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Review

A Concise Review of Power Batteries and Battery Management Systems for Electric and Hybrid Vehicles

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Abstract

The core powertrain components of electric vehicles (EVs) and hybrid electric vehicles (HEVs) are the power batteries and battery management system (BMS), jointly determining the performance, safety, and economy of the vehicle. This review offers a comprehensive overview of the evolution and current advancements in power battery and BMS technology for electric vehicles (EVs). It emphasizes product upgrades and replacements while also analyzing future research hotspots and development trends driven by the increasing demand for EVs and hybrid electric vehicles (HEVs). This review aims to give recommendations and support for the future development of power batteries and BMSs that are widely used in EVs, HEVs, and energy storage systems, which will lead to industry and research progress.

Keywords: electric and hybrid vehicles; power batteries; battery management system; a review

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1. Introduction

Under the challenges of the global fossil energy crisis and intensified climate change, electric vehicles (EVs), as the core carrier of low-carbon transformation in the transportation sector, are reshaping the automotive industry pattern at an unprecedented speed. In addition, EVs are also the best carrier for autonomous driving and vehicle to everything (V2X). EVs, particularly those that are powered by renewable energy, have fewer carbon emissions throughout their entire lifecycle than gasoline vehicles.

Power batteries and the battery management system (BMS) are the essential elements of both EVs and hybrid electric vehicles (HEVs), which are responsible for the vehicle's performance, safety, and economy [1,2]. As the energy heart, the energy density and fast charging ability of power batteries directly determine the range and user experience, while the BMS is the brain of power batteries, which can achieve accurate state estimation, thermal runaway warning, and full lifecycle management, ensuring battery safety and efficiency [3,4].

Power batteries and the BMS for EVs and HEVs have been developed as a result of technological advances and consumer demand and have gone through various stages from early exploration to mature commercialization. The development of power batteries and the BMS has always revolved around four core areas: improving battery energy density, enhancing battery safety, reducing battery costs, and extending battery life. The focus of this review is on the evolution and state of the art of power batteries and the BMS, as well as future new technologies for EVs and HEVs. The organization of this paper is outlined

as follows: The current development status of power batteries for electric and hybrid vehicles are described in Section 2. Future technologies of power batteries are analyzed in Section 3. Section 4 provides a comprehensive explanation of the fundamental functions, composition, and state of the art of the BMS in both academic and commercialized products. In Section 5, the development trend of the BMS is analyzed, including algorithms, methods, and techniques applied for solving the key concerns with the BMS in the future, revolving around artificial intelligence (AI) technology, high-integration technology, high-precision technology, and cloud networking technology. Finally, conclusions are reached in Section 6.

2. Development Status of Power Batteries for Electric and Hybrid Vehicles

Since Alessandro Volta invented the volt stack in 1800, battery technology has undergone over 200 years of development and made significant progress. Reliable EV batteries must have high power and capacity and safe, durable, lightweight, and inexpensive [5]. Lead-acid batteries, nickel metal hydride (NiMH) batteries, and lithium-ion batteries (LIBs) are all commonly used in Evs [6,7]. The important development process of power batteries is shown in Figure 1. Lead-acid batteries, the earliest practical rechargeable or secondary batteries, were developed by French inventor Gaston Plante in 1859. In 1976, Ovshinsky [8], a scientist at the Philips Research Center, successfully developed NiMH batteries. In 1991, rechargeable LIBs were introduced by Sony Corporation, which used lithium cobalt oxide (LCO) as the positive electrode material and graphite as the negative electrode material [9]; however, the first 18650 LIB produced in the laboratory only had a capacity of 600 mAh. In 1995, Sony Corporation advanced the development of 100 Ah LIBs and applied them to EVs, demonstrating their superior performance as batteries, which was widely noticed. In 1996, the research team led by Goodenough [10] at the University of Texas discovered that lithium iron phosphate (LFP) batteries had high thermal stability and quickly became the mainstream battery choice for EVs. In 2004, Johnson et al. [11] applied for a patent for the nickel cobalt manganese oxide (NCM) lithium-rich cathode, which was later developed than LFP batteries but rapidly grew due to its higher energy density. Solid state batteries (SSBs) are currently in the research and development stage and are expected to solve the bottleneck of existing LIBs in terms of safety and range, leading EVs to a new stage of development [12,13]. After 2025, SSBs are predicted to gradually become commercialized, with the aim of achieving higher energy density, stronger safety performance, and faster charging speeds. However, these objectives necessitate a deeper discussion and a perspective [14]. The performance indicators of different EV batteries such as nominal voltage, energy density, cycle life, charging/discharge temperature range, and safety are compared in Table 1. We will provide a comprehensive overview of the advantages and disadvantages of these various power batteries, their main applications, and future development trends based on the battery development history.

Table 1. Comparison of different power batteries.

