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REVIEW PAPER

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A review on battery management system from the modeling efforts to its multiapplication and integration

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Summary
Progress in battery technology accelerates the transition of battery management system (BMS) from a mere monitoring unit to a multifunction integrated one. It is necessary to establish a battery model for the implementation of BMS's effective control. With more comprehensive and faster battery model, it would be accurate and effective to reflect the behavior of the battery level to the vehicle. On this basis, to ensure battery safety, power, and durability, some key technologies based on the model are advanced, such as battery state estimation, energy equalization, thermal management, and fault diagnosis. Besides, the communication of interactions between BMS and vehicle controllers, motor controllers, etc is an essential consideration for optimizing driving and improving vehicle performance. As concluded, a synergistic and collaborative BMS is the foundation for green-energy vehicles to be intelligent, electric, networked, and shared. Thus, this paper reviews the research and development (R&D) of multiphysics model simulation and multifunction integrated BMS technology. In addition, summary of the relevant research and state-of-the-art technology is dedicated to improving the synergy and coordination of BMS and to promote the innovation and optimization of new energy vehicle technology.

KEYWORDS
battery management system, battery modeling, functional application, system integration

Nomenclature: AET, average execution time; AUKF, adaptive unscented Kalman filter; BMS, battery management system; BTMS, battery thermal management system; CAN, controller area network; CC-CV, constant current-constant voltage; CFD, computational fluid dynamics; DCE, dissipative cell equalization; DC/DC, direct current to direct current; DOD, depth of discharge; ECM, equivalent circuit model; FEA, finite element analysis; EKF, extend Kalman filter; EMS, energy management strategy; EPS, electronic power steering; EV, electric vehicles; E_{RDE}, remaining discharge energy; FLC, fuzzy logic control; GPS, global positioning system; HEV, hybrid electric vehicles; HPPC, hybrid pulse power characteristic; ITS, intelligent transport system; $LiCoO_2$, lithium cobalt oxide; LIB, lithium-ion battery; $LiFePO_4$, lithium iron phosphate; $LiMnO_4$, lithium manganese oxide; MCU, motor control unit; NCA, nickel-cobalt-alumina; NCM, nickel-cobalt-manganese; P2D, pseudo two dimensional; PDU, power distribution unit; PRA, power relay assembly; R&D, research and development; RMSE, root-mean-square error; OCV, open circuit voltage; OEMs, original equipment manufacturers; PCM, phase change material; PDEs, partial differential equations; PF, particle filter; MAE, mean absolute error; NAS, sodium-sulfur; NEs, nonlinear equations; RC, resistance and capacitance; SBMs, smart battery modules; SEI, solid electrolyte interphase; SOC, state of charge; SOE, state of energy; SOF, state of function; SOH, state of health; SOP, state of power; SP, single particle; UDF, user-defined function; UKF, unscented Kalman filter; VCU, vehicle control unit; ZEBRA, sodium/nickel chloride

1 | INTRODUCTION

Challenges of the oil crisis and environmental pollution have increased the demand for electricity in consumers and industry, which bring opportunities and challenges for energy storage. In electrochemical energy storage systems, lithium-ion batteries (LIBs) are the most promising candidate for new energy vehicles due to the high energy density, power density, and superior cycle performance relative to other secondary batteries. The BMS, as a connecting link between batteries and vehicles, plays a significant role in the development of automobile. The in-depth research of it is the need to develop new energy vehicles and is also a requirement for energy-saving and emission reduction measures. Therefore, it is urgent to exploit a maturer and more comprehensive BMS.[1-3]

The LIB pack of electric vehicles (EVs) has a large capacity, various series-parallel topologies, and limited working range. It needs to be effectively controlled and managed by BMS, which can not only ensure the reliable operation of battery pack (safety) but can also fully utilize the existing energy (power) and prolong the service life, thereby reducing the overall cost of vehicles (durability).[4] The BMS consists of various sensors, actuators, controllers, and so on. The key technologies are as follows: the state estimation of cell and battery pack (state of charge [SOC], state of health [SOH], state of function [SOF], state of energy [SOE], etc), battery variation identification and equalization, thermal safety, and fault diagnosis.

In order to develop an advanced BMS, a battery model should be firstly established by determining the main factors and changing the rules that affect the battery performance. And then the model-based functional application and optimization algorithms can be applied in BMS design, and the battery system can thus run at its optimal status safely.[5] As we can see, it is fundamental and crucial to establish a model that can fully reflect the battery characteristics. On the one hand, the battery internal microstructure and mechanism can be modeled to optimize the battery design. On the other hand, the battery external macroscopic characteristics are simulated from a single cell to a module to assist the BMS design. However, most of the research is currently on the unilateral performance of LIB, such as temperature distribution,[6] potential change,[7] aging degree,[8] and stress cracking.[9] Correspondingly, the implementation of model-based management system is also decentralized. Some of them are to protect the battery and its circuitry systems by restricting the occurrence of deterioration in operations, such as fluctuations in charging schemes.[10] Some are to evaluate and notify abnormalities over the battery performance by evaluating SOC (actual energy content of the battery pack and charge unbalances), SOH (internal resistance),[11,12] or to facilitate performance optimization by monitoring the voltage in the individual cells of a battery pack,[13] as well to stabilize temperature across the module.[14]

BMS is the multifunctional integrated organic brain behind the battery pack.[15] As early as 1991, the battery management BADICHEQ system was the first to take up the running tests. Based on this, BMS has evolved from a mere monitoring unit to an intelligent and integrated unit that to decide that what battery pack should do at different operation modes. The "EVI" BMS developed by General Motors used a microcomputer to manage the battery pack and increased the functions of high-voltage power-off protection, power mileage calculation, ground insulation detection, and so on. Meanwhile, the BatOpt battery management system is composed of a monitoring system for each battery and a central control unit by American AC Propulsion to form a distributed system for optimization control.

Many researchers have concentrated on identification and improvement of battery performance parameter, safe and efficient operation, and rational power allocation. Ungurean et al[16] reviewed the relevant battery models and special methods for SOH estimation. And Al-Zareer et al[17] and Wang et al[18] reflected the detailed descriptions of the battery thermal management techniques. Besides, Geetha and Subramani[19] also explored the topologies, control, and optimization of energy storage device. Motivated by the previous studies, this survey would make a review on the modeling, management, and application of electric vehicle power battery from a progressive and comprehensive perspective.

In order to manage batteries and even vehicles better, safer, and more efficiently, a BMS-centric theoretical framework has been established for the modern and future power system. The first part of the paper briefly describes the modeling techniques from features to limits. In terms of physical field, different approaches, namely, thermal model, electrical model, aging model, mechanical model, and multicoupled model, are explained. Then the paper investigates the development of model application in battery state estimation, energy equalization, thermal management, and fault diagnosis. The last part of this study deepens the development of multifunction BMS and multicontroller integration to optimize driving and vehicle performance. Under the diversified and complex operating modes, the key issues and challenges in the process of developing synergistic and collaborative BMS are prospected to promote the innovation of new energy vehicle techniques.

2 | BATTERY MODELS

A precise battery model contributes to the battery's behavioral description and analysis, as well as the premise of battery state estimation and management. Lithium-ion batteries are a complex polysystem with strong nonlinearity and time varying, and its parameters are susceptible to external environment, which increases the modeling difficulty. Based on the in-depth analysis of battery mechanism and the existing battery model, the following part describes the battery modeling method from the perspective of multiphysics, heat, electricity, aging, and machine field.

2.1 | Thermal modeling

The temperature of a LIB is determined by the heat output and cooling methods under different conditions. The thermal model combines the battery's phrases of heat generation, heat transfer, and heat dissipation to analyze the temperature distributions of battery cells, modules, and stacks in the time and space domains, to optimize the design and safety of the battery thermal management system (BTMS).

The battery heat transfer process is a typical unsteady, time-varied subject with an internal heat source. In addition to determining the thermal conductivity and boundary conditions of batteries, the heat generation rate q is an essential part of the modeling. And its calculation can be derived from the battery heat generation expression based on the thermodynamic energy balance proposed by Bernardi et al.[20] The expression took into account the heating process of electrochemical reaction, phase transition, and heat mixing. Further, Thomas and Newman[21] found the total by heat mixing and phase change is usually small, and the entropy heat is equivalent to the Joule heat. After neglecting the heat exchange between the battery and the outside, the basic form that used the average heat capacity method is obtained.

$$q = \frac{I}{V_b}\left[(U - U_0) + T\frac{\partial U_0}{\partial T}\right], \tag{1}$$

where q is the unit heat generation rate of battery, I is the battery current, U is the measured voltage of battery, U_0 is the open circuit voltage, T is the battery temperature, and $\frac{\partial U_0}{\partial T}$ is the entropy heat coefficient.

Under the premise that the total heat of LIB is quantitatively guaranteed, the idea of building a thermal model of lithium-ion battery has gradually deepened. Based on the assumption that the heating rate of the entire module is uniform, but allows the variation over time, the thermal conductivity of the material is converted into a temperature output. A lumped parameter model was built for predicting the thermal behavior of a single cell and a battery stack by Pals et al.[22,23] They accurately predicted the battery stack temperature profile using heat generation rates calculated by the one-cell model under the isothermal discharges. The model is simple, universe, and can be accurate to calculate the overall average temperature variation of batteries. However, this assumption does not apply to the condition with large temperature changes and high heat generation rates, and it is not possible to describe the spatial distribution of temperature inside the battery.

In order to explore the multidimensional temperature distribution of batteries, Onda et al[24] used the Sony $LiCo_2/C$ cylindrical LIB as the research object to establish a one-dimensional thermal model along the radial direction. The thermal behavior of the battery is presented by measuring overpotential resistance, heat capacity, and heat transfer coefficient of the battery to the ambient environment. As for large-scale batteries or high-rate loading conditions, one dimension is insufficient. Therefore, the finite element method was applied to establish a two-dimensional simplified model of the electrode unit (positive electrode and negative electrode) for the LG 14.6-Ah $LiMnO_4/C$ cell in Kim et al.[25] The charge conservation law was used to describe the material transport relationship between the two electrodes, which predicted the thermal behaviors of an LIB during charge and discharge processes. The two-dimensional model extends the battery temperature prediction to large-scale batteries. To further improve the accuracy of calculation, Du et al[26] selected a laminate $LiFePO_4/C$ battery and put forward a three-dimensional thermal model considering the heat generated by the body and the current collector. The results showed that the battery thermal behavior of discharge process can be simulated effectively by coupling the dynamic changes of the cell temperature, internal resistance, and temperature coefficient.

As can be seen, the above methods promote the accuracy of prediction but made the calculation complex. It is not conducive to the application in vehicles. Lin et al[27] regarded the battery as two layers inside and outside and proposed a thermal model that can capture the battery surface and core temperature. Compared with the traditional lumped parameter model (single state), it can simultaneously acquire two battery temperatures. For ease of distinction, it can also be called a dual-state lumped parameter model. It has moderate complexity and can reflect of the differences between the battery internal and surface temperature, which is beneficial to real-time control. Similar to the original intention of this method, Xiao[28] applied the equivalent circuit thermal model to battery temperature estimation to analogize the thermal simulation system of electricity. That is, when the heat source is activated, the current is converted into heat flow, causing the temperature to rise. The current is used to represent the heat flow, the voltage is the temperature, the resistance is the heat transfer resistance, and the capacitance is the heat capacity. With this hypothesis, the material thermodynamic properties of the battery can be converted into equivalent electrical parameters. A model based on the analogy principle for LIBs was presented, as shown in Figure 1. The heat balance equation was established to predict the core and surface temperature of the battery according to the law of electricity. And convection phenomenon between the battery surface and surroundings was also considered. Meanwhile, Forgez et al[29] further simplified the dual-state equivalent circuit thermal model. The correctness of the internal temperature estimation of the model is verified by current pulse experiment and full charge and discharge experiment, and it is within 1.5°C. This approach is simple enough to be applied in the BMS for EVs. The mathematical equations and diagrams for the above models are shown in Table 1.

2.2 | Electrical modeling

The electrical property model can either respond to the macroscopic electrical parameters of batteries, save test time and cost, or characterize the particle domain parameters in the microstructure to analyze battery performances for meeting different levels of management system requirements. Existing models for the field of EVs can be divided into two categories: electrochemical model and equivalent circuit model.

Electrochemical models, starting from internal reaction mechanism of battery, establish a series of electrode and electrolyte kinetic partial differential equations (PDEs). It can accurately predict the macroscopic physical quantities (such as voltage and current) of batteries; meanwhile, it can also stimulate the distribution of microscopic physical quantities (such as electrolyte overpotential, electrode current density, and solid-state/liquid-phase lithium-ion concentration). Such kind of model is accurate, but with high calculation cost. It is worth noting that the electrochemical models are suitable for battery optimal design and safety analysis and can also be applied to the battery management technology after proper simplification.

