensing accuracy. Extensions of current standards will be necessary for future advancements like solid state batteries and wireless charging systems, therefore constant alignment with changing frameworks is crucial.

5. STATE ESTIMATION: SOC, SOH, AND RUL

The core of BMS is state estimation, which makes it possible for next generation EVs to have dependable monitoring, safe operation, and efficient use of battery packs. The SOC, SOH, and RUL are the three most important states. Predictive maintenance, effective energy management, and maintaining user trust in EV technology all depend on accurate estimate of these factors. However, accurate assessment is very difficult due to battery nonlinearity, temperature sensitivity, deterioration mechanisms, and intricate electrochemical processes. The most recent techniques, difficulties, and developments in SOC, SOH, and RUL estimates are reviewed in this section.

5.1 State of Charge Estimation

The SOC, which is frequently given as a percentage, shows a battery's accessible capacity in relation to its nominal or rated capacity. In addition to optimizing driving range and preventing overcharge and overdischarge, accurate SOC calculation boosts user trust.

- Direct Measurement Approaches: Traditional methods include Coulomb counting (measuring charge/discharge current over time) and OCV methods. Coulomb counting is simple but suffers from cumulative error due to sensor drift. OCV methods are accurate at steady-state but unsuitable for dynamic EV conditions. Recent studies have combined Coulomb counting and OCV algorithms to estimate battery SOH and SOC simultaneously, accounting for battery parameters such as internal resistance, polarization capacitance, and OCV variation with battery health [75].
- Model-Based Approaches: ECMs, such as Rint, Thevenin, and dual polarization models, are widely used to capture battery dynamics. Recent studies have proposed modified ECMs that account for the effects of current rate, SOC, and temperature on internal resistance and capacity, with corrections stored in look-up tables. Estimators like the unscented Kalman filter are then employed to refine SOC predictions by combining model knowledge with real-time measurements, improving accuracy while reducing computational cost [76].
- Data Driven Approaches: Recent works leverage ML and deep learning (DL) techniques, including linear regression, support vector regressors, k-nearest neighbors, random forest, gradient boosting, artificial neural networks, convolutional neural networks (CNNs), and LSTM networks, to model nonlinear relationships between voltage, current, and SOC. These methods enable more accurate SOC estimation under dynamic EV conditions and support analysis of battery deterioration, though they require realistic and diverse training datasets [77].
- Hybrid Approaches: Combining model-based and data-driven methods, such as embedding neural networks into physical models, has gained traction to balance interpretability with predictive accuracy. Recent studies propose hybrid architectures where data-driven models are integrated into deformed physical models for parameter identification and error characterization, achieving accurate, interpretable, and robust modeling [78].

SOC estimation faces difficulties under temperature variations, aging effects, sensor noise, and high C rate operations, which require adaptive and robust techniques.

5.2 State of Health Estimation

The SOH, which is frequently calculated as the ratio of current capacity to original rated capacity or based on internal resistance increase, measures the general health and degree of deterioration of a battery. For EV safety assurance, warranty evaluation, and predictive maintenance, accurate SOH monitoring is essential.

- Direct Measurement Indicators: Common metrics include capacity fade i.e. loss of charge-holding capability and internal resistance increase. These indicators are measurable but require intrusive procedures or extended downtime, making them impractical for onboard estimation [79].
- Model Based Approaches: Physics-informed models incorporate degradation mechanisms such as SEI layer growth, lithium plating, and electrode cracking. Recent studies combine ECMs with techniques like electrochemical impedance spectroscopy (EIS) and distribution of relaxation time analysis to extract low-dimensional health features, enabling real-time SOH tracking with reduced computational cost and memory usage [80].
- Data Driven Approaches: ML techniques, such as Random Forests, Gradient Boosting, and deep neural networks, predict SOH by learning from historical cycling data. Recent studies have enhanced prediction accuracy by extracting aging features from voltage curves and implementing gradient boosting-based methods with online incremental learning, enabling faster and more precise SOH estimation [81].
- Feature Extraction Approaches: Time domain, frequency domain, and incremental capacity analysis are widely employed to extract degradation sensitive features, which serve as inputs to estimation algorithms. Recent studies have also proposed novel feature extraction methods, such as energy accumulation of equal discharge voltage difference, combined with improved relevance vector regression and optimization algorithms to enhance estimation accuracy and robustness [82].