Category	Lead Acid	NiMH	NCM	LFP
Nominal voltage (V)	2	1.2	3.7	3.2
Energy density (Wh/kg)	30~45	60~70	200~300	160~200
Cycle life (Times)	400~600	300~1000	1000~2000	1000~2000
Charging temperature range (°C)	5~40	0~45	0~55	−10~55
Discharge temperature range (°C)	0~45	−10~45	−10~60	−20~60
Element toxic (Yes/No)	Yes	Yes	Yes	No

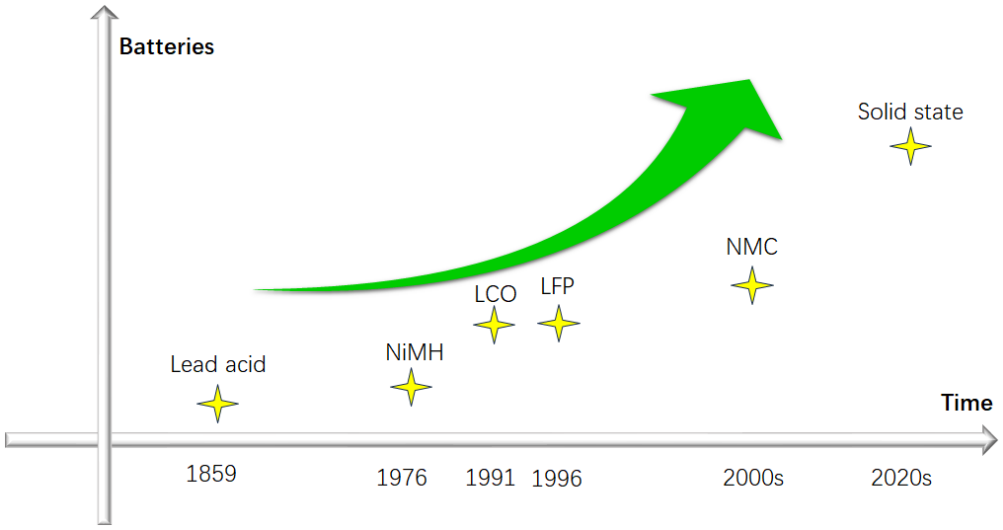


Figure 1. The development of power batteries for electric vehicles.

The performance of lead-acid batteries is still improving despite over 160 years of technological advancement [15]. The initial procurement cost is much less than NiMH batteries and LIBs because of the mature technology. Lead-acid batteries are better suited to low-speed, low-cost EVs, like certain electric bicycles and short-distance electric scooters. Therefore, lead-acid batteries will still be used for a period of time. However, lead metal and its compounds are toxic to the human body, and it is almost impossible to significantly improve the performance of lead-acid batteries. Eventually, lead-acid batteries will be replaced by more advanced batteries [16].

NiMH batteries have high power and a long lifespan and are mainly used in HEVs [17,18]. Currently, Japan is at the forefront of global research and industrialization in NiMH batteries. NiMH batteries are commonly utilized in industrial HEVs that can last for up to 10 years, such as Toyota's Prius HEV, Honda's CIVIC HEV, and Ford's Escape HEV, all of which are highly commercialized. NiMH batteries, with their advantages of high power density and mature technology, will continue to be stably applied in HEVs, and future research and development hotspots will mainly focus on improving their energy density [19,20].

With the development of new materials, especially the emergence of electrode materials, the cycle life of LIBs has been greatly improved; simultaneously, the material and costs of LIBs have been reduced, making them the most promising power batteries in recent years [21,22]. Currently, the positive electrode materials of LIBs mainly include LFP, NCM, LCO, lithium manganese oxide (LMO), and lithium nickel oxide (LNO), which have the advantages of high capacity, high specific energy, a long cycle life, and high cell voltage. Research into and the development of EV batteries is now focused on LIBs [23,24]. In recent years, the vast majority of EVs launched by major automobile companies have adopted LIBs, becoming a hot research topic in the field of power battery applications. A performance comparison of LIBs using different positive electrode active materials is shown in Table 2. The radar plots of five LIBs on four indicators are shown in Figure 2. What we can see from the performance comparison of different lithium-ion batteries in Figure 2 and Table 2 is that LFP and NCM batteries have the best comprehensive cost and energy density, becoming the mainstream in the market. These two types of batteries are the primary batteries used in EVs and large-scale energy storage power stations at present. LFP batteries refer to LIBs using LiFePO4 as the positive electrode material, which can be charged and used as needed, without the need to discharge it before charging. Furthermore, LFP batteries are highly safe because they do not produce any combustion or explosion,

regardless of the damage caused internally or externally [25,26]. LFP batteries do not contain any heavy metals or rare metals, while NiMH batteries require rare metals, so they are non-toxic and pollution-free. NCM batteries refer to LIBs with nickel, manganese, and cobalt compounds as the main positive electrode materials [27], which have the advantages of high energy density, good safety and stability, support for high rate discharge, and a moderate price. They have been widely used in small and medium-sized lithium battery fields such as industrial equipment, medical instruments, and digital electronic products and have shown strong development potential in new energy vehicles, robots, logistics vehicles, drones, and other fields [28,29].