The battery is usually stacked or wound by a multilayer structure (micron-sized electrode sheets, centimeter-size body), and the large size span makes it difficult to build a high-quality model when simulating the actual battery structure. Therefore, when establishing a three-dimensional model, the average volume method is generally adopted, that is, the average behavior of a certain volume is taken as the overall battery characteristics for calculation. The US NREL[30-32] presented a general multiscale LIB modeling framework. It input parameters (potential φ, temperature T, etc.) in the high dimension into the low dimension in the form of the field, and the parameters (current i, heat generation q, etc.) in the low dimension were entered into the high dimension as a volume source. The particle mechanism model and the

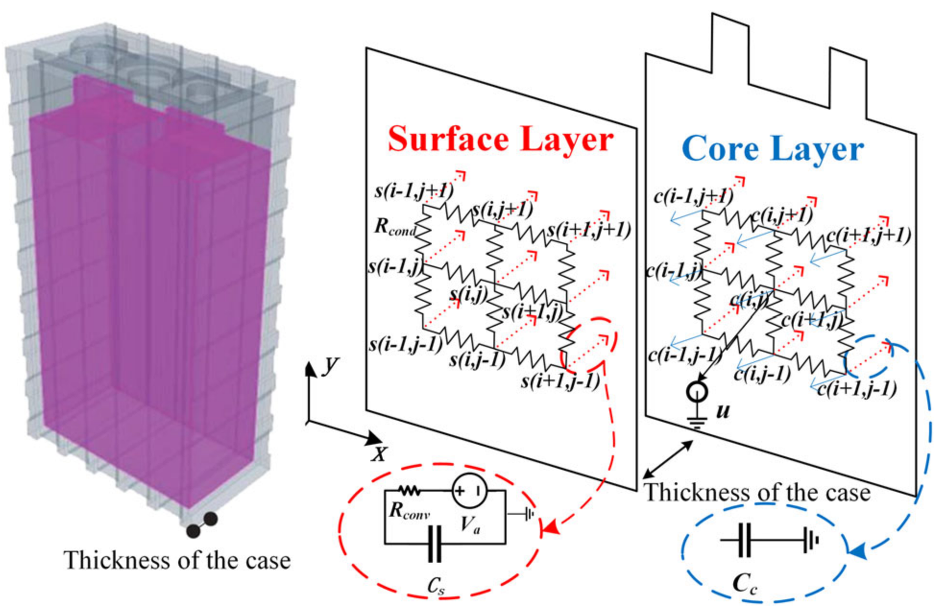
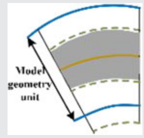
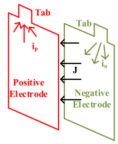
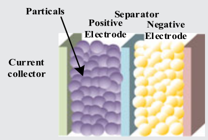
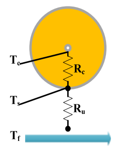


FIGURE 1 Equivalent electrical representation of the thermal model for the battery[28] [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Modeling equations and illustrations on battery thermal model

Model	Equations	Diagram
Lumped thermal models	$\rho c\frac{\partial T}{\partial t}=q$	
One-dimensional model	$\rho c\frac{\partial T}{\partial t}=k_r\left(\frac{\partial^2 T}{\partial r^2}+\frac{1\partial T}{r\,\partial t}\right)+q$	
Two-dimensional model	$\rho c\frac{\partial T}{\partial t}=\left(k_r\frac{\partial^2 T}{\partial r^2}+\frac{k_r\partial T}{r\,\partial r}+k_z\frac{\partial^2 T}{\partial z^2}\right)+q$	
Three-dimensional model	$\rho c\frac{\partial T}{\partial t}=\left(\frac{1}{r}\frac{\partial}{\partial r}\left(k_r r\frac{\partial T}{\partial r}\right)+\frac{k_z\partial^2 T}{r^2\,\partial\theta^2}+k_z\frac{\partial^2 T}{\partial z^2}\right)+q$	
Two-state lumped thermal models	$C_c\frac{dT_c}{dt}=q+\frac{T_s-T_c}{R_c}$ $C_s\frac{dT_s}{dt}=\frac{T_f-T_s}{R_u}-\frac{T_s-T_c}{R_c}$	

electrode model were packaged separately, which simplified the calculation and update of the model.

Generally speaking, there is a repetition of a plurality of identical structures (sandwich structure) inside the battery, so it is unrealistic and unnecessary to establish a multilayer model to simulate the overall performance of the battery. To achieve a certain simplification, Newman et al[33-36] assumed that the current density on the electrode was equal, and the three line segments respectively represented the positive electrode, separator, and negative electrode. Of course, there was a dimension on the cell size. At the same time, the model used Fick law of diffusion to idealize the battery active material into uniform spherical particles to describe the embedding and disembedding of li-ions in the solid phase material. Since Fick's law was solved only in the radial direction of particles, it meant that there was a radial dimension. However, due to the smaller radial dimension relative to the battery size dimension, it is not a two-dimensional model in the strict sense. For the convenience of identification, it is called a pseudo-two-dimensional (P2D) model, as shown in Figure 2. The model can directly simulate the internal microscopic information of the battery (such as particle concentration distribution and current potential distribution) and evaluate the material performance of the battery quickly, which is difficult to complete for the traditional experimental methods. And the control equations are given in Table 2.

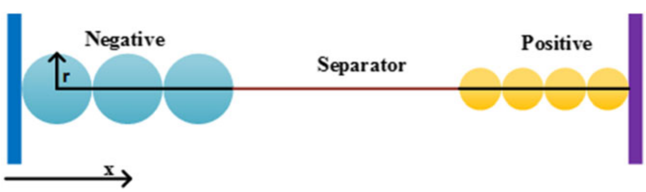


FIGURE 2 The schematic diagram of pseudo-two-dimensional (P2D) model [Colour figure can be viewed at wileyonlinelibrary.com]

This marks an establishment of a relatively fast and complete scientific system for evaluating battery performance from a material perspective. Therefore, the P2D model has gained wide attention and application since its birth. The model study shifts from single-phase (lithium manganese oxide [LMO][37-39] and lithium cobalt oxide [LCO][40,41]) to multiphase materials, (lithium iron phosphate [LFP],[42-44] nickel-cobalt-manganese [NCM],[45] and nickel-cobalt-alumina[NCA][46,47]). What is more, when Newman et al established the P2D model, a set of BAND program derive from the finite difference method was proposed to settle the coupled PDEs. Then the endless simplified algorithms have been introduced into the calculation, including the finite element method,[45,47] finite difference method,[48] lattice Boltzmann.[49,50] Other than using mathematical method to reduce or reconstruct the PDEs, there is also a method of approximating some physical and chemical processes inside the battery, for

TABLE 2 Mathematical equations and boundary conditions of P2D model

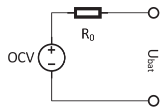
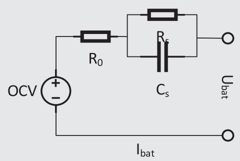
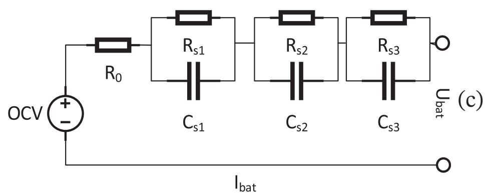
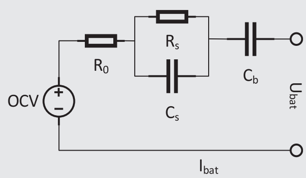
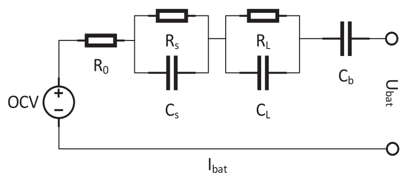
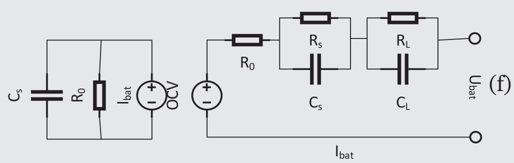
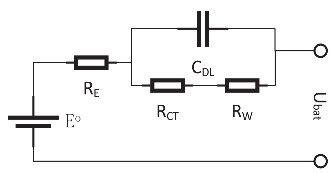
Description	Equations	Boundary Conditions
Solid phase charge conservation	$j^{Li}=\frac{\partial}{\partial x}\left(\sigma_s^{eff}\frac{\partial\varphi_s}{\partial x}\right)$	$-\sigma_-^{eff}\frac{\partial\varphi_s}{\partial x}\vert_{x=0}=+\sigma_+^{eff}\frac{\partial\varphi_s}{\partial x}\vert_{x=L_c}=\frac{I_{app}(t)}{A}$ $\frac{\partial\varphi_s}{\partial x}\vert_{x=L_n}=\frac{\partial\varphi_s}{\partial x}\vert_{x=L_n+L_s}=0$
Material conservation in solid phase	$\frac{\partial c_s}{\partial t}=\frac{1}{r^2}\frac{\partial}{\partial r}\left(D_s r^2\frac{\partial c_s}{\partial r}\right)$	$\frac{\partial c_s}{\partial r}\vert_{r=0}=0$ $D_s\frac{\partial c_s}{\partial r}\vert_{r=R_s}=-\frac{j^{Li}}{a_sF}$
Electrolyte phase charge conservation	$\frac{\partial}{\partial x}\left(k^{eff}\frac{\partial\varphi_e}{\partial x}\right)+\frac{\partial}{\partial x}\left(k_D^{eff}\frac{\partial \ln c_e}{\partial x}\right)+j^{Li}=0$	$\frac{\partial\varphi_e}{\partial x}\vert_{x=0}=\frac{\partial\varphi_e}{\partial x}\vert_{x=L_c}=0$
Material conservation in electrolyte phase	$\frac{\partial(\varepsilon_e c_e)}{\partial t}=\frac{\partial}{\partial x}\left(D_e^{eff}\frac{\partial c_e}{\partial x}\right)+\frac{1-t_+^0}{F}j^{Li}$	$\frac{\partial c_e}{\partial x}\vert_{x=0}=\frac{\partial c_e}{\partial x}\vert_{x=L_c}=0$
Butler-Volmer equation	$j^{Li}=k(c_e)^{\alpha_a}(c_{s,\max}-c_{s,e})^{\alpha_a}(c_{s,e})^{\alpha_c}\left\{\exp\left[\frac{\alpha_aF}{RT}\eta\right]-\exp\left[-\frac{\alpha_cF}{RT}\eta\right]\right\}$	

example, the single-particle (SP) model[38,51] where the battery electrode is regarded as a material particle for calculation.

The equivalent circuit model (ECM) refers to the use of circuit elements such as constant voltage source (indicating open circuit voltage), resistance (indicating the difficulty of electron and ion movement), and RC network (indicating the polarization inside the battery) to capture the *I-V* characteristics and transient behavior of the battery. This model provides a good trade-off between the characterization of the external dynamic behavior of the battery and the insight into internal or microscopic behavior. And ECMs are generally divided into two types: the ECM in the time domain and in the frequency domain.

The time-domain ECM establishes a circuit through capacitance, inductance, resistor, and other circuit elements to simulate the external characteristics like the battery terminal voltage and current. The model is widely used in electric vehicle management system for its few parameters and easy identification.[52] The time-domain ECMs are presented in Table 3. The simplest time-domain ECM is a structure, in which a resistor is connected in series with a voltage source. It is designed to describe the open circuit voltage of batteries, also known as the Rint model shown in figure (a).[65] This model is easily parameterized and integrated into battery performance simulation.[66] However, owing to the simplified form, the results react too quickly to capture the dynamics that occur inside the battery, such as charge transfer. To further improve the model accuracy is to add a parallel RC network in the circuit of a single resistance model, also called the Thevenin equivalent circuit model,[67] as shown in figure (b). This model can reflect the polarization between electrode and electrolyte and describe the battery dynamic behavior more accurately. And multiorder Thevenin equivalent circuit model was applied to a 47.8-kW LMO battery,[56,57] as shown in figure (c). Moreover, many people proposed some extended model for different situations on the basis of Thevenin model. Among them, the PNGV battery test manual added a series capacitor based on it to describe the performance of batteries under high-power pulse condition,[68,69] as shown in figure (d). For the battery composed of $LiFePO_4$, the response has a short-time and long-term characteristics. Tsinghua University put forward the GNL model and split the parallel RC circuit into two on the basis of the PNGV model, as shown in figure (e). The entire circuit includes a series resistor and two RC branches to consider the ohmic internal resistance, the electrochemical polarization internal resistance, and the concentration difference polarization internal resistance, respectively.[70] Min and Rincon-Mora[61] also introduced an ECM based on the predecessors. The left part was a capacitor and a current source, inherited from the Rint model, modeled the capacity, SOC, and runtime of the battery. The right part was similar to the GNL model, which was used to simulate the battery transient response, as shown in figure (f). The model combined characteristics and advantages of the aforementioned model to meet the accuracy requirements for battery runtime, steady-state characteristics and transient response analysis. These improved models can be called equivalent circuit models based on the Thevenin model. Besides, some researchers have proposed the dynamic equivalent resistance electrical model that used only one variable resistor to describe the battery electrical characteristics.[71,72] It mainly gives a reasonable method for the steady-state and transient battery modeling in the form of internal resistance as a function of current and DOD

TABLE 3 Schemes of battery time-domain ECM

Model Structure	Expression	Model Type	Model Variables	Refs.
 (a) Rint model	$U_{\text{bat}} = U_{\text{OCV}} - I_{\text{bat}} \cdot R_0$ U_{bat} is the terminal voltage, U_{OCV} indicates the open circuit voltage, I_{bat} is the discharging current, and R_0 is the Ohm resistence.	Analytic function	SOC, T, C-rate	Pathiyil et al[53] and Sibi Krishnan et al[54]
 (b) Thevenin model	$U_{\text{bat}} = U_{\text{OCV}} - U_{\text{s}} - I \cdot R_0$ R_s is the polarization resistance and C_s is the polarization capacitance U_s is the voltage of the RC network.	Analytic function	SOC, T, C-rate	Antaloae et al[55]
 (c) Multiorder Thevenin model	$U_{bat} = U_{OCV} - U_{s1} - U_{s2} - U_{s3} - I{\cdot}R_0$	Look-up table	SOC, T, C-rate	Dambone et al[56] and Benato et al[57]
 (d) PNGV model	$U_{\text{bat}} = U_{\text{OCV}} - U_{\text{b}} - U_{\text{s}} - I \cdot R_0$ C_b is the bulk capacitance.	Look-up table	SOC, T	Zhang et al[58]
 (e) GNL model	$U_{\text{bat}} = U_{\text{OCV}} - U_{\text{b}} - U_{\text{s}} - U_{\text{L}} - I{\cdot}R_0$ R_L, C_L are the concentration polarization resistance and capacitance.	Analytic function	SOC, T, C-rate, SOH	Saxena et al[59] and Serrao et al[60]
 (f) Improved model	$U_{\text{bat}} = U_{\text{OCV}} - U_{\text{s}} - U_{\text{L}} - I{\cdot}R_0$	Analytic function	SOC	Min and Rincon-Mora[61]
 (g) Impedance-based model[62]	$U_{\text{bat}} = U_{E^o} - U_{CT} - U_W - I{\cdot}R_E$ R_E is the electrolyte and electrode resistance, R_W is the linear ohmic characteristics, R_{CT} is the charge transfer, and C_{DL}electrochemical double layer effect.	Analytic function	SOC, T	Dai et al[63] and Greenleaf et al[64]

and has obtained satisfactory verification results in Na-beta family batteries.