SOH estimation is complicated by complex degradation mechanisms, nonlinear aging behaviors, and limited availability of labeled degradation data for diverse chemistries such as NMC, LFP, and solid state batteries.

5.3 Remaining Useful Life Estimation

The RUL predicts the amount of time or number of cycles a battery can operate before reaching its end of life threshold commonly defined as 70-80% of nominal capacity. RUL estimation is critical for fleet management, second life applications, and warranty optimization.

- Model-Based Methods: Degradation models based on electrochemical kinetics or semi-empirical aging laws are used to forecast future battery states. Recent studies have enhanced RUL prediction by integrating model-based feature extraction with deep learning, such as 1D CNNs for capturing battery features and BLSTM networks for time-series dependencies, improving accuracy, generalization, and prediction reliability across diverse usage conditions [83].

- Data-Driven Prognostics: Machine learning and deep learning methods, including LSTM, GRU, CNN, and transformer architectures, have shown high accuracy in predicting long-term battery life from partial cycling data. Recent studies have further improved RUL prediction by combining CNN for feature filtering with LSTM for capturing long-term degradation patterns, achieving better accuracy and efficiency across different ageing conditions [84].
- Probabilistic and Hybrid Methods: Bayesian approaches, Gaussian processes, and Monte Carlo simulations are increasingly adopted to quantify RUL uncertainties. Recent hybrid frameworks combine physical or statistical models with advanced data-driven techniques, such as entropy-based health indicators and transformer-based regression, to improve prediction accuracy and generalization under varying operating conditions [85].

RUL prediction is hindered by long training times, variability in driving/charging patterns, incomplete data, and sudden degradation phenomena. Real world deployment demands computationally efficient algorithms that balance accuracy with embedded system constraints.

5.4 Comparative Summary

Table 3 summarizes the key techniques, advantages, and limitations of SOC, SOH, and RUL estimation strategies.

Table 3 Comparative Summary of SOC, SOH, and RUL Estimation Approaches.

State	Approaches	Advantages	Limitations
SOC	Coulomb counting, OCV, KF, EKF, PF, ML/DL models	Simple, real-time feasible, high accuracy under stable conditions	Drift errors, temperature sensitivity, requires large datasets
SOH	Capacity fade, resistance growth, ICA, EIS + ML	Provides direct insights into degradation	Requires long-term data, complex degradation mechanisms, difficult online
RUL	Physics-based models, ML/DL (LSTM, CNN), Bayesian inference	Enables predictive maintenance, useful for fleet optimization	High uncertainty, requires computational resources, limited generalization

Instead of considering SOC, SOH, and RUL as separate states, emerging trends suggest unified estimate frameworks that take them into account together. It is anticipated that developments in cloud-based battery analytics, federated learning, and digital twins will transform state estimation by facilitating ongoing learning across automobile fleets. Furthermore, real-time state estimation with low latency will be possible through integration with 5G enabled IoT and edge AI systems, eventually opening the door for EV batteries that are safer, more durable, and more effective.

6. OPTIMIZATION TECHNIQUES FOR BMS

BMS design and operation, especially for next generation EVs, heavily relies on optimization. Traditional rule based approaches frequently fail because of the high complexity of battery models, nonlinear electrochemical dynamics, and conflicting goals like optimizing performance while guaranteeing safety and prolonging longevity. As a result, sophisticated optimization methods are being used more and more to solve problems in scheduling, control, state prediction, and battery modeling. This section examines the main optimization techniques used in BMS, including clever heuristics, developing machine learning driven techniques, and traditional mathematical approaches.