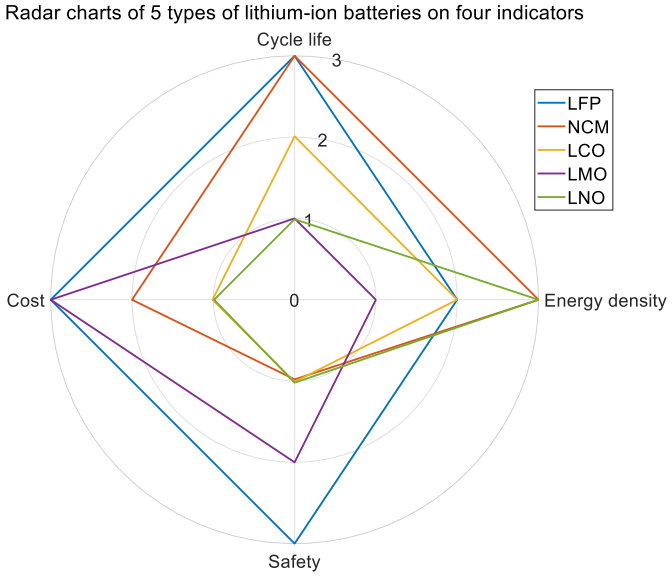


Figure 2. The radar charts of five types of lithium-ion batteries on four indicators.

Table 2. Comparison of performance of different lithium-ion batteries.

Cathode Material	Chemical Composition	Energy Density (Wh/kg)	Cycle Life (Times)	Cost	Safety
LFP	$LiFePO_4$	Medium (160~200)	High (1000~2000)	Low	High
NCM	$LiNi_xCo_yMn_{(1-x-y)}O_2$	High (200~300)	High (1000~2000)	Medium	Low
LCO	$LiCoO_2$	Medium (150~200)	Medium (500~1000)	High	Low
LMO	$LiMn_2O_4$	Low (100~150)	Low (300~700)	Low	Medium
LNO	$LiNiO_2$	High (180–220)	Low (100~200)	High	Low

It should be further pointed out that, in addition to the types and characteristics of the batteries mentioned above, there are significant differences in the design, performance, and application of power batteries when they are applied to battery electric vehicles (BEVs) and HEVs. While BEVs commonly utilize NCM and LFP batteries that have high capacity and high energy density, HEVs frequently utilize NiMH and power-type LIBs that have small capacity and high power density. Therefore, in terms of cost, the power battery cost of BEVs accounts for a high proportion, accounting for 30% to 40% of the total vehicle cost, and is the main factor in price. In HEVs, the cost of power batteries is fairly low, with only 5% to 10%, with a maximum of 20%.

3. Future Technologies of Power Batteries

The innovation of battery materials will directly affect the development of future power batteries. The innovation focus of power batteries under different battery material systems varies with different technological routes from LIBs to SSBs. In summary, power batteries will be able to upgrade in four dimensions: high energy density, fast charging, low cost, and zero carbonization [30]. Chen et al. [31] outlined an overview of the scientific challenges, fundamental mechanisms, and design strategies for SSBs, particularly emphasizing the instability issues of solid-state electrolytes and their connection to both cathode and anode electrodes. Xiao et al. [32] summarized the experimental findings for different types of solid electrolytes and interconnected them with computational predictions. The aim is to give a greater comprehension of the interfacial reactions and give insight into the future design and engineering of interfaces in SSBs. A small set of chemical and physical principles can be used to capture electrochemical stability and interfacial reaction products in general [32]. The problem of electrolyte interface impedance will gradually be solved for SSBs in the future and is expected to achieve large-scale application before 2030 [33]. SSBs that have specific energy above 400 Wh/kg, energy density beyond 1000 Wh/L, and more than 90% energy efficiency at a 1C rate can be reached, as the key challenges have been resolved [34].

Sodium ion batteries (SIBs), as a supplement to LIBs, are used in low-end vehicle models or energy storage fields. They have the advantages of the wide availability and low cost, but their energy density needs to be improved. Founded in 2011, Faradion became the world's first non-aqueous SIB company based in the UK, developing SIBs with an impressive energy density of 140–160 Wh/kg and a robust cycling lifespan of 1000 to 3000 cycles within a voltage range of 4.0 to 1.0 V [35]. If SIBs have a good enough performance, they are very suitable for energy storage applications and can also meet the needs of specific automotive scenarios. SIBs are promising next-generation alternatives [36] and will occupy a place in the future battery industry [37,38].