The frequency-domain ECM also uses the same components to construct a circuit from the time-domain ECM. The difference is the principle of the constructed circuit, making the response of sinusoidal excitation in a certain frequency range coincide with the measured electrochemical impedance spectrum of the battery. And the idea is a simulation of battery impedance spectrum, not a description of battery terminal voltage and current. The relevant instrument measures the potential across a battery by applying small AC currants over a wide range of frequencies, and then a Nyquist plot is drew to show the complex impedance of the battery over the entire frequency range, as shown in Figure 3.[73] These features can be divided into three regions over the frequency range. The mass transport (ie, diffusion effect) in the low-frequency region from millihertz to hertz is similar to the linear ohmic characteristics. There is a semicircle in the middle of hertz to kilohertz, similar to the RC parallel circuit, which represents the charge transfer phenomenon at the electrode. The high frequency ranging from kilohertz to megahertz reveals the conductance effect, which is similar to the inductor characteristics. A frequency-domain ECM can be made on the basis of this plot, as shown in figure (g). The model more specifically abstracts the electrochemical reactions occurring in the battery and maps the physical meanings to the circuit components to make the components more practical. More comprehensive, meanwhile, there are also shortcomings such as large calculation and difficulty in parameters extraction, which restricts its application in battery state monitoring and management to some extent.[74]

Dynamic representation of electrical characteristics of the battery model depends largely on the expression type and variables selection. For instance, temperature, SOC, and charge and discharge rate, involving in model parameterization, will have a great impact on model accuracy. Table 3 also lists some literatures that use the ECM to reflect the electrical characteristics of battery from the aspects of model structure, expression type, and variable selection.

2.3 | Multiphysics modeling

The individual thermal or electrical properties are not sufficient to characterize all the properties of batteries. As a closed organic system, it is necessary to combine various physical characteristics with a more comprehensive vision for battery modeling.

2.3.1 | The coupling of thermal and electrical characteristics

The amount of heat, acting as the joint, directly affects the thermodynamic properties of the battery like the rate of temperature changes. Conversely, the battery temperature also affects the size of battery parameters, such as resistances, thereby changing the battery voltage characteristics. In general, the higher the temperature, the

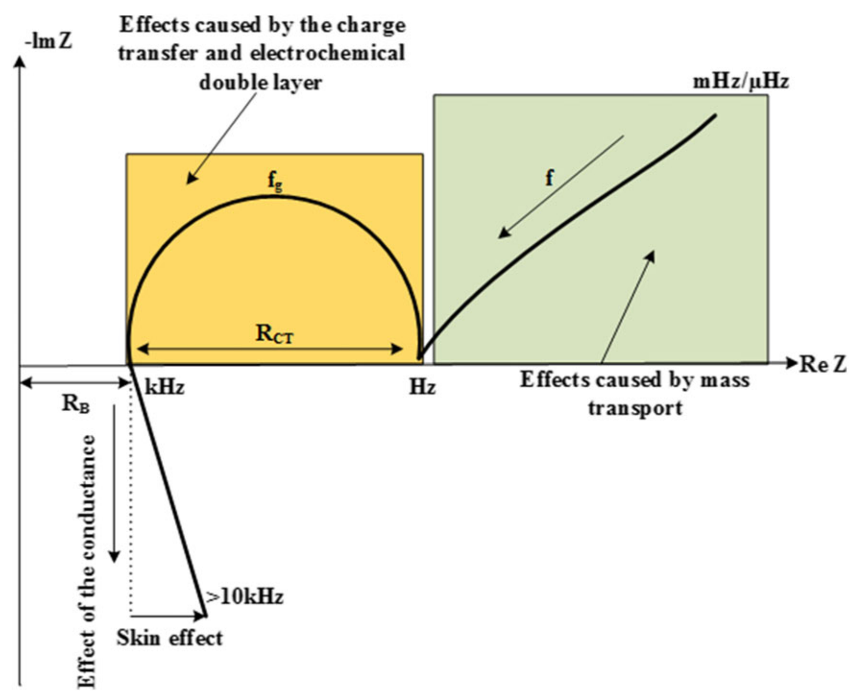


FIGURE 3 Typical Nyquist plot of a battery[73] [Colour figure can be viewed at wileyonlinelibrary.com]

smaller the internal resistance and the lower the battery voltage at a relatively load current. In order to fully reveal this coupling relationship and accurately simulate the dynamic characteristics of batteries, the development of a thermal and electric coupling model has a significant scientific and engineering application value.

Electrochemical-thermal coupled model, as one of the coupling forms, usually uses the electrochemical model as the electrical characteristic model and couples a thermal model based on the heat equations at the same time. Therefore, the model is all described by PDEs, which can reveal battery voltage and temperature response characteristics very accurately. The studies on the thermo-electric coupling characteristics of batteries are shown in Table 4.

In addition, there is the electro-thermal coupled model adopts ECMs as the electrical characteristic model and couples a thermal model to simulate the electro-thermal response of LIBs. This kind of model is relatively simple and easy to promote on real vehicles. Miranda and Hong[81] established the coupling model of Thevenin equivalent circuit model and thermal model for high-power $LiFePO_4$ batteries under normal temperature and achieved the estimation of the relative error in average temperature and voltage as 1% and 5%. In order to extend the temperature ranges of the model usage, especially for the low-temperature condition, Jiang et al[82] developed an electro-thermal coupled model with lower computation based on the frequency-domain ECM. The novel model yielded a promising candidate for developing the fast charging and internal heating strategy and stimulating the power batteries in cold weather. Besides, Ping et al[83] established a complete electro-thermal model that described variations in heat, voltage, and current throughout the entire transformation from normal running to thermal runaway. Results demonstrated that the model was helpful to predict the potential occurrence of thermal runaway and assist the BMS. As for the construction of pack model, a three-dimensional thermal model was built in Sun et al[84] for better understanding the thermal behavior of batteries under various operations. The approach comprised a pack-level CFD model and an electro-thermal cell-level model, which are in three dimensions, as well a one-dimensional battery network model. Thereby, it is possible to quickly predict the characteristic parameters of the battery, such as nonuniform heat generation rate, temperature distribution, and variations. The flow diagram of the calculation process is shown in Figure 4.

2.3.2 | The coupling of thermo-electric and aging characteristics

The battery aging, that is, capacity/power reduction, internal resistance increasing, voltage drop, and self-discharge is inevitable. And it degrades the battery performance and life. Through tracking of aging phenomenon, the prediction of the remaining life and health management of batteries can be completed. Therefore, the development of coupled models that consider aging is critical to assessing and improving the life of LIBs for EVs.

Like all electrochemical cells, LIBs consist of an anode, a cathode, an electrolyte, and a separator. In the charge and discharge cycle, lithium metal embedded in the carbon material is ionized and travels among the electrolyte, the cathode material, and the anode material

TABLE 4 Summary of Electrochemical-thermal coupled models used in literature

Modeling Dimension	Analysis Objects	Keywords	Ref.
1D electrochemical-thermal model	$LiFeP0_4$	Dynamic response analysis, effects of current collectors	Li et al[42]
	NCA	Cell performance prediction at various conditions	Basu et al[47]
	$LiCoO_2/LiMn_2O_4$	Terminal voltage and core temperature prediction for BMS	Farag et al[75]
2D electrochemical-thermal model	$LiFeP0_4$	Effect of contact resistances on thermal and electrical performance	Ye et al[76]
	$LiMn_2O_4$	Contribution of individual heat source terms and asymmetric tab configuration	Xiao and Choe[77]
3D electrochemical-thermal model	$LiFePO_4$	Tab location design	Xu et al[78]
	$LiFePO_4$	Analysis the anode's important meaning	Li et al[79]
	-	Interdigitated arrangements of the electrodes	Allu et al[37]
	NCA	Temperature prediction considering contact resistance and cooling for battery packs	Basu et al[46]
1D electrochemical and 3D thermal model	NCA	The influence of tab and contact resistance on battery thermal behavior	Ghalkhani et al[80]

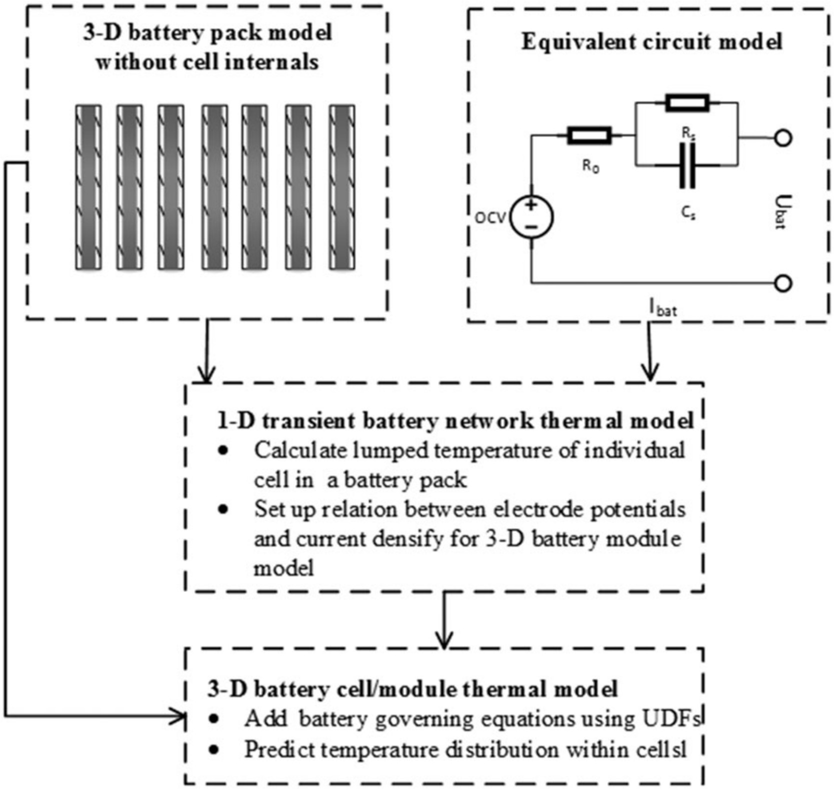


FIGURE 4 Typical Nyquist plot of a battery[84]

through the porous medium to release or accept electrons. From the microscopic point of view, the main factors affecting the aging degradation of LIBs are metal deposition, formation of passivation film, crack propagation, and dissolution of active material in the electrode.[85]

The porosity modification mechanism caused by the growth of the solid electrolyte interphase (SEI) film at the negative electrode was added to the electro-thermal model to develop the theoretical relationship between the battery capacity and performance attenuation in Prada et al.[86] The aging model covered the effects of different battery impedance changes, such as the SEI film resistance and the electrolyte mass transport resistance, as shown in the following formula:

$$R_{SC} = R_{ct}^{p} + R_{ct}^{n} + R_{SEI} = \frac{RT}{Fi_{0,p}S_p} + \frac{RT}{Fi_{0,n}S_n} + \frac{\delta_{SEI}}{\kappa_{SEI}S_n}, \quad (2)$$

where $S_p = 3\varepsilon_{s,\ p}\delta_p A/R_{s,\ p}$ and $S_n = 3\varepsilon_{s,\ n}\delta_n A/R_{s,\ n}$ are the electro-active surface areas of the positive and negative electrodes, respectively, and C_{LOSS} to be expressed as a function of the R_{SC} increase as follows:

$$\begin{aligned} C_{LOSS}(t) &= 100 \times \frac{Q_{z,init} - Q_z(t)}{Q_{z,init}} \\ &= 100 \times \frac{2F\rho_{SEI}\kappa_{SEI}}{M_{SEI}} \left(\frac{{S_n}^2}{Q_{s,init}} \right) \Delta R_{SC}. \end{aligned} \quad (3)$$

The data analysis pointed out that a degradation mechanism, such as cracking of the SEI film, would take an essential role in the driving cycles. However, the degradation occurring at anode was not considered at the above work, Kupper and Bessler[87] proposed a model framework, allowing the flexible multiphase electrochemistry approach to declare reactions of SEI formation at the anode. Besides, it also integrated a 0D model of the void volume to describe gas concentration and pressure variation when the aging happened. Ganesan et al[88] also selected a single typical model and scaled it through special factors to gain the response of battery pack and discussed the effect of negative electrode changes on the pack-level aging.

It can be seen that the microscopic factors affecting the battery aging are diverse and intricate, and the effect of various mechanism interactions even more so. From a macro perspective, battery aging can be divided into two parts: calendar aging and cycle aging. The significance of cycle aging is needless to say. For calendar aging, since 90% to 95% of the life of vehicles is in parking, it is also an important factor in battery aging.[89] In general, overcharge, overdischarge, high or low temperature, high SOC during storage, and high DOD would lead to a certain degree of capacity or power reduction, and these degradations are also macroscopic representations of several chemical and mechanical processes at the microscopic level. Therefore, a coupling model constructed by parameterizing different stress factors in combination with an electro-thermal coupling model was born. Wang et al[90] collected a large-span temperature, DOD and C-rates cycle test data of 2.2 Ah, 26650 cylindrical cells and summarized a general battery cycle life model as follows:

$$Q_{loss} = B \cdot \exp\left[\frac{-31700 + 370.3 \times C - rate}{RT}\right](Ah)^{0.55}, \quad (4)$$

where B is the preexponent factor and Ah is the Ah-throughput. Also lots of efforts have been made to understand the impact of different stress factors on battery aging; Table 5 lists some of the research status.

2.3.3 | The coupling of thermo-electric and mechanical characteristics

Except for electrochemical performance, the battery mechanical properties have gradually attracted people's attention, especially for manufacturing process. During the charging/discharging process, the volume change of electrode and the accumulation of mechanical stress in the battery are caused by the continuous extraction and insertion of lithium-ions. When stress is accumulated to a certain extent, the electrode may be broken, which reduces the durability of batteries. Therefore, it is necessary to add mechanical stress analysis for LIB modeling.