6.1 Classical Mathematical Optimization

For charge/discharge scheduling, thermal control, and optimal power distribution, BMSs frequently employ mathematical programming techniques including linear programming (LP), quadratic programming (QP), and Nonlinear Programming. For instance, QP is frequently used in Model Predictive Control (MPC) frameworks to guarantee the real time feasibility of control inputs, whereas LP-based formulations are effective for optimizing battery charging under grid-constrained situations. However, as battery packs become larger and more complex, scalability and computational burden become significant challenges, highlighting the need for advanced optimization strategies similar to those used in BESS operation and scheduling [86].

6.2 Meta Heuristic Optimization

For nonlinear and multi objective BMS optimization issues, meta-heuristic algorithms which draw inspiration from nature or social processes offer adaptable and reliable solutions. For SOC estimation, parameter identification, and charging profile design, methods including PSO, genetic algorithms (GA), cuckoo search (CS), and ant colony optimization- fuzzy sliding mode control (ACO-FSMC) have been used. Metaheuristic algorithms, such as particle swarm optimization (PSO), genetic algorithms (GA), and improved variants, are increasingly applied in BMS for charge/discharge scheduling, energy management, and control optimization. Recent studies demonstrate that enhanced particle swarm optimization (IPSO) can improve convergence speed, balance exploration and exploitation, and achieve superior performance in optimizing battery operation, energy costs, and grid stability compared to traditional heuristics [87].

Table 4 summarizes representative meta heuristic techniques applied in BMS. Each algorithm demonstrates unique advantages depending on the complexity and objective of the BMS application [88-90].

Table 4 Meta-Heuristic Optimization Algorithms Applied in BMS

Algorithm	Inspiration Source	BMS Application Area	Strengths	Limitations
PSO	Bird flocking behavior	SOC/SOH estimation, model parameter tuning	Fast convergence, simple implementation	Premature convergence in local minima
GA	Natural selection	Multi-objective battery optimization	Global search capability	Computationally expensive
CS	Brood parasitism of cuckoos	Battery model fitting, charge scheduling	Efficient exploration	Requires fine-tuned parameters
ACO-FSMC	Ant foraging behavior	To maintain the battery pack temperature	Robust against nonlinearities	Computational infeasibility

6.3 Model Predictive Control Based Optimization

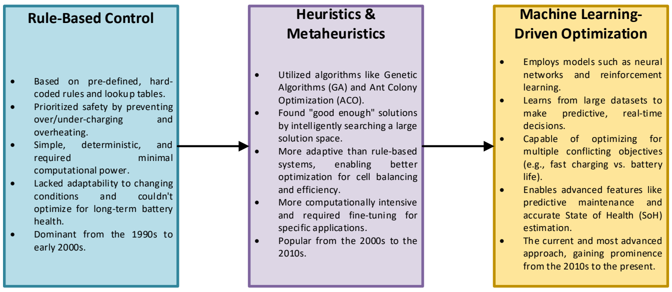
Because it can handle multi objective control problems with dynamic constraints, MPC has become one of the most effective techniques in BMS optimization. MPC works very well in EVs to maximize charging currents while preserving thermal safety. Battery electro thermal models are included, allowing MPC to dynamically modify control actions in response to future state predictions. Fast optimization solvers or reduced order models are integrated because real time implementation necessitates substantial computing resources. Recent studies have demonstrated that advanced MPC implementations, such as mixed-integer quadratic constrained programming, can further optimize interactions among distributed energy resources, improve efficiency, and maintain robustness against prediction errors [91].

6.4 Multi Objective Optimization

Battery operation entails making trade offs between a number of goals, including increasing cycle life, minimizing charging time, limiting thermal stress, and optimizing range. Pareto-based methodologies and other multi-objective optimization techniques enable the simultaneous assessment of various competing criteria. Recent studies have demonstrated that combining predictive models, such as BPNN, with evolutionary algorithms like NSGA-II can efficiently optimize battery thermal management, improving cooling performance and reducing system pressures while balancing multiple operational goals [92].