In addition to the innovation of batteries themselves, fast-charging technology [39,40] and the secondary life utilization of retired power batteries [41,42], as well as dismantling and material recycling technology after the end of life [43,44], are also the focus of future technological development, as shown in Figure 3. The entire lifecycle of power batteries, including material preparation, manufacturing into new batteries, becoming retired batteries, secondary life applications, and ultimately dismantling and recycling materials, forms a complete closed loop, which involves many key technologies. And every key technological innovation will drive the development of EVs and power batteries.

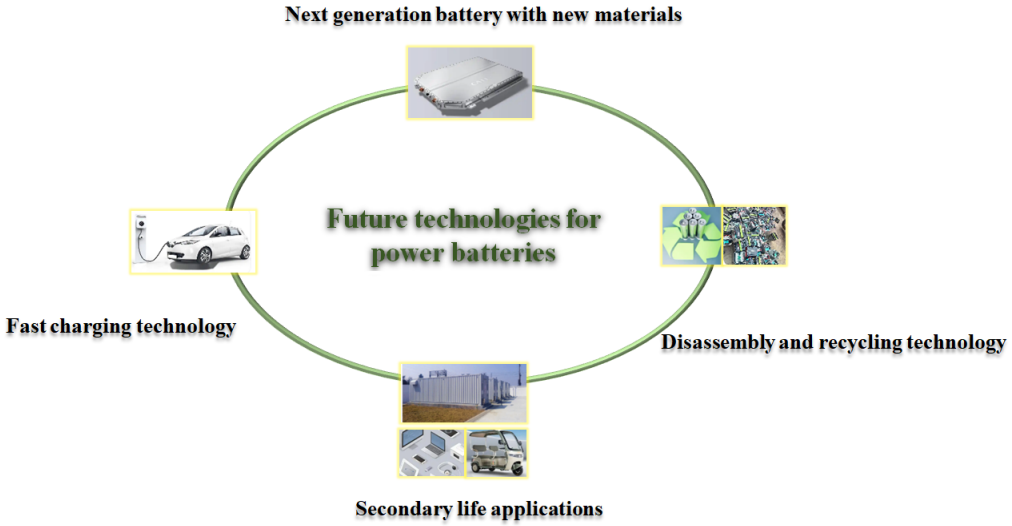


Figure 3. The future technologies for power batteries.

4. Development Status of BMS

4.1. Basic Functions of BMS

The battery's energy density, power density, and service life are still insufficient to match the vehicle's objectives, and the current power battery technology has not yet reached the ideal application state. Therefore, it is necessary to rely on a reliable BMS to maximize the performance of the power batteries under limited conditions, ensuring the safe and reliable operation of the power battery system [45].

The BMS is responsible for controlling EVs and energy storage systems as a central unit. The BMS is referred to as the brain of the battery system, responsible for managing hundreds or thousands of battery cells in series and parallel and keeping an eye on the battery's health status. The BMS plays a crucial role in ensuring the safe operation and efficient use of batteries. In fact, the safe and dependable operation of batteries in EVs relies heavily on online surveillance and status estimations of charges [46]. A high-performance BMS requires the real-time measurement of voltage, current and temperature to master the complex internal and external states of all cells in the battery system. Through battery models and control algorithms, various faults are diagnosed in the battery system in a timely and accurate manner, and the charging and discharging current and working temperature of the batteries are accurately controlled to ensure that all cells operate within a reliable and efficient working range.

To ensure the efficient, reliable, safe, and long-life operation of the power battery, the basic functions and key technologies of the BMS mainly include battery modeling, state estimation, life prediction, equalization technology, low-temperature heating technology, thermal management technology, and fault diagnosis, as shown in Figure 4. The BMS has also been supported by IoT-based and wireless technology [47]. The accurate estimation of the internal state of the battery is a core function of the BMS, which is also necessary for managing battery safety and efficient operation.