The different components of LIB have different the mechanical characteristics. For the example of qualitative analysis, the current collector has anisotropy, strain hardening, ductile fracture, and rate-dependent mechanical behaviors. And the separator is orthotropic, elasto-viscoplastic, and temperature dependent.[99] The mechanical behavior of a battery cell is not just the sum of the contributions of each component. Instead, it is the result of the mechanical interaction among various components. Golmon et al[100] proposed a multiscale modeling approach for studying electrochemical and mechanical interaction phenomena at macroscopic and microscopic scales. The electrochemical porous electrode models presented by Newman et al were extended to the macroscopic elastic deformations. The Butler-Volmer equation was used to explain the interface surface conditions and pressures of the composite cathode matrix at microscale. And the mesoscale was introduced into the aggregate model to relate microscopic and macroscopic mechanical effects. Sauerteig et al,[101] likewise, applied a coupled 2D electrochemical-mechanical model of LIB to study the volume change caused by intercalation and aging of electrodes. The calculation approach took into consider the electrode expansion, stress generation, the compression of electrodes and separator, and finally the lithium-ion transport. However, these approaches ignore the effects of thermal fields. Valentin et al[102] discussed thermal expansion leading to the mechanical stresses. A thermo-mechanical model was established to predict the thermal gradient and stress along the cell, especially at the material interfaces. And the stress level at the anode/copper and cathode/aluminum interfaces is shown to be stronger in LFP/graphite cells. Actually, the charge and discharge cycles of the battery contained coupling problems of electrochemical, mechanical, and thermal aspect, and whether thermal or stress field, each of them had a great effect on the electrochemical reaction. Duan et al[103] developed a similar multiphysical coupled model of the battery to describe the electrochemical properties, thermal and stress status under different operations. In addition to the conservation of charge, electrochemical kinetics, mass conservation, and energy balance in the well-known thermoelectric coupling model, mechanical conservation of the electrodes was also established. It also considered the effects of a common mechanical strain and two other eigenstrains. The stress state of

TABLE 5 Key elements of presented battery aging models

Type of Aging Considered	Stress Factors Considered	Model Output	Ref.
Cycle aging	C-rate, Temperature, SOC, Ah-throughput	Capacity loss	Shen et al[91]
	Initial capacity, SOC, Temperature	Internal resistance	Anseán et al[92]
	C-rate, Temperature, DOD	Capacity loss and internal resistance	Omar et al[93]
Calendar aging	Temperature, SOC	Capacity loss	Grolleau et al[94]
Calendar and cycle aging	Temperature, SOC	Capacity loss and internal resistance	Ecker et al[95]
	C-rate, Temperature, SOC,	Capacity loss and internal resistance	Prada et al[86]
	Temperature, DOD, , voltage, Ah-throughput	Capacity loss and internal resistance	Schmalstieg et al[96]
	Ah-throughput, Temperature, DOD	Remaining capacity	Onori[97]
	Ah-throughput, Temperature, SOC, C-rate	Remaining capacity	Serrao et al[98]

electrodes was obtained by the solid mechanical equations as follows:

$$\varepsilon_{ij} = \varepsilon_{ij}^{me} + \varepsilon_{ij}^{ei\_T} + \varepsilon_{ij}^{ei\_c}, \tag{4}$$

where $\varepsilon_{ij}^{me} = \frac{1}{E}\left((1+\nu)\sigma_{ij} - \nu\sigma_{kk}\delta_{ij}\right)$, $\varepsilon_{ij}^{eiT} = \alpha\Delta T\delta_{ij}$, and $\varepsilon_{ij}^{eic} = \frac{1}{3}\Delta c\Omega\delta_{ij}$.

Further, for the dynamic behaviors estimation and control, Oh et al[104] exploited a novel model for LIBs under actual vehicle operations, such as US06 duty cycle. The multiphysics model was mainly consisted of the following parts: an electro-thermal mode for estimation of the temperature and SOC of the battery, a swelling model for calculation the value of battery swelling, and a force estimator for figuring out the acting force of the variation of battery volume. In summary, the diagram of the multiphysical coupling model is shown in Figure 5. Electrical models are able to predict load voltage in response to the working conditions; thermal models are able to forecast real-time temperature in response to battery heat generation; aging models are able to dope out capacity or power loss in response to the different stresses; and mechanical models are able to predict structure stress in response to the internal and external pressure shock. According to what the model is intended to describe, a battery cell/pack model is composed of one or more coupled models.

3 | MODEL-BASED BMS APPLICATION

The first step is to choose appropriate battery model and algorithm for realizing the corresponding function of BMS. On the basis of this, this chapter briefly reviews the development of BMS from the aspects of state estimation, energy equalization, thermal management, and fault diagnosis.

3.1 | State estimation

BMS needs to monitor the key data, such as battery current and voltage, to estimate the state of batteries. This is the premise and basis for the implementation of other management algorithms. Battery state estimation plays a core role in the BMS. It mainly includes battery temperature, SOC, SOH, SOP/SOF, and SOE, wherein the temperature estimation can be referred to the thermal modeling chapter, other parameters are mutually influenced by the temperature parameters. For the relationship between various state estimations, see Figure 6.

The role of SOC in electric vehicles is similar to that of fuel gauges in traditional internal combustion engines.[70] SOH characterizes battery's ability to store energy relative to a new battery.[105] SOP indicates the ability of the battery to withstand the charge and discharge power. Some literatures are also called SOF, or peak power.[106] Compared with the above state estimation, there is less concern about SOE. It is a new concept proposed by academia in recent years, which represents the ratio of the battery current remaining energy to the nominal total energy.[107] These parameters has a direct effect on the battery life, the dynamic performance, and mileage range of vehicles. However, the state value cannot be measured directly; it can only be estimated indirectly using the battery model through terminal voltage, current, internal resistance, and other battery parameters.

The content of model-based SOC estimation method incorporates of two main parts: application of battery models and appropriate algorithm. The battery model is used to calculate the voltage, current and temperature, and the estimation algorithm evaluates the SOC.[108] At

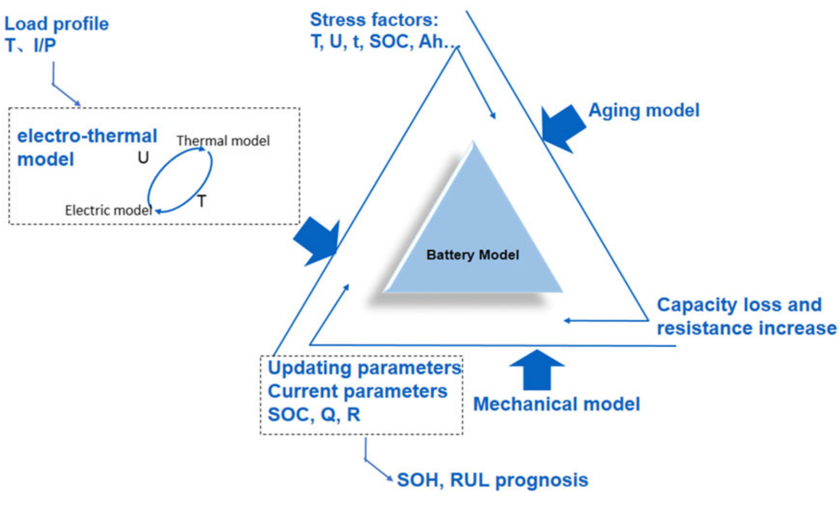


FIGURE 5 Electro-thermal-aging-mechanical model coupling [Colour figure can be viewed at wileyonlinelibrary.com]

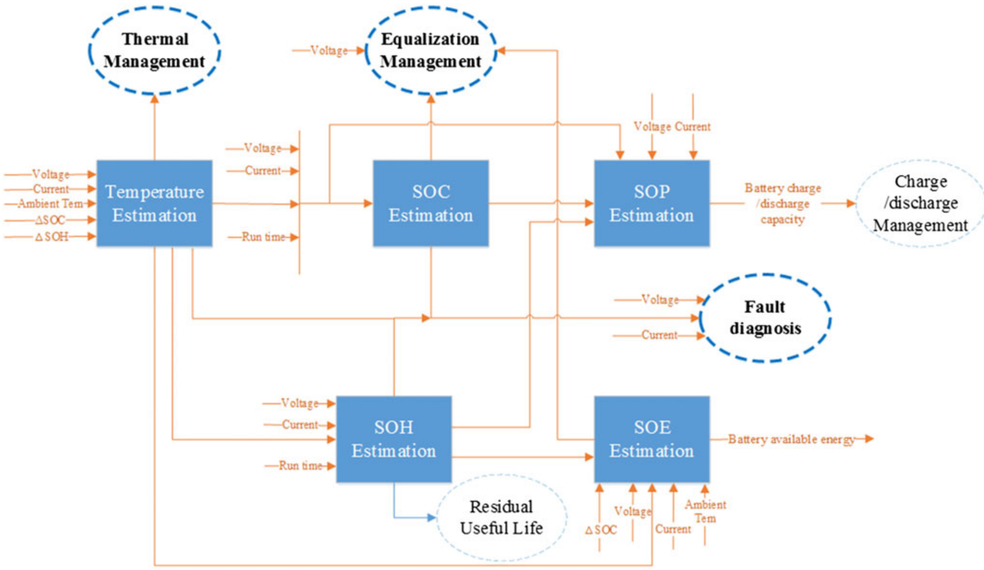


FIGURE 6 Battery state estimation algorithm framework [Colour figure can be viewed at wileyonlinelibrary.com]

present, there are two kinds of electrical battery models used in SOC estimation, namely, electrochemical model and ECM. Bizeray et al[109] used the orthogonal collocation method solve the DAEs of the P2D model, and a modified extend Kalman filter (EKF) was used to estimate the model. It is obvious that the method can rapidly recover the model states from the wrong initial conditions while maintaining high precision. In addition, based on the second-order ECM, Peng et al[110] combined the noise statistical estimator and the model parameter regulator to estimate the series-connected battery pack SOC using adaptive unscented Kalman filter (AUKF). At the same time, some mixed techniques, such as simple corrections and weighting, have also been proposed to avoid the defects of using a single estimation method. Li et al[111] implemented the high-precision and low-runtime online SOC estimation by utilizing the two algorithms according to the running time. When the initial error was large, the particle filter algorithm was adopted to decrease the convergence time. Or else the unscented Kalman filter algorithm was applied to gain on the actual battery SOC with low-computational cost. Figure 7 shows the SOC estimation errors of EKF, UKF, PF, and the combined method and the performance comparison of the four algorithms. The figure shows that the combined method displayed a good accuracy and trade-off among MAE, RMSE, and AET.

The method of SOH estimation based on the battery model is either from the perspective of internal parameters such as the aging mechanism, or from the external parameters such as the load conditions. Combined with the battery aging model, it is predicted by two kinds of the most common evaluation indexes: capacity loss and resistance increase. One of them is to create a degradation mechanism model from the nature of LIBs reaction. An electrochemical model has been developed to estimate the power fade of LIBs in Ramadass et al.[112,113] It uses an empirical formula to correct the growing rule of battery

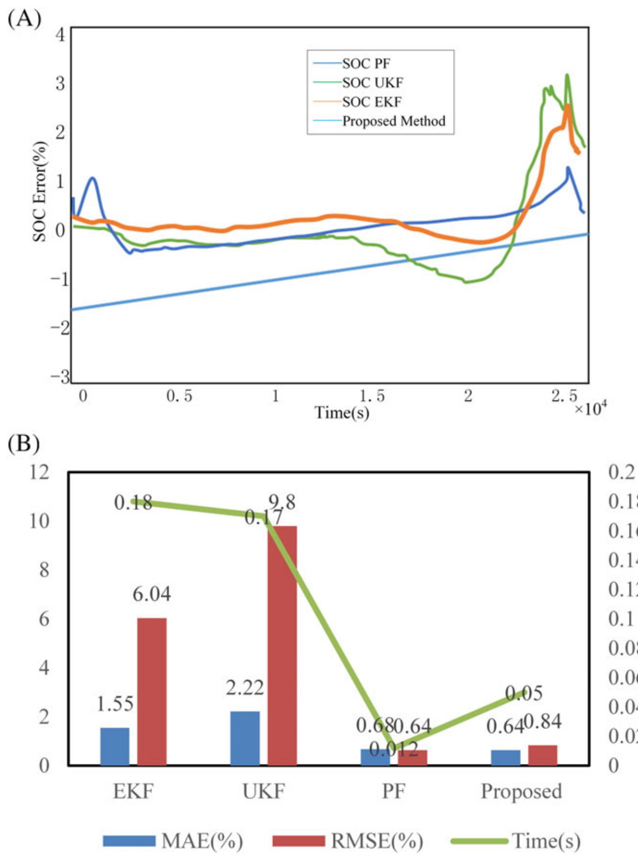


FIGURE 7 A, Comparison of state of charge (SOC) errors with an initial value of 100%. B, Comparison of SOC errors with a 10% initial value[111] [Colour figure can be viewed at wileyonlinelibrary.com]

SEI resistance and then estimates the SOH. It not only gives the discharge voltage characteristics of batteries but also reflects the influence of SOH and discharge current on capacity losses. The estimation method has a high prediction accuracy, a clear physical meaning, and a wide adaptability. However, the estimation process has a high complexity and a great dependence on the model, which makes the monitoring algorithm difficult to implement on low-cost microcontrollers. Therefore, another SOH estimation method based on the circuit model has drawn attention. The major idea is to use the optimal evaluation techniques, such as least squares method, and to combine the measurable state signals to identify parameters related to battery SOH. A novel approach deduced from ECM was proposed in Remmlinger et al.[114] The method utilized the internal resistance change as a judgment and combined the specific signal interval occurring in hybrid vehicle battery operation to realize the estimation of SOH. Dong et al[115] used the electrolyte impedance and charge transfer impedance to establish a capacity degradation model and to estimate the SOH and combined with support vector machine-particle filter to identify the model parameters. Shui et al[116] also proposed the evaluation of battery SOH based on the principles and the relationship among battery state parameters and mechanical characteristics like stack stress.

At present, SOF/SOP estimation generally acquires the maximum charge and discharge current according to the battery model, considering the current, SOC, and terminal voltage constraints of the battery, thereby obtaining the maximum charge and discharge power and the SOF/SOP. Plett[117] proposed two methods to estimate discharge and charge power that incorporate voltage, SOC, and current of the battery: one was the hybrid pulse power characteristic (HPPC) method; it used the open circuit voltage and internal resistance in the current state to estimate the instantaneous battery SOP, and the other method based on SOC was obtained the limit current value by the maximum and minimum SOC limits, thereby calculating the battery power state over a period of time. And the method can accurately predict the pack-level available power by using an appropriate cell model and SOC information. Zhang et al[118] also gave a method for estimating SOP from the battery cutoff voltage. It generally used a more accurate dynamic battery model (ECM, combined model, etc) to establish the state space equation of the battery terminal voltage, SOC, current, and other parameters. Then, the linearization was performed. The following solution was similar to the HPPC method. Finally, the battery peak power in the current state was calculated through the maximum current under limit of cutoff voltage.