6.5 Machine Learning and Data Driven Optimization

ML driven optimization has accelerated with the use of massive data from EV fleets and onboard sensors. Without the need for explicit battery models, methods like neural networks, deep learning, and reinforcement learning may adaptively improve charging, balancing, and temperature management procedures. Recent studies highlight the effectiveness of ML in forecasting SOC and SOH, predicting RUL, and even guiding materials discovery, demonstrating its transformative potential for sustainable and high-performance battery management [93]. In particular, reinforcement learning is appropriate for adaptive SOC and RUL optimization as it learns optimum policies through interaction with the environment. The transition in BMS from rule based to ML driven optimization paradigms is depicted in Figure 5.



Rule-Based Control

- Based on pre-defined, hard-coded rules and lookup tables.
- Prioritized safety by preventing over/under-charging and overheating.
- Simple, deterministic, and required minimal computational power.
- Lacked adaptability to changing conditions and couldn't optimize for long-term battery health.
- Dominant from the 1990s to early 2000s.

Heuristics & Metaheuristics

- Utilized algorithms like Genetic Algorithms (GA) and Ant Colony Optimization (ACO).
- Found "good enough" solutions by intelligently searching a large solution space.
- More adaptive than rule-based systems, enabling better optimization for cell balancing and efficiency.
- More computationally intensive and required fine-tuning for specific applications.
- Popular from the 2000s to the 2010s.

Machine Learning-Driven Optimization

- Employs models such as neural networks and reinforcement learning.
- Learns from large datasets to make predictive, real-time decisions.
- Capable of optimizing for multiple conflicting objectives (e.g., fast charging vs. battery life).
- Enables advanced features like predictive maintenance and accurate State of Health (SoH) estimation.
- The current and most advanced approach, gaining prominence from the 2010s to the present.

Fig. 5 Evolution of optimization paradigms in BMS.

6.6 Hybrid Optimization Approaches

According to recent research, hybrid strategies that combine heuristics, machine learning, and mathematical optimization provide the optimal balance between accuracy and practicality in real time. For instance, MPC combined with heuristic solvers like PSO-MPC enables real time feasibility and global search efficiency. Similarly, hybrid and co-estimation approaches using ML models can accelerate computationally intensive optimization tasks, offering improved accuracy and resilience across diverse operating conditions [94].

7. CONCLUSION AND FUTURE DIRECTIONS

EVs and renewable ESS may now operate safely, effectively, and dependably thanks to BMS, a key piece of technology. Cell monitoring, balancing, protection, communication, and state estimation SOC, SOH, and RUL are among the basic BMS tasks that have been addressed in this article. Additionally, it has offered insights into more sophisticated methods including artificial intelligence, data driven modeling, and optimization frameworks. In order to emphasize the interaction between academic advancements and real world implementation in commercial systems, industrial standards, hardware designs, and new optimization techniques were also investigated.

The next generation of BMS must go beyond conventional voltage- and current-based control schemes, according to one of the survey's main findings. The traditional methods of state estimation and cell balancing are inadequate to manage the nonlinearities, uncertainties, and dynamic operating conditions that come with the growing use of fast-charging infrastructure, high-energy-density chemistries such as solid state batteries, and decentralized renewable ESS. In order to achieve both precision and flexibility in real-world operation, future BMS systems will need to include hybrid approaches that combine data driven machine learning techniques with physics based electrochemical models.

Another noteworthy finding is that cybersecurity and communication are becoming significant aspects of BMS design. Ensuring safe and reliable data interchange will be just as crucial as attaining precise state estimates as BMS becomes more and more integrated into cloud-based fleet management platforms, V2G systems, and smart grids. To take into account these new issues, standards like ISO 26262, IEC 61508, and cybersecurity recommendations need to be revised. Furthermore, it is anticipated that hardware designs will move toward distributed and modular BMS topologies, which would allow for scalability and lessen system bottlenecks in large scale energy storage installations.