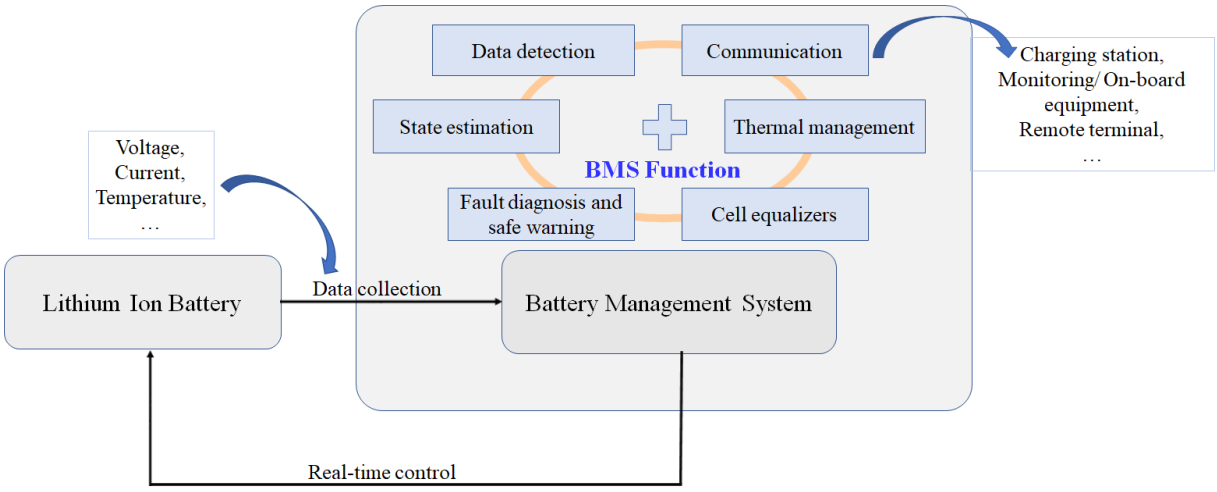


Figure 4. Basic functions of BMS.

The state of the battery mainly includes the state of charge (SOC), state of health (SOH), state of power (SOP), and state of energy (SOE). The battery's performance indicators are different depending on the state. A number of scholars have proposed targeted estimation methods for different battery states. The extended Kalman filter (EKF), deep learning (DL), AI, etc., are used in SOC estimation [48–52]. In 2004, Plett [48] began to explain the applications of the EKF to the BMS. The EKF state estimate was used to calculate the SOC and dynamic maximum power, while a dual EKF was also introduced for state and parameter estimation. Afshar et al. [49] designed an EKF-based adaptive observer via a

low-order approximation of an electrochemical model. Hou et al. [50] presented a method of estimating the combined SOE and SOC based on long short-term memory (LSTM) optimization and an adaptive extended Kalman filter (AEKF), in which LSTM is introduced to optimize the Ohmic internal resistance, actual energy, and actual capacity parameters in real time to improve the accuracy of the model. Kim et al. [51] proposed a new DL model for estimating battery capacity by utilizing voltage, current, and temperature measurements. Advanced feature extraction was performed by introducing a spectrogram, which was not the case with the conventional model. Tejaswini et al. [52] explored various AI-based and direct measurement techniques. An optimal feed-forward artificial neural network (ANN) has been suggested, which is able to achieve a mean absolute error (MAE) range of 0.5–1.4% during a complete cycle. In terms of SOH estimation, the current methods are often divided into model-based methods and data-driven methods. However, as summarized in the review by Berecibar et al. [53], there are currently no unique perfect solutions for SOH estimation, with the current methods divided into two categories: experimental techniques or adaptive models. One of the most significant findings is that experimental techniques like open-circuit voltage (OCV) and Coulomb counting methods require much fewer measurements and less computational effort than adaptive models such as Kalman Filtering (KF). Contrary to this, the precision of the methods based on experimental techniques is not as high as in adaptive models. Shao et al. [54] created a network architecture that uses a convolutional gated multi-attention network (CGMA-Net) to effectively tackle battery capacity degradation. Electrochemical impedance spectroscopy (EIS) data is a valuable source of information about the internal state of the battery and can help predict battery SOH by reflecting its degradation characteristics. Accurate SOP estimation for LIBs poses a significant challenge in current EV development. Shen et al. [55] reviewed SOP estimation methods, categorizing them into four major types, characteristic maps, models, data-driven machine learning, and multi-state joint estimation, and proposed a novel SOP estimation framework that leverages hybrid modeling and multi-state joint estimation.

Because of the complex and variable operating conditions, the performance of power batteries used in EVs can be significantly influenced by multiple factors, including the temperature, discharge rate, and depth of discharge. The result is that the estimation accuracy of various battery states is severely reduced. And more importantly, the battery life is severely shortened, and there may even be safety issues. Most accidents were caused by issues with the power battery system. Currently, the BMS is not yet fully developed, and its core issues remain unresolved. As a result, the BMS cannot accurately determine the true state of the battery, which can easily lead to overcharging and overdischarging. This, in turn, causes battery performance degradation and aging. As shown in Figure 5, these issues can lead to EVs breaking down midway and even leading to safety accidents in the future.

Therefore, the fault diagnosis and safety warning technology of EV power batteries is the key to ensuring the reliable operation of the battery system. Battery failures mainly include electrical faults, thermal faults, mechanical faults, aging faults, and sensor faults. The related technologies mainly involve real-time monitoring, fault type identification, warning algorithms, and safety protection measures. Zhang et al. [56] studied an early soft internal short-circuit fault diagnosis method based on the incremental capacity curve by calculating the local outlier factor value of each cell within the battery pack. Ouyang et al. [57] performed incremental capacity analysis to identify the characteristics of the lithium deposition-induced battery aging mechanisms, which were quantified using a mechanistic model. Zhang et al. [58] proposed a method for diagnosing faults that involves using isolation forest and boxplot methods to detect anomalies in battery voltage. Ma et al. [59] proposed a new method of alarming thermal runaway with voltage–temperature

awareness by utilizing an advanced deep learning model. The combined relative error for temperature and voltage prediction in a 7 min time window is less than 0.28%, and the ability to predict thermal runaway in real-world scenarios can be achieved in 8–13 min. Su et al. [60] analyzed and talked about improvements that permit the implementation of practical battery measurements for both internal and external parameters. Local temperature, strain, pressure, and refractive index are the primary factors used for general operation, while temperature gradients and vent gas sensing are used for thermal runaway imminent detection.