By definition, the key to SOE estimation is to determine the current remaining discharge energy (E_{RDE}). The E_{RDE} refers to the energy that the battery can provide from the current state to the full discharge under certain operating conditions. And the E_{RDE} depends on battery terminal voltage, future conditions, and many other factors. Liu et al[119,120] proposed an energy prediction approach for the dynamic driving condition based on the valid control algorithm. On this basis, the variation of the future battery state and model parameters were coupled and predicted in the E_{RDE} prediction process. Specifically, the method further predicted the voltage variation of the future discharge process, and the cumulative energy was obtained by the first-order ECM. During the prediction process, the model parameters was modified according to the current measurement values, and the prediction results of the terminal voltage sequence and the E_{RDE} was updated. Moreover, as an example research of the embedded BMS, Wang et al[121,122] presented the E_{RDE} prediction method on the basis of the μC/OS-II real time operating system. And a model for SOE estimation was presented based on a first-order ECM and Bayesian learning technique. See Table 6 for more information on model applications in state estimation.

Meanwhile, the data-driven method, that is, neither considering the battery actual reaction nor requiring the accurate mode construction but paying more attention to the relationship between input excitation and target response, is proposed, promoted, and popularized along with the development of artificial intelligence. On the basis of some test data of the battery, the connection with the state parameters is established to make prediction. It mainly includes neuro-fuzzy approaches, SVM, regression technique, and other machine learning methods. Further analysis are as follows, such as artificial neural network (AN),[134] fuzzy neural network (FNN),[135] support vector machine (SVM),[136] relevant vector machine (RVM),[137] autoregressive model (AR),[138] and Gaussian PROCESS REGRESSION (GPR).[139] However, such algorithms rely on a large amount of experimental data for parameter integration to obtain better accuracy, resulting in long training time and low generalization ability. In addition, such research is mostly concentrated on single cell, and the prediction of the battery pack as a whole is less, and correspondingly, the amount of data and algorithm costs will also increase.

3.2 | Energy Equalization

The electric vehicle power batteries usually obtain high voltage in series and high capacity in parallel. However, due to internal reasons (the inconsistency of the physical

TABLE 6 Overview of battery model application in state estimation

Model	Estimation Parameters	Algorithm	Ref.
Equivalent circuit model	SOC	AEKF	Partovibakhsh and Liu[123]
	SOC	Sliding mode observer	Sun and Chen[124]
	SOC	Particle filtering	Wei et al[125]
	SOH	EKF	Bhangu et al[126]
	SOC SOH	Fitting on the data	Qiao et al[127]
	SOC SOH	dual unscented Kalman filter	Wang et al[128]
	SOC SOH SOP	least squares method	Shen et al[129]
	SOC SOE	EKF and an H infinity filter	Zhang et al[130]
Electrochemical model	SOC SOH	EKF	Bartlett[131]
	SOC SOH SOP	Electrochemical simplification algorithm	Han[132]
	SOE	AFEKF (adaptive fractional order extended Kalman filter)	Li et al[133]

volume in manufacturing process) and external causes (temperature difference of the whole package, energy imbalance caused by battery charge/discharge), the long-term cycle will lead to a decrease in battery capacity and life without the equalization management. The essence of the equalization is the redistribution of energy among the cells. It includes the circuit topology and strategy and complement each other. Topology is mainly divided into dissipative type, such as resistance equalization,[140] and nondissipative type, such as capacitive equalization.[141] In addition, there are equalization structures with inductors and transformers.[142,143] An excellent topology can achieve fewer components, more reliable structure, and easier control. And the quality of the equalization strategy directly affects its efficiency. Equalization strategies fall into three aspects: voltage, SOC, and capacity equalization strategies. In the process of R&D and production, the establishment of a battery model is fundamental and critical for reducing costs, avoiding measurement errors of voltage and realizing online acquisition of SOC and capacity.[144]

The early equalization strategy is mainly proposed for lead-acid battery. Since the voltage characteristic curve of the lead-acid battery has an obvious correspondence with the remaining power,[145] the correspondence relationship was used to judge the degree of the battery imbalance, and the consistency of the final battery voltage was used as a criterion for equalization. So this method is simply referred to as voltage-based equalization. Previous literatures[141,146,147] used voltage as the judgment standard. The measurable voltage, simple control algorithm, and low hardware requirements make this method be widely used in engineering. However, due to the existence of measurement error and hysteresis characteristics, it is difficult to achieve accurate equalization control according to the voltage. And when voltage equalization is achieved in a single aspect, the other parameters of the battery are still biased.

Compared with the voltage-based equalization strategy, the state of batteries can be better reflected by SOC. Owing to $LiFePo_4$, battery has a relatively flat relationship between SOC and OCV; the SOC can be evaluated on the basis of the tracking of OCV. Thus, Zheng et al[148] used the mean difference method to estimate the consistency of the battery SOC by the first-order equivalent circuit model. Besides, Zhang et al[149] also used this mapping relation as a basis for battery equalization and calculated the energy utilization ratio of batteries. Further, the Thevenin ECM and the EKF algorithm were employed for SOC estimation of the battery in Ma et al.[150] The two-stage bidirectional equalization circuit and the fuzzy logic control (FLC) were designed to achieve the equalization between battery cells in the battery pack. The diagram of the related method is shown in Figure 8. The proposed FLC algorithm was compared with the traditional mean difference method to verify the superiority of the developed one.

Again, researchers have proposed an equalization strategy on the basis of the total capacity, rechargeable capacity, or releasable capacity, whose goal is to maximize the available capacity of the battery. Zheng et al[151,152] built a first-order ECM in SIMULINK and verified the effectiveness of the dissipative cell equalization (DCE) strategy with remaining charging capacity (RCC) as the online estimation target. Furthermore, according to the battery voltage curve, a fuzzy logic DCE algorithm was used to reduce the battery pack capacity deviation effectively. In contrast, an active equalization approach on the basis of the available capacity of the battery was proposed to in Cui et al,[153] which was derived from the state space equation established by the second-order ECM. And a feedback balancing circuit was selected to modify the topology structure. The results showed that the proposed equalization strategy had more excellent performance in improving the capacity of battery pack than the other balancing benchmark methods. Moreover,

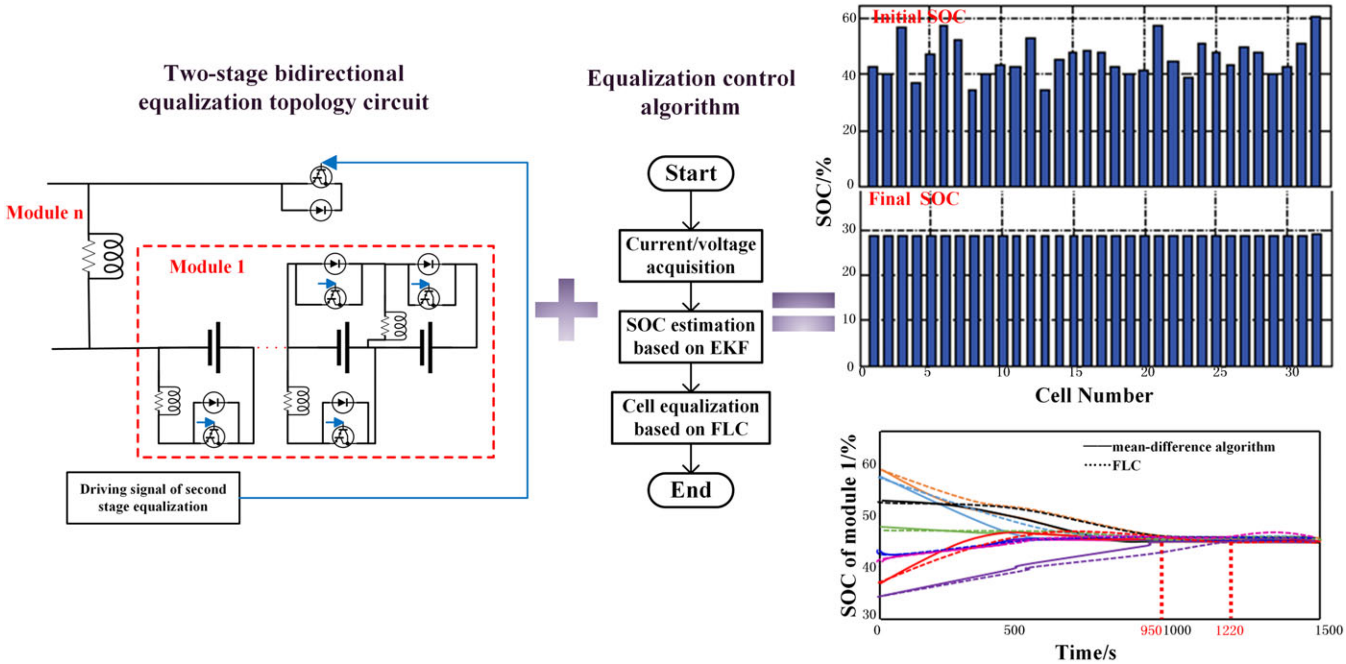


FIGURE 8 Diagram of the two-stage equalization method based on fuzzy logic control (FLC) for battery packs[150] [Colour figure can be viewed at wileyonlinelibrary.com]

Diao et al[154] presented a special active battery cell equalization technique based on the maximum residual available capacity, in which the change of internal resistance and capacity of a single cell in the battery pack was integrated by the Thevenin battery model. The DC/DC transformer equalization structure was verified by analyzing the experimental results in energy utilization efficiency.

3.3 | Thermal management

Temperature is an essential parameter affecting battery performance. The methods of changing battery electrolyte formulation or developing new positive and negative materials cannot balance the high- or low-temperature performance, and the difficulties are serious for battery packs. Therefore, analysis of the heat generation mechanism and temperature characteristics is of great significance for improving battery performance and safety. The battery model is not only to meet the detection demand of any temperature point but also to avoid the problem of delay in temperature transfer during actual measurement and to facilitate the efficiency of BTMS. The BTMSs have various structures and types, and the common cooling methods are shown in Figure 9.

The air cooling is simple in structure, low in cost, and easy to install, which is widely used in electric vehicles.[155] For example, the Toyota Prius hybrid vehicle used a parallel air passage to adjust the battery system temperature.[156] Yang et al[157] investigated the effects of radial spacing between batteries and gas flux on the thermal performance of the axial-flow air cooling structure. Through the numerical simulation based on the P2D model, the increase of the radial spacing made a better temperature uniformity and a smaller average temperature rise of battery pack, but the space efficiency was reduced. The liquid cooling is a relatively efficient and compact, using water, oil, or coolant as the heat transfer medium and the jackets or pipes on the bottom or side of batteries to remove the heat. A two-dimensional fully coupled electrochemical-thermal model for two different cell designs (8 and 20 Ah) was simulated with both air and liquid surface cooling in Bandhauer et al.[158] Despite the liquid cooling significantly reduced peak temperature across the battery, it imposed the difference in temperature. And as the cell size increased, liquid cooling exhibited an increased temperature gradient. Since liquid cooling is difficult to ensure the battery uniformity, PCM cooling has been proposed to improve the relative performance. Lazrak et al[159] exploited 1D and 3D modelling to analyze the effect of PCM thermo-physical properties and define an improved design with PCM integration in battery packs, respectively. Although the conventional PCM cooling can reduce the rise of temperature, the heat absorbed by PCM cannot be effectively diffused to the surroundings. Therefore, researchers have proposed a forced convection system in combination with PCM to eliminate heat accumulation,[160] or used composite phase

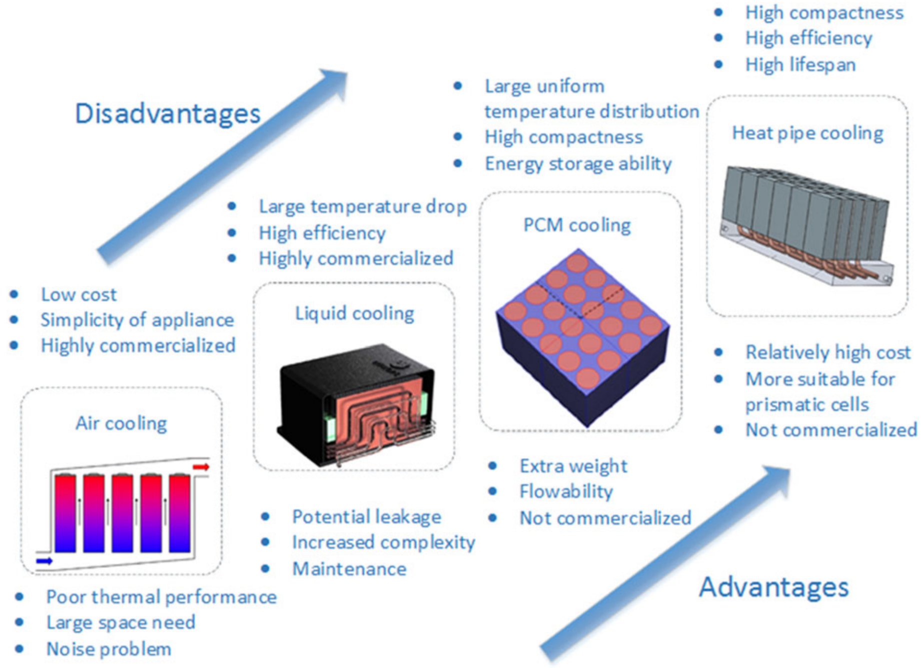


FIGURE 9 Common battery cooling methods and their pros and cons [Colour figure can be viewed at wileyonlinelibrary.com]

change materials to increase the PCM thermal conductivity.[161] What is more, the heat pipe BTMS is another compact, light, and high-efficiency alternative.[162,163] Because the mechanism and process of two phase flow in heat pipe are complex to model,[164,165] studies are primarily based on experiment. Zou et al[166] developed an integrated thermal management structure that incorporates a heat pipe type BTMS with an air-conditioning system to fulfill the comprehensive heat domination for EVs. Notably, some researchers have also proposed new BTMSs, such as jet cooling[167] and boiling cooling.[168] More importantly, due to insufficient vertical temperature gradient control caused by external cooling strategies at high heat generation, the internal cooling strategies were investigated to mitigate battery heat problems.[169,170] Bandhauer et al[171] utilized a passive liquid-vapor phase change heat removal inside micro-channels embedded into the cell to demonstrate the possible performance improvement based on a 3D electrochemical-thermal model. Figure 10 shows the maximum temperature rise and difference for the internal cooling simulations as compared with the traditional air and liquid cooling reports in Bandhauer et al.[158] Based on the three-dimensional thermal swelling model with coupled thermo-mechanical, Oh and Epureanu[172] indicated the elevated core temperature and uneven temperature distributions play a vital role in the performance of the battery pack. This model is beneficial to the design thermal management of battery packs, as well as the development of stress-strain sensors and the optimal configuration.