Looking forward, several research directions stand out as promising avenues for the development of high performance BMS:

1.Integration of Artificial Intelligence: Deep learning, reinforcement learning, and federated learning methods for real time SOC/SOH/RUL estimation and adaptive fault detection.
2.Cybersecurity in BMS: Designing secure communication protocols and intrusion detection mechanisms for V2G-enabled and cloud connected BMS.
3.Advanced Optimization Techniques: Multi objective and meta-heuristic optimization frameworks to jointly address efficiency, cost, thermal management, and battery lifetime extension.
4.Solid State and Next Generation Chemistries: Tailoring BMS architectures to emerging chemistries such as solid-state, lithium sulfur, and sodium ion batteries, where conventional control strategies may not be directly applicable.
5.Digital Twin Technology: Real time co-simulation platforms for predictive diagnostics and proactive maintenance of EV battery packs.
6.Sustainability and Circular Economy: Integration of recycling, second-life applications, and life-cycle assessment into the BMS framework to reduce the environmental footprint of battery technologies.

To provide a holistic visualization of emerging pathways, a conceptual roadmap of future BMS directions is illustrated in Figure 6. This framework consolidates advancements across sensing technologies, communication, optimization, cybersecurity, and AI-driven state estimation, offering researchers and industry stakeholders a clear trajectory for the next generation of BMS solutions.

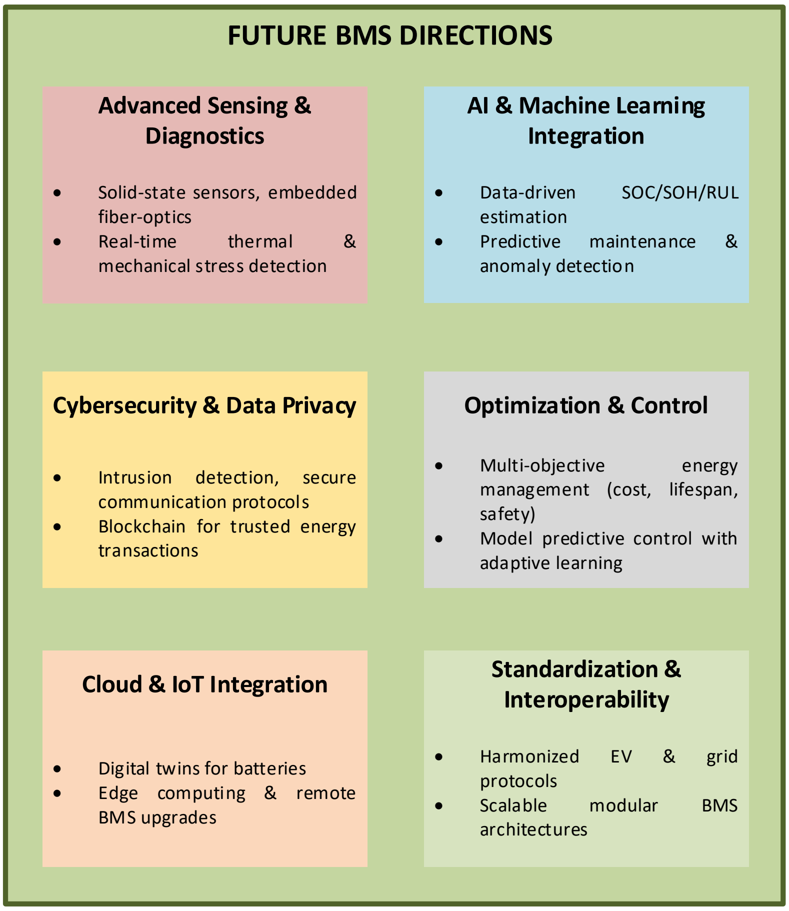


Fig. 6 Conceptual roadmap for future directions in advanced BMS research and development.

In summary, BMS's future is situated at the nexus of systems integration, data science, electrical engineering, and optimization. Researchers and industry stakeholders may create BMS solutions that improve the safety and dependability of EVs and renewable energy systems while also hastening the shift to a sustainable, low carbon energy future by utilizing transdisciplinary advancements.

CONFLICT OF INTEREST

All authors declare no conflict of interest.

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