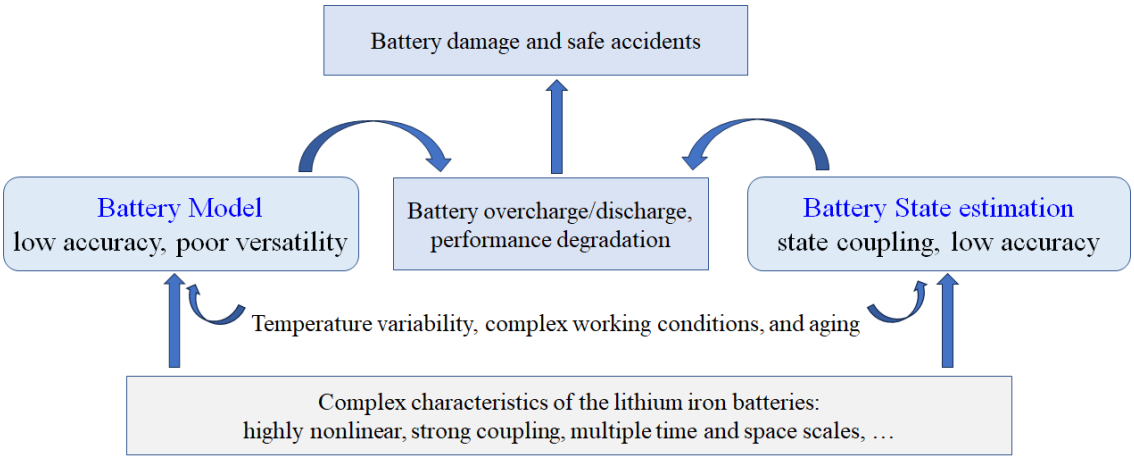


Figure 5. The crucial importance of battery models and state estimation for battery safety.

4.2. Basic Composition of BMS

A BMS comprises a variety of actuators, sensors, signal lines, and controllers [47]. According to the basic functions of a BMS, its composition includes the battery module, BMS protection board, control module, communication module, display module, acquisition module, etc.

The battery pack is a crucial component of the BMS, typically consisting of multiple individual cells connected in series and parallel configurations to achieve higher voltage and capacity. The BMS protection board is connected to the battery pack through sampling lines and nickel sheets to achieve real-time monitoring and management of the battery pack. To ensure battery safety, it also prevents overcharging, overdischarging, and short circuiting and extends battery service life. The control module is responsible for monitoring and managing the status of the battery and is connected to the communication module and display module through a communication interface for data acquisition and display, such as voltage, current, and temperature. The communication module supports multiple communication protocols, such as a controller area network (CAN) bus, UART, or wireless [61], for communicating with external devices and transmitting battery status data. The collection module is in charge of gathering battery parameters like voltage, current, and temperature and sending them to the control module for processing.

4.3. Four Generations of Development of BMS

According to the widely recognized classification based on BMS functions, BMS products have gone through four generations of development from scratch and from weakness to strength, as shown in Figure 6. The functional characteristics and application areas of these four generations of products are summarized in Table 3. It can be seen that the BMS has evolved from its initial basic functions to the second generation of digitalization and algorithm applications and is now continuing to evolve from the third generation of intelligence and integration to the fourth generation of cloud collaboration and AI

driven to achieve full lifecycle management of batteries. The current BMS products are able to achieve functions such as internal component management, state estimation, fault diagnosis, thermal runaway warning, aging and life prediction, active balancing, and thermal management including low-temperature heating.