It is universally acknowledged that the heating mode of battery pack can be divided into external heating and internal heating. The former uses an external electric heating devices, such as positive temperature coefficient (PTC) heater, to heat the battery pack.[173] And the heat transfer mode used is the same as the above-mentioned cooling structure. The heat transfer medium can be air or liquid. Due to the existence of heat exchange with the external environment, some of the heat will be lost to the air and also may lead to the uneven temperature of batteries. The latter uses internal resistance heat by the pulse current, which the temperature increase is faster and the consistency is better. Zhu et al[174] indicated that except for the amplitude and frequency of current, the wave shapes also had an effect on the heating efficiency as well. For example, the sinusoidal current heated the battery from −24°C to 7.79°C, while the rectangular pulse waveform was heated from −24°C to 25.6°C at the same condition in their investigation. All of these methods consume energy to heat the battery, thereby sacrificing battery capacity.

3.4 | Fault diagnosis

If state estimation is the basis for other functions, then security is the common and most basic goal for all. Generally, the evolution mechanism of LIB safety is divided into two cases. One is the reduction in reliability caused by self-aging. As mentioned earlier, this is a slow process

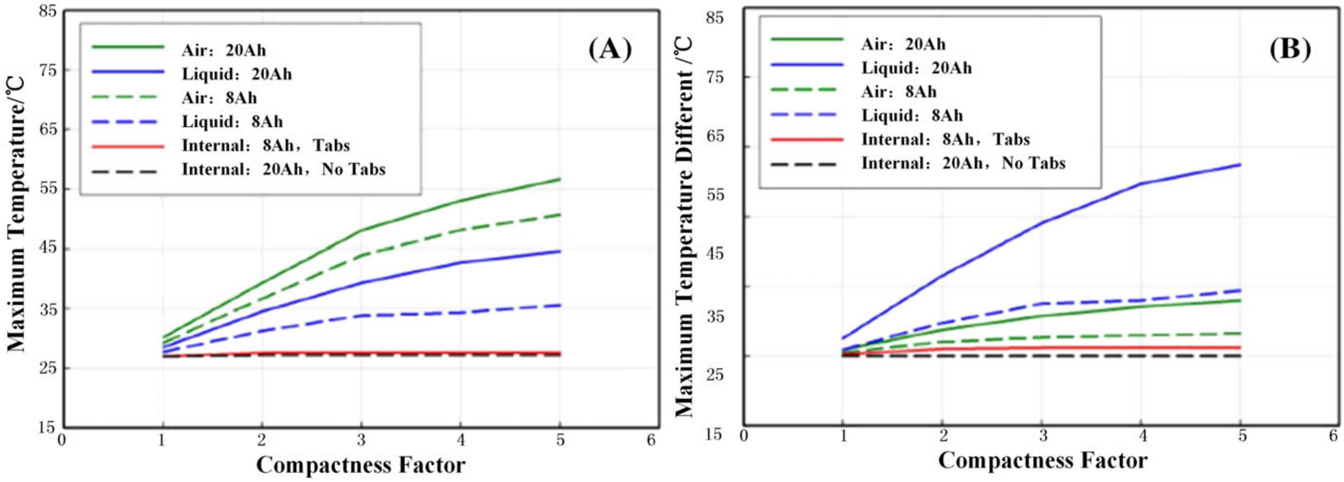


FIGURE 10 Comparison of internal, air, and liquid cooling strategies at different compactness factors: A, maximum temperature; B, maximum[171] [Colour figure can be viewed at wileyonlinelibrary.com]

of change for the LIB aging mechanism. The other is a sudden failure of LIBs. With regard to technologies to enhance battery safety, most of the safety techniques in the former are related to the production of battery manufacture. The latter is created by some unexpected events, even a safety accident. The BMS is required to promptly warn of the failure that has occurred or will occur and give a corresponding response according to the severity (terminating battery charging or discharging, limiting battery power or reporting alarm, etc). The LIB safety mutation mechanism mainly caused by external mechanical trigger (such as vibration, extrusion) and environmental trigger (such as high temperature, high humidity), causing short circuit of the battery, forming an electrical trigger (such as internal or external short circuit), which leads to a thermal trigger (such as overheating) even thermal runway.

According to the signal collected by BMS, the main faults of power system are as follows: voltage fault, current fault, temperature fault, SOX fault, insulation fault, short-circuit fault, and the like. These critical functions rely deeply on measurements of embedded current and voltage sensors. However, sensors may experience various forms of failures due to production defects, prolonged exposure to wretched conditions, and external shocks. Liu and He[175] proposed a valid model-based fault diagnostic scheme to determine if there was current or voltage sensor issue. The EKF was applied to calculate battery terminal voltage based on ECM, and the carrying fault signals were obtained by comparing the observed voltage with the evaluated. It also pointed out the conventional method of the model-based battery fault diagnosis, which was to obtain residual signals and process fault information by the difference between the model's prior information and the measurement information from the diagnostic object. Ouyang et al[176] used the same method to analyze the short-circuit fault in the battery. A recursive least square algorithm based on the mean difference model (MDM) deriving from ECM, which consisted of the average and difference of a cell voltage and resistance, was employed. The algorithm first estimated the basic parameters of the MDM, and then calculated the characteristic values, like the voltage differential and the fluctuation function of internal resistance, and finally made short-circuit diagnosis according to the magnitude of fluctuation. For the LIBs, current and voltage can only reflect the external characteristics, and the dynamics characteristics need to be described by internal state variables such as SOC and SOE. The diagnosis of these parameters can only be represented by modeling, and see Section 3.1.

Gradually, researchers found that the battery internal resistance is sensitive to the battery health state or fault state, so some fault diagnosis methods based on resistance value have been born. Wang et al[177] quantitatively estimated the insulation resistances at anode and cathode, and troubleshooting was performed by the change of insulation resistance value. Zhang et al[178] focused on the parallel-connected battery group (PCBG) and used the PCBG resistance as a standard to identify PCBG faults and their causes. For an online aging inconsistency fault and a loose contact fault, the fault can be detected by distinguishing the difference of the single resistance among PCBGs. In terms of the reasons of the problem, it was implemented by discriminated the changes in the PCBG resistance.

Apart from the resistance, Feng et al[179] extended the diagnostic parameters and proposed a novel diagnosis approach for online internal short-circuit detection. The method converted the battery voltage and temperature into the inherent state (SOC) and parameter (ohmic resistance), respectively, reflecting the incompatible capacity and heat loss. Kong et al[180] also detected the short diagnosis according to the RCC variations between batteries. The RCC of each cell can be obtained by the CC-VC conversion, then the leakage current was obtained by the change of RCC after each cycle, and it would be further turned into the short-circuit resistance. The experimental devices and results are depicted in Figure 11. We can see that the normal and short-circuit cell were distinguished obviously. The short-circuit resistances varied little with time, and the estimated average resistances had very small error compared with the actual. The method did not identify state parameters of the battery during the diagnosis process and can be simply and credibly assembled into the actual BMS. Unlike the usual fault diagnosis approaches, the fault severity was evaluated based on the size of short-circuit resistance. From another perspective, Zhu et al[181] developed a detailed finite element model to cover the geometry and mechanical properties of almost all components of a cell. Through the accurate analysis of mechanical behavior, it found that a short circuit occurred at a displacement of 4 mm during axial loading. In addition, Tsutsui et al[182] further refined the failure mechanism and pointed out that the mechanical deformation alone could not predict battery failure well, and both SOC and deformation need to be considered. At low SOC, the electrical performance failure of the battery was closely related to voltage drop, and it stood alone against the external deformation stress. However, at high SOC, a premature voltage drop was born, attributing to the swelling phenomenon inside the battery and the tendency of the anode and cathode contact.

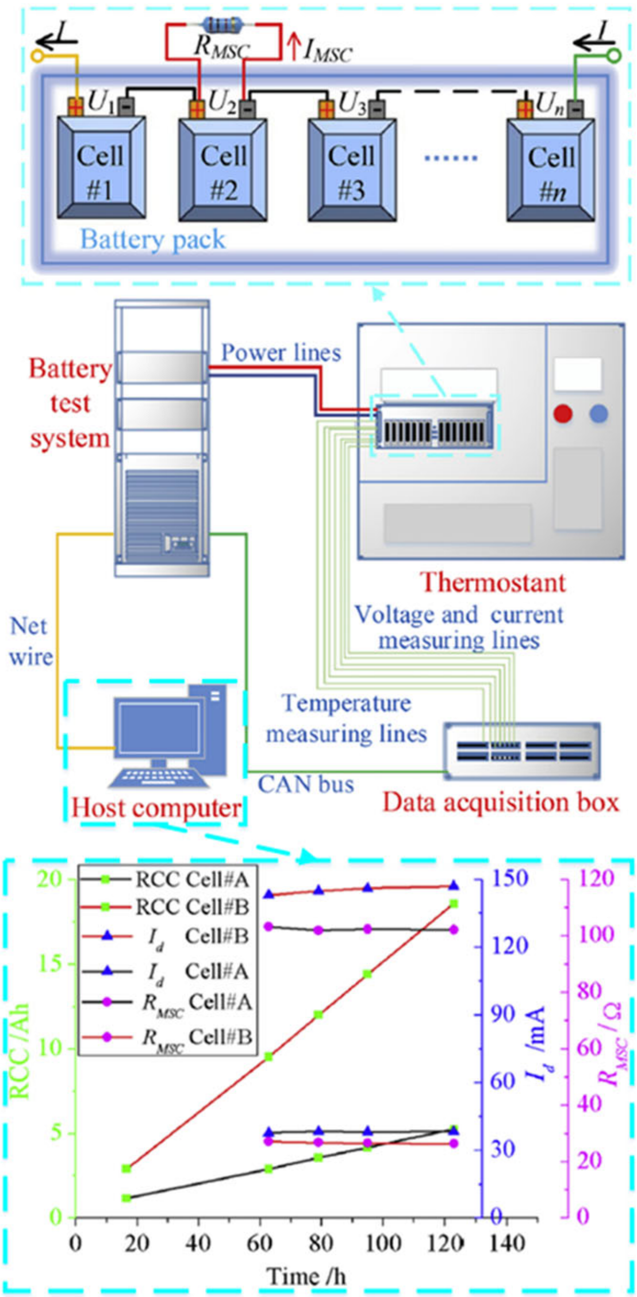


FIGURE 11 Diagram of test principle and results[180] [Colour figure can be viewed at wileyonlinelibrary.com]

4 | R&D OF BMS FUNCTIONALITY AND INTEGRATION IN VEHICLES

Faced with the complex conditions of vehicles and the diverse demand from users, the R&D of multifunction integrated BMS system is an inevitable requirement for the electric vehicle battery technology. While ensuring its various functions are carried out efficiently and orderly, the cooperation with other controllers is the guarantee of performance and safety at the vehicle level. The following is developed from multifunction and multicontroller integration based on BMS.

4.1 | Multifunction application

If a fixed series-parallel battery topology is devoid of any active management systems, the system is unable to adapt to the dynamic behavior of battery cells thus causing the following: possibilities of overcharge and overdischarge, cell unbalance, fluctuation of temperature across battery pack, and minimized energy conversion efficiency. Furthermore, LIBs itself degrades over time, even if the system is left unused. They are very sensitive systems, and the aforementioned problems may cause severe safety issues, such as thermal runaway and overheating caused by explosion. The BMS must be multifunctional in the actual application, which requires the cooperation of hardware and software technology. Some OEMs and suppliers have carried out a lot of researches

TABLE 7 Summary of the representative BMS

Manufacturers	BMS Functions
Mentzer Electronie GmbH and Wemer Retzlatf in Germany[183]	BADICOACH System ●First vehicle–experiment ●Voltage, temperature and current measurement of 20 batteries ●Control of charging current of charger ●Single cell equalization
Tesla Motors[184-187]	●Monitoring and Management of 7104 Lithium Batteries ●Acquisition and estimation of voltage, current, SOC, and insulation signals ●Thermal management and safety protection system ●Low cost passive equalization
Bosch Rexroth Group[188-191]	●Data stratified acquisition ●Radio network remote transmission signal ●Invalid or depleted battery isolation system ●Startup or initialization judgment
Axeon UK Ltd	●Transferring information to the host ●Data recording ●Diagnosis and prediction ●Error and alarm functions
AeroVironment	SmartGuard System ●Distributed mode of collection parameters ●Automatic overcharge monitoring ●Battery history and archiving ●Provide information about the worst cell
Toyota Motor Corporation[192-194]	●Suppress battery imbalance ●Judgment of battery maintenance and replacement needs

on the key technologies of on-board BMS. Table 7 lists some of the more representative R&D results.

Then again, some scientific institutions have also made corresponding explorations. The University of Toledo[195] presented a typical battery system. This particular version included an electronic control unit (ECU) that monitored the battery pack real-time situation and assured the data collection, processing, and transmission. And an equalizer (EQU) balanced the charge levels of the battery segments and controlled an onboard charger. Compared with the above system, the BMS system developed by Korea Ajou University and Institute for Advanced Engineering[196] has fully considered the control and protection of charging/discharged, the calculation and display of SOC, thermal management, communication with the PC and the motor controller, etc, as shown in Figure 12.