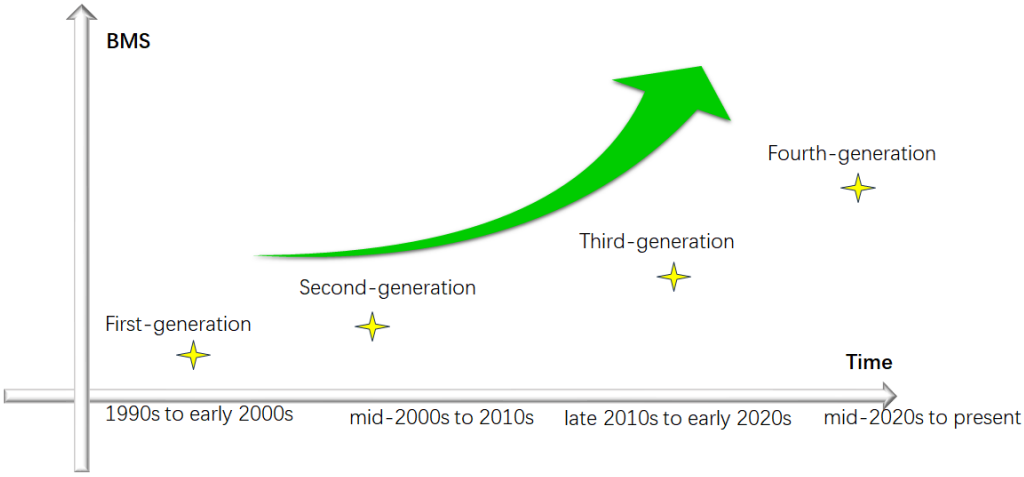


Figure 6. The development of BMS products.

Table 3. The functional characteristics and application areas of four generations of BMS.

Generation	Functional Characteristics	Application Area
First	Basic functional	Early electric tools, lead-acid battery systems, low-end EVs
Second	Digitalization and algorithms	HEVs and early EVs
Third	Intelligent and integrated	High-end EVs and energy storage systems
Fourth	Global collaboration and AI-driven	Next-generation intelligent EVs and large-scale energy storage

The first generation of the BMS was in its basic functional state from the 1990s to the early 2000s. The core function is the collection of key parameters, which can easily monitor voltage, current, and temperature without complex algorithms and only achieve basic protection functions such as overcharging, overdischarging, and overheating. It has a weak communication ability. It was mainly used in early electric tools, lead-acid battery systems, and some low-end EVs [62,63].

The second-generation BMS played a role in digitalization and algorithm development during the mid-2000s to the 2010s. To obtain accurate data acquisition and digital filtering, a high-performance MCU or DSP was employed. The implementation of state estimations like the SOC and SOH involved the use of relatively simple algorithms. It supports CAN bus, LIN bus, etc., and interacts with the entire vehicle system. Passive balancing through resistive energy dissipation has become standard for it. It was mainly used in HEVs and early BEVs [64,65].

The third-generation BMS is categorized as the intelligent and integrated stage that takes place from the late 2000s to the early 2020s. High-precision monitoring and multi-channel temperature sampling can be achieved. The SOC/SOH estimation method integrates dynamic models such as machine learning and Kalman filtering. Active balancing technology was adopted to improve energy efficiency. It realized remote monitoring and cloud interconnection through 4G/5G. It was mainly used in high-end EVs and energy storage systems [66,67].

The fourth-generation BMS is in the stage of global collaboration and has been powered by AI since the mid-2020s until the present day. In the future, full lifecycle management and the deep integration of AI will be achieved, and fault prediction based on big data will

be deeply linked with vehicle thermal management, charging stations [68,69], and vehicle to power grid (V2G). With the distributed BMS, it provides ultra-fast charging management for high-voltage platforms up to 800 V. It is mainly used in next-generation intelligent EVs and large-scale energy storage [70].

5. Future Technologies of Intelligent BMS

Leveraging cutting-edge technologies such as cloud computing, digital twin, blockchain, and the internet of things (IoT) [71], the future development trend of intelligent BMS will revolve around AI technology, high-integration technology, high-precision technology, and cloud networking technology, as shown in Figure 7, while also addressing challenges such as complex sensing, advanced embedded systems, robust communication protocols, the effective prevention of thermal runaway, and full lifecycle management.

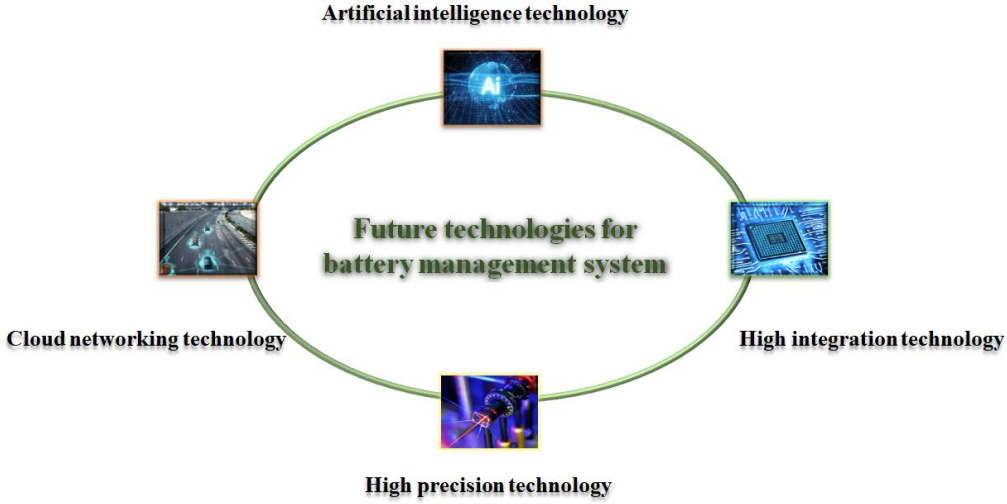


Figure 7. The future technologies for the intelligent BMS.