Based on the existing BMS techniques, there are more and more studies focusing on the smart battery modules (SBMs) to promote the development of a generalized design method. That is, a microcontroller is installed in a battery module and integrated with relevant circuits and then packaged them as a whole. A plurality of SBMs are connected to a main control module, and other auxiliary devices are added to constitute a SBMs-based management system. Hong Kong University of Science and Technology[197] discussed the development of an original BMS platform consisting of multiple local management units for power supply, voltage and current detection, and central management unit as an interface between internal BMS network and external components. It can provide a full management to a pack with up to 16 batteries. And the military electric vehicle BMS developed by American Micron Corporation adopts this prototype and Hnatczuk et al's.[198]

On the basis of the basic functions of BMS above, Chatzakis et al[199] provided additional functions, a fault-tolerant capability and battery protection, with the same structure, and Figure 13 shows a block diagram of this typical BMS topology. Zhu[200] proposed an intelligent BMS with an updated system that inherited the functions of the traditional BMS. This BMS was capable of storing and analyzing the measurement data in order to detect battery failures and improve the battery safety by shortening the measurement and communication time intervals. Carkhuff et al[201] applied multifrequency impedance measurement technology (1-1000 Hz) to the BMS. Except for the conventional voltage, temperature, and internal impedance monitors, it can track faults associated with anode, cathode, and electrolyte to identify battery mismatches and emerging faults. And real-time monitoring of changes in each battery was acted, including charging/discharging, as well as at rest. Further, through a physics-based battery model, Prada et al[202] studied the BMS specifications law that can be generalized to different lithium-ion chemistries batteries. The model can not only effectively implement the BMS traditional functions, including battery limitations in terms of potential, current, temperature, and aging mechanism, but also indicate the charge and discharge allowable current limit at different temperatures under safety and the SOC estimation for a given pulse duration according to vehicle operation.

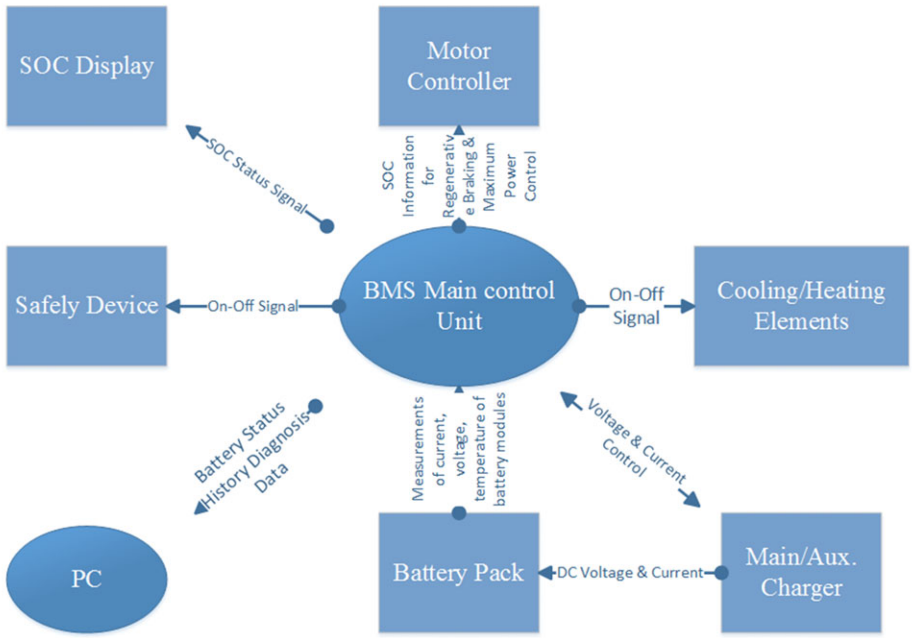


FIGURE 12 Schematic structure of battery management system (BMS)[196] [Colour figure can be viewed at wileyonlinelibrary.com]

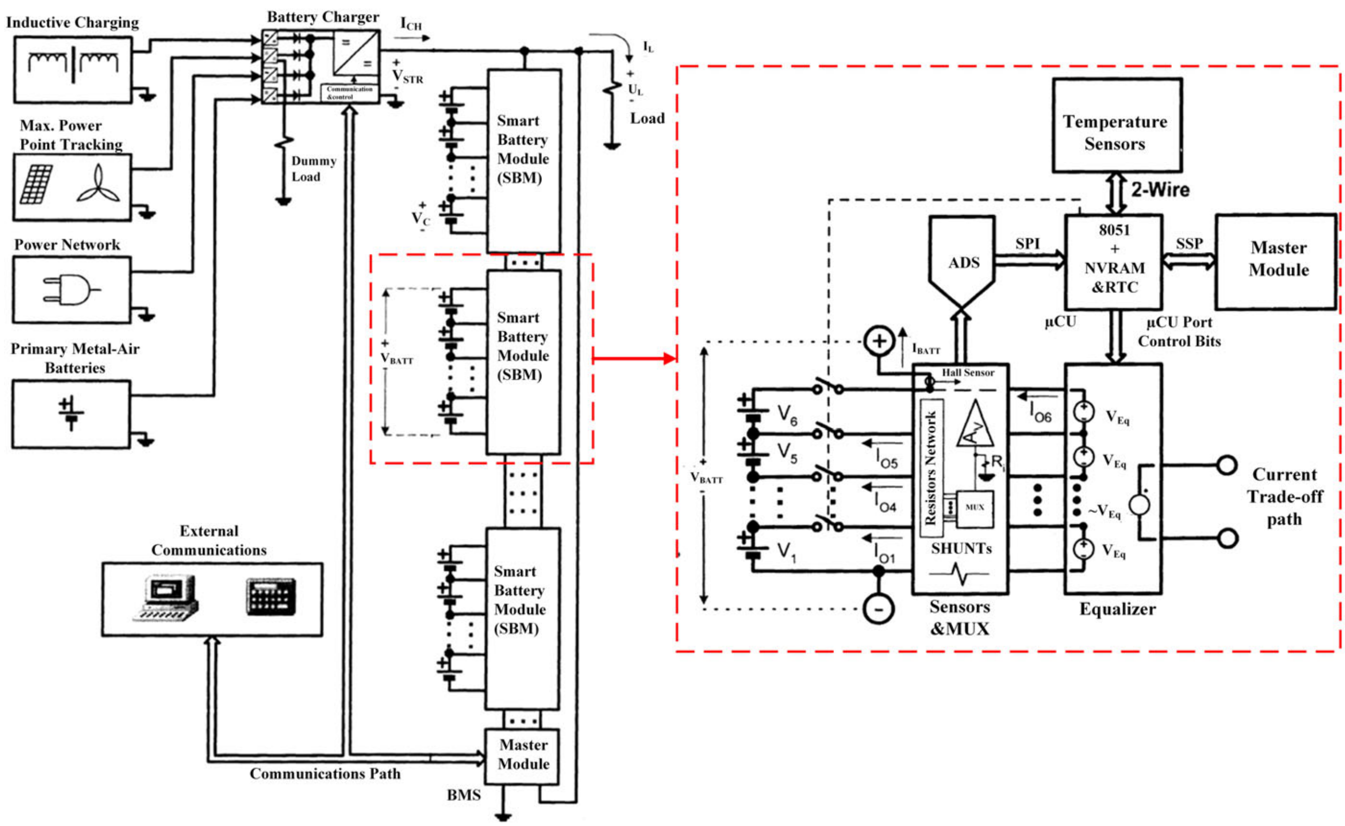


FIGURE 13 Block diagram of a typical battery management system (BMS) topology[199] [Colour figure can be viewed at wileyonlinelibrary.com]

4.2 | Multicontroller interaction

Internally, BMS takes battery modules as the control object to ensure their order and safety. It only realizes the supervision of the power source level. Externally, BMS provides operating status of power batteries for the whole vehicle and works in conjunction with other on-board controllers to ensure the optimization and improvement of energy control management for vehicles. This is a nonnegligible link in the development of establishing a complete BMS.

The most used energy control management method for EVs in engineering is based on the stability of motor, engine (HEVs), and other components, according to the driver's acceleration and braking requirements, vehicle and battery status, etc to switch the power system working mode. A vehicle power management system was provided to minimize the number of components for the parallel connection of sub battery packs through integrating a power relay assembly (PRA) with a power distribution unit (PDU) by HYUNDAI Motor Co, Ltd.[203] The integrated battery pack included sub-relays placed in the sub-battery packs, a sub-BMS that controlled the sub relays, and a main BMS for managing the whole power of the sub-battery packs. The PDU included a PRA for selectively connecting voltages inputted from the integrated battery pack with an electric load of a vehicle. Wang[204] also disclosed a parallel charging and power supply system for EVs, composed of multiple power system and an energy storage system, to increase the traveling mileage of electric vehicles. The BMS was used for monitoring the voltage and the current of battery unit and realizing hybrid control on battery unit with a conversion module. The interaction mode among MCU, VCU, and BMS was the same as the traditional form. Unlike pure electric vehicle energy control management research, hybrid electric vehicles mostly focus on selecting and switching control strategies for pure electric mode, hybrid mode, engine working mode, and feedback braking mode. Combined with the user's requirements, BYD Company Ltd[205] presented a control system based on battery SOC as an automatic conversion standard. As for the technique whether the hybrid vehicle should transition between the EV mode or HEV mode, Kia Motors Corporation[206] checked the driver's requisite torque calculated by monitoring the accelerator position sensor, the gear position sensor, the determined engine on map value, and the hypothetical map value.

In addition to the conventional power transmission control, the battery pre-charge communication,[207] power up and down of the whole vehicle,[208] and so on are inseparable from the coordination of various controllers. Up to present, the team has explored the battery modeling and its application in battery thermal management, and the communication and control between the heat pump system and BTMS by BMS and VCU.[209,210] On the basis of conventional battery modeling, the SEI decomposition in superheated state was considered, and the battery model from normal to overheated under adiabatic condition was established. The based-refrigerant cooling and emergency jet cooling system was added to the common liquid thermal management system. And the cascade cooling was used to ensure the battery thermal safety. For example, when the battery is in an overheated state, the temperature curve of the test battery (18650) from normal state to superheated state is as shown in Figure 14. Under adiabatic conditions, the battery initial temperature was 25°C, and the temperature reached a maximum of 125°C at 4000 seconds. The side reaction starts from 60°C and as it continues, the battery temperature changes from a proportional increase to an exponential one. When refrigerant was used to spray the battery pack at 60°C, the temperature rising is effectively suppressed.

Despite the rational construction of vehicle energy management framework, the control strategy is also important to improve the energy-saving level of the electrification vehicles. The above control method for realizing the related functions is widely used in engineering practice because it is effective, simple, and easy to implement. However, they cannot optimize the system operation and cannot fully utilize the energy-saving potential of EVs and HEVs. Therefore, intelligence automobiles have become another important trend in the development of EV industry. In recent years, due to the great progress in technologies such as machine vision and deep learning, the development of advanced assistant driving and autonomous, or "self-driving," vehicle technologies has been promoted. At present, there are many researches on vehicle environment perception,[211,212] intelligent driving, and interaction,[213,214] but there are few studies on applying intelligent technology to vehicle energy-saving control. Other than considering the fuel economy of the vehicle, Montazeri-Gh et al[215] also considered the impact of the control strategy on the vehicle's

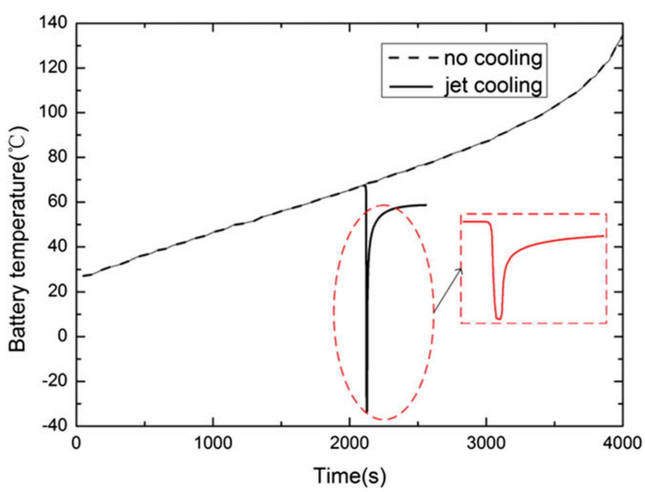


FIGURE 14 Battery temperature curve [Colour figure can be viewed at wileyonlinelibrary.com]

emission performance: According to the engine critical control line and the battery SOC, the working mode was divided into two steps. Firstly, the fuel consumption, hydrocarbon, carbon monoxide, and nitrogen oxide emissions were normalized as the optimization target, then genetic algorithm was used for optimization, and the optimized control strategy was improved in fuel economy and emission performance. Meanwhile, particle swarm optimization (PSO),[216] DIRECT algorithms,[217] etc were also used to optimize or adjust the relevant parameters of energy management strategy (EMS). Further, intelligent information provided by global positioning system (GPS)/intelligent transport system (ITS) also plays an important role in energy management. Kim et al[218] used GPS to predict future driving conditions and then used dynamic programming algorithms for rolling optimization to obtain an optimized EMS. Gong et al[219] exploited ITS and neural networks to predict the trend of future vehicle speeds and then used dynamic programming algorithms for energy optimization and power allocation. Moreover, learning-based energy management strategies from recorded historical or driving data have also been developed.[220,221] The internet of vehicles can transmit the vehicle and traffic information back to the cloud platform and then use the technologies such as cloud computing to learn and optimize EMS. Take HEV as an instance, Figure 15 discloses the key procedures of EMS in the vehicle control system and gives example of future speed prediction. Obviously, whether learning from historical data or predictive information, these EMSs still require more precise control models and expert experience. The development of these intelligent

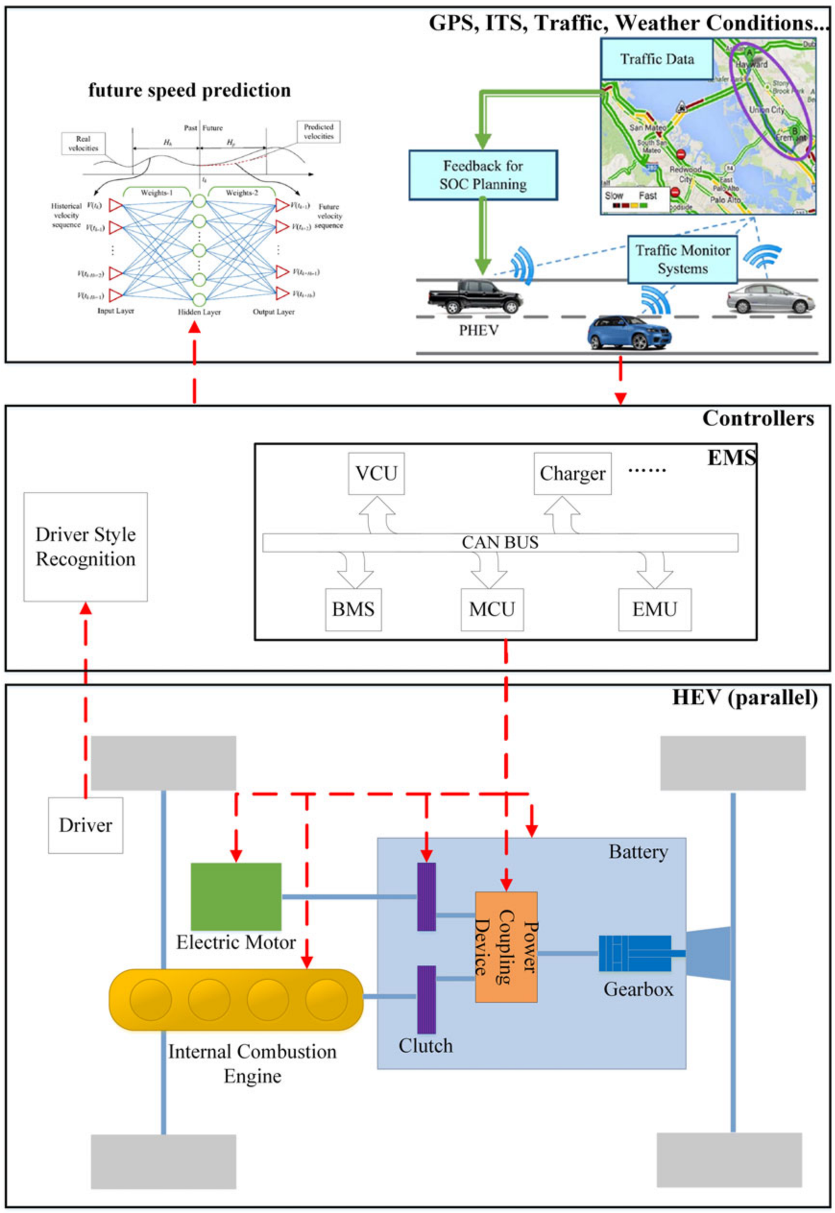


FIGURE 15 A block diagram of energy management strategy [Colour figure can be viewed at wileyonlinelibrary.com]

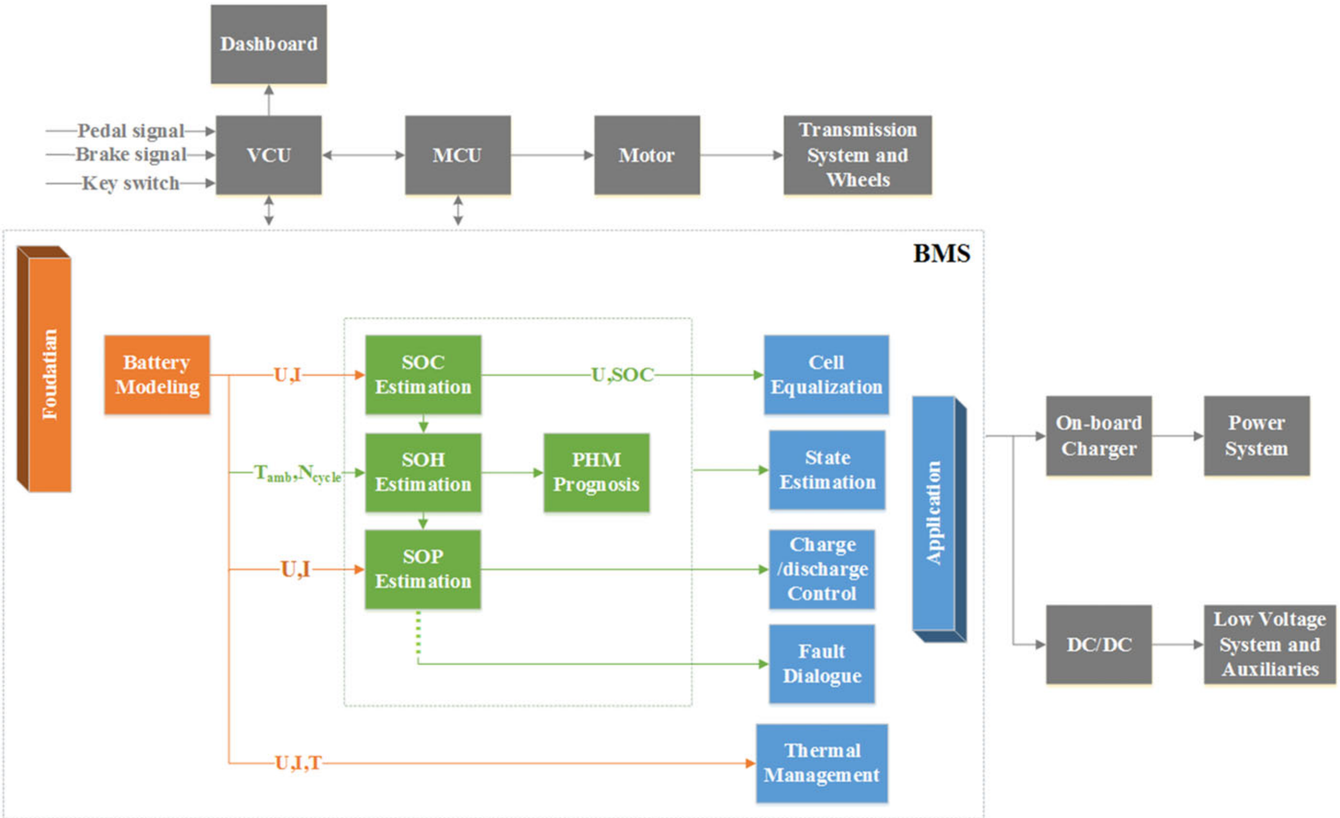


FIGURE 16 Diagram of battery management system (BMS) from multiphysics modeling to multifunction application and integration [Colour figure can be viewed at wileyonlinelibrary.com]

technologies has certain enlightening significance for the research of electric vehicles energy management.

Lithium-ion power battery and its control technology are either the key or the bottleneck of EV progress. Power battery is the core of energy output, and the control technology is integrated in the BMS. A set of vehicle control development process on BMS from multiphysics modeling to multifunction application and integration is shown in Figure 16.

5 | TASKS AND CHALLENGES IN THE FUTURE

As a link between power source and vehicle, state-of-the-art algorithms and control approaches about BMS are developed and used in EVs in order to promote the innovation and development of new energy vehicle techniques. Nevertheless, there is still a long way for BMS to go,[3] and the user suspicion of the reliability of BMS needs to be addressed through future research caused by the gap between laboratory tests and actual demands. In view of the synergistic improvement of BMS under complex conditions, this paper proposes the following guidance from the battery model to BMS function application and integration.

Battery is a combination of electrochemistry science, materials science, thermal science, and mechanical science. Regarding it as a multiphysics field is necessary and an inevitable trend. There are several key issues and challenges in the future construction of coupled models for EVs and HEVs:

1. It improves the accuracy of battery lumped thermal models. By referring to the internal mechanism to explain battery thermal phenomenon, the lumped model is modified and optimized, and the simple and accurate online algorithm is integrated into the BMS to identify and manage the battery internal and surface temperature.
2. It is the organic combination of the circuit model and the mechanism model in battery electrical model. The relationship between the equivalent components or fitting parameters and electrochemical parameters is established to obtain an electrical model that can not only reflect the internal chemical characteristics but also retain the certain ability of fast and dynamic tracking.

3. It is the development of parameters of battery aging model. By increasing other performance parameters (such as overvoltage and heating rate) except for capacity loss or internal resistance increase, the statistics of the effect of complete parameters on aging are gradually realized.
4. The mechanical model should be added to the coupling model in the form of mechanical internal/external stress or internal gas pressure equation, so as to facilitate the establishment of a universal, modular model to switch the form for different application conditions and battery material types.
5. The adaptive model should be developed to update or modify itself and to realize more accurate on-line model parameter identification and vehicle control.
6. The above problems are not only the situation faced by the single cell but also the battery pack needs to solve. Meantime, the random variability of the battery, the electric topology, the battery thermal management, etc should be taken into consideration. The system model is combined with the aging propagation dynamics to establish a battery system model on the basis of the performance and state parameter evaluation of individual cells.

The growing demand for EVs, user-friendly functions, safety-restricted design, wireless communication and etc are enormous innovations that offer a great deal of growth opportunities in this organic system, while there are several key issues and challenges in the process:

1. In terms of traditional functions, the state estimation as the basic function should pay more attention to the accurate estimation under a wide range, multiple temperature condition to meet the demand of full operating mode.
2. In order to achieve the improvement of charge and discharge efficiency, meanwhile, it is necessary to take into account of minimizing the damage to the battery itself during the process in equalization technology. And the simplification of the equalization topology, the consideration of multiparameters algorithm are necessary to avoid the overcharge and overdischarge of batteries.
3. Prediction and location of fault diagnosis. In the early period of the failure of the system, many features are not reflected. If the fault prediction of energy storage system can be realized by the weak characteristics in the early stage, the fault of the system can be detected as soon as possible. At the same time, battery packs consist of dozens or even hundreds of cells in series and parallel. Determining how to quickly locate faults and isolate them in complex energy storage systems is a significant topic for future research.
4. A good trade-off between BMS versatility and complexity. The increasing requirements of luxury functions, such as environment control and intelligent driving, create more obstacles for factories to develop a BMS that enable to make system more appropriate while dealing with additional features.
5. BMS manufacturing standards. With the increasing demand of diversification, intelligence, and high-end, a lot of manufacturers provide a BMS with diverse specifications that enormously limit the industrial production and application of products. Manufacturing standards are urgent to be established to develop a BMS with comprehensive functions, anti-interference, low-energy, high integration for expanding cascade, and generality for promotion.
6. As a complex power machine, the electric vehicles need BMS to interact with VCU, MCU, and other control units in real time. In this process, applying intelligent algorithms to the energy management of electric vehicles is also an effective way to improve the energy utilization rate.

Despite the upgrade of software technology, there is also lots of progress room for improving the hardware. The sensor layout is reasonable, the cost is low, and the overall detection balance is good; the sensor type is complete, and the ultrasonic pulse diagnoses the internal electrochemical abnormality. What is more, when the software algorithm is more difficult to simplify and the historical data storage is huge, the sensor based on the internet cloud computing is used to realize the remote data transmission, which greatly improves the hardware simplification of BMS. We can not only design EMSs based on intelligent algorithms but also use advanced intelligent traffic information such as GPS/ITS to predict road traffic information for a period of time in the future, thereby predicting the vehicle speed, acceleration and deceleration behavior, and so on.

In recent years, autonomous driving technology is also rapidly developing, and many emerging automobile enterprises generally develop autonomous driving systems based on the EV platforms. The combination of autonomous driving technology with the electrification technology is bound to deal with the issue of coordinated control between the autonomous driving system and the EV system. Determining how to analyze their coupling relationship, how to build an integrated model of intelligent EVs, and how to carry out multisystem integrated control of intelligent EVs, these problems are urgently needed for intelligent EVs, especially for self-driving EVs.

Finally, the research and technology mentioned is mainly for LIB (traditional LIB). There are still many efforts on new high-energy density systems, like solid-state LIB with high safety, replacing current organic electrolytes and separators,[222] high-temperature NAS battery, ZEBRA battery with low cost and long life, lithium-sulfur battery with friendly environment,[223] and price and metal-air battery without charging.[224] Among them, the core technology of high-temperature NAS batteries is ceramic preparation and high-temperature insulation. It is widely used in the infrastructure construction of large-scale storage,[225] stable power grid, and emergency energy supply. At present, the NAS battery produced by Japan NGK Corporation has a relatively complete management system. It can realize continuous remote monitoring and 3-year thorough inspection, reaching unattended and fully automated state.[226] ZEBRA battery, also with a high-temperature system, is used in automobile. It is a fully enclosed system that includes packaging and essential BMS, providing an interface to VCU.[227] The industrialization of the remaining battery systems has had some application obstacles at present. The solid-state LIB mainly depends on the breakthrough of material technology, ie, the mature preparation technology of solid electrolyte membranes. The key to the development of ZEBRA battery is the solution for low conductivity and volume change of sulfur, and the "shuttle" of lithium sulphide. Most metal-air battery is the issue of electrode corrosion and self-discharge. The research of energy storage equipment has never been interrupted, and commercialization and industrialization will be gradually realized through continuous in-depth research and optimization design.

6 | CONCLUSION

There are a multitude of researches and technologies in the field of BMS range from the simplest monitoring to a complex controller. Consequently, a large number of papers on this topic have been published in the art, and some of them are analyzed in this review.

First and foremost, this paper has summarized techniques of battery modeling from a multiphysics perspective. Among them, the thermal model is mostly coupled with the electrical model for modeling. When coupled with the equivalent circuit model, it is mostly used in the electric vehicle management system, while with the electrochemical model, it is common in the internal characteristics research of the batteries. Advances in improving and reducing electrochemical models will certainly be a strong candidate for further increasing the accuracy while ensuring a simple algorithm. Meanwhile, the model built by the influence of aging phenomenon and mechanical stress is a more comprehensive and realistic consideration of batteries and is also a requirement for the development of the battery modeling technology in the future.

Furthermore, this paper, on this basis, has deepened the application and development of BMS. It involves the acquisition of unmeasurable state parameters, the expansion of the equalization index except voltage for optimal battery status, the avoidance of temperature transfer delay for timely thermal management, and the improvement of diagnostic accuracy for vehicle safety. Among them, the battery state estimation is the basis for the operation of the other functions of BMS, and the accuracy of prediction results will directly affect the normal implementation of the management system. Meanwhile, SOC or capacity as an equalization standard for engineering, reasonable coupling of advanced battery thermal management system with other systems, such as air-conditioning and motor thermal management system, as well as location, isolation or alarm after fault determination still need to continue to explore. Besides, the appropriate selection of model and algorithms should be reflected in accordance with the relevant conditions.

Last but not the least, this paper has reviewed the development of the multifunctional integrated battery management system, combining with other on-board controllers and intelligent technology, to form a complete idea from multiphysics modeling simulation to multifunction integrated technology. The higher the sophisticated functional requirements, the greater the computational burden. Consequently, a generalized development rule or manufacturing standard about BMS is waiting to be solved. It puts forward several reasonable suggestions to realize the synergetic efficiency of the BMS under the diversified and intricate conditions and to promote the innovation and development of new energy vehicles from electrification to intelligence.

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