The intelligent BMS will be deeply integrated with AI technology [72], such as estimating a battery's SOH using an AI optimization algorithm [73], predicting battery remaining useful life (RUL) through machine learning [74], and adjusting parameters dynamically when charged and discharged to extend battery RUL based on user habits and environmental temperature adaptively. AI-driven techniques improve battery state predictions and temperature regulation, providing greater accuracy than traditional methods [75]. Through the deep integration of AI, future battery systems will be smarter, more efficient, and safer.

High-integration technology mainly integrates the BMS, charging management system, and inverter controller into a single chip, reducing size and cost [76]. By incorporating AI acceleration chips specifically designed for the BMS, the functionality and computing power of the BMS will be greatly improved [77]. And wireless communication will also be promoted to replace traditional wiring harnesses and reduce weight and failure rates [78].

High-precision technology is mainly reflected in the integration of new sensors, such as fiber optic sensors to monitor internal temperature and pressure [79]. Functional optical fiber sensors can also be embedded inside the battery to monitor dendrite growth on the negative electrode surface by detecting imperceptible physical/chemical changes [80]. Ultrasonic sensors detect lithium deposition to enhance safety [81]. New sensors are driving BMSs to transition from traditional monitoring to intelligent perception.

The cloud networking technology is mainly reflected in cloud-end collaboration and full lifecycle management [82]. Battery digital models will be built in the cloud, and physical BMS data will be synchronized in real time to optimize maintenance strategies.

Cloud-based high-fidelity models will be used in the real-time simulation of battery status and prediction of faults [83].

Of course, opportunities also mean challenges. AI chips need to undergo a qualitative leap, which is supported by advanced packaging technology and chiplet technology [84]. The high degree of integration requires an improvement at the industrial design level, such as considering electromagnetic interference and heat dissipation in limited space [85]. A millisecond-level response is necessary for BMS overcharge and overdischarge protection, while cloud computing's network latency is typically several hundred milliseconds, which may not be adequate for real-time control requirements. Cloud battery data may expose user behavior or trade secrets, and cloud platforms may also become targets for hacker attacks [86,87]. Therefore, the value of cloud computing in the BMS lies in long-term optimization and global collaboration, but it requires a hybrid architecture of edge and cloud to solve real-time and reliability issues [88] while also combining security and standardized design.

6. Conclusions

EVs and energy storage systems are developing in a promising way, with extensive application possibilities that are encouraging the development of LIBs, BMSs, and industries. The key technologies of power batteries involve various disciplines, including battery materials, battery electrochemistry, battery manufacturing technology, battery secondary applications, battery disassembly and recycling, and others. And the key technologies of BMSs also involve many fields, including but not limited to battery modeling, battery state estimation technology, thermal management and thermal runaway, fault diagnosis, active balancing, and low-temperature heating.

There are still many technical fields and theoretical research issues involved in the key technologies of power batteries and BMSs, so there are still some aspects that have not been addressed. However, this paper provides an overall overview of the development history and the state of the art of power batteries and the BMS, which mainly focuses on the future development trends of power batteries and BMS technology from the perspective of the demand for EVs and HEVs. It is important to note that intelligent BMSs play a crucial role in ensuring the safe, efficient, and long-lasting operation of power batteries through the use of intelligent technology. Supported by advanced cutting-edge technologies such as cloud computing, digital twin, blockchain, and the IoT, the intelligent management of battery systems will be deeply integrated with AI, and the intelligent BMS will gradually be implemented in EVs and HEVs.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ANN	Artificial neural network
BEV	Battery electric vehicle
BMS	Battery management system
CAN	Controller area network
DL	Deep learning
EKF	Extended Kalman filter
EV	Electric vehicle
EIS	Electrochemical impedance spectroscopy
HEV	Hybrid electric vehicle
KF	Kalman filter
LIB	Lithium-ion battery
LFP	Lithium iron phosphate
LCO	Lithium cobalt oxide
LMO	Lithium manganese oxide
LNO	Lithium nickel oxide
LSTM	Long short-term memory
MAE	Mean absolute error
NCM	Lithium nickel cobalt manganese oxide
NiMH	Nickel metal hydride
OCV	Open-circuit voltage
RUL	Remaining useful life
SIB	Sodium ion battery
SOC	State of charge
SOH	State of health
SOP	State of power
SOE	State of energy
SSB	Solid-state battery
V2G	Vehicle to power grid
V2X	Vehicle to everything

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