Front. Mech. Eng. 2019, 14(1): 47–64
https://doi.org/10.1007/s11465-018-0516-8

REVIEW ARTICLE

Kailong LIU, Kang LI, Qiao PENG, Cheng ZHANG

A brief review on key technologies in the battery management system of electric vehicles

Abstract Batteries have been widely applied in many high-power applications, such as electric vehicles (EVs) and hybrid electric vehicles, where a suitable battery management system (BMS) is vital in ensuring safe and reliable operation of batteries. This paper aims to give a brief review on several key technologies of BMS, including battery modelling, state estimation and battery charging. First, popular battery types used in EVs are surveyed, followed by the introduction of key technologies used in BMS. Various battery models, including the electric model, thermal model and coupled electro-thermal model are reviewed. Then, battery state estimations for the state of charge, state of health and internal temperature are comprehensively surveyed. Finally, several key and traditional battery charging approaches with associated optimization methods are discussed.

Keywords battery management system, battery modelling, battery state estimation, battery charging

1 Introduction

Electric vehicles (EVs) and hybrid electric vehicles (HEVs) have been widely regarded as the most promising solutions to replace the conventional internal combustion (IC) engine-based vehicles, and the recent years have seen a rapid development of EV and HEV technologies. Batteries have been widely applied as the power supply for EVs and HEVs due to the advantages such as high energy density, low environmental pollution and long cycle life. On the other hand, batteries require particular care in the EV applications. Improper operations such as over-current, over-voltage or over-charging/discharging will cause significant safety issue to the batteries, noticeably accelerate the aging process, and even cause fire or explosion [1]. Therefore, the battery management system (BMS) plays a vital role in ensuring safety and performance of batteries.

Key technologies in the BMS of EVs include the battery modelling, internal state estimation and battery charging. An effective battery model is crucial in battery behaviour analysis, battery state monitoring, real-time controller design, thermal management and fault diagnosis. Besides, some battery internal states, such as state of charge (SOC), state of health (SOH) and internal temperature, cannot be measured directly, while these states play important roles in managing the operation of batteries, and thus need to be monitored using proper estimation methods. Further, battery charging is also of great importance in BMS due to its direct impact on the operation safety and service availability of battery. A well-designed charging strategy will protect batteries against damage, limit temperature variations as well as improve efficiency of energy conversion. Slow charging has negative effect on the availability of EV usage, but charging too fast may adversely lead to large energy loss and temperature rise [2]. Large temperature variation further leads to rapid battery aging and even causes overheating or supercooling, which will eventually shorten the battery service life [3].

This paper aims to give a brief review of the key technologies especially for battery modelling, state estimation and battery charging in the BMS of EVs. Recent approaches to tackle the problem of battery modelling of the electric and thermal characteristics are surveyed first. These established battery models are used to capture battery electric and thermal behaviours. Then the

Received September 30, 2017; accepted January 9, 2018

Kailong LIU, Kang LI (✉)
School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, BT9 5AH Belfast, UK
E-mail: kliu02@qub.ac.uk; k.li@qub.ac.uk

Qiao PENG
School of Physics and Optoelectronic Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, China

Cheng ZHANG
IDL, Warwick Manufacturing Group, University of Warwick, CV4 7AL Coventry, UK

corresponding independent or joint state estimation methods of battery SOC and internal temperature are also reviewed. On the basis of battery models and estimated internal states, battery charging approaches are discussed, together with optimization algorithms for improving the performance of these charging approaches.

The remainder of this paper is organized as follows. Section 2 discusses some typical battery types used in EVs and key technologies for BMS. Then battery electric models, together with thermal models as well as coupled electro-thermal models are reviewed in Section 3. Section 4 focuses on a comprehensive review of the battery SOC estimation, SOH estimation, internal temperature estimation and joint state estimation. Then several traditional charging approaches and their optimization methods are discussed in Section 5. Finally, Section 6 concludes this paper.

2 Battery types and key technologies for BMS

In EV applications, many types of battery can be adopted as the power supply. There are a number of functional modules in the BMS. Some popular battery types and key technologies for BMS are analysed and summarized in this paper.

2.1 Battery types in EVs

Batteries are generally grouped into two categories based on the ability of recharging: Primary and secondary battery. The primary battery can be just used once after being fully discharged, and the secondary battery is capable of being recharged after discharging process. For the applications of EVs and HEVs, the secondary battery with long cycle life, small energy loss, high power density and enough safety level is indispensably required. Some popular types of batteries used in EVs include lithium-ion (Li-ion), lead acid, nickel-cadmium (NiCd) and nickel-metal hydride (NiMH), etc. Table 1 illustrates some key characteristics for these popular battery types. It is clearly shown that Li-ion battery is significantly better than other types of battery, especially in terms of large cycle life which is key to long service of EVs (e.g., 6–10 years' service life). Besides, Li-ion battery is also composed of eco-friendly materials without toxic gassing problem and has high safety level. Therefore, Li-ion battery becomes a most popular power supply for EVs.

2.2 Key technologies for BMS

On the other hand, battery needs particular care in the EV applications. Incorrect operations such as too high or too low temperature, over charging or discharging will speed up the degradation process of battery dramatically. Besides, battery pack in EVs is generally composed of hundreds of battery cells connected in series or parallel configuration to satisfy the high power and high voltage requirement for the vehicles. Particular care also needs to be taken to operate such a complicated battery pack. Therefore, a proper BMS is crucial in protecting batteries from damages, which needs be carefully designed [4,5]. In this paper, some key technologies including battery modelling, battery state estimation and battery charging which are required in designing an effective BMS in EVs will be surveyed. The relationship of these key technologies is illustrated in Fig. 1. In the applications of EVs, battery current and voltage can be detected by on-board current sensor and voltage sensor directly, and surface temperature of battery pack can be also detected by temperature sensor or thermocouple conveniently. Then the well-trained battery models together with suitable estimation methods can be adopted to achieve independent or joint state estimations of battery SOC or internal temperature. After capturing battery electric and thermal behaviours, battery charging approaches can be optimized by proper optimization algorithms, and further to charge battery from initial state to final target with the equilibration of various charging objectives such as fast charging, high efficiency of energy conversion and low temperature rise. If any abnormal situations of battery states occur in the operation process, the alarm module and safety control module will work to record or eliminate these cases accordingly. Therefore, battery modelling, state estimation and battery control are vital technologies in the BMS, and

Table 1 Popular types of battery in EVs

Battery type	Service life /cycle	Nominal voltage/V	Energy density /($W\cdot h\cdot kg^{-1}$)	Power density /($W\cdot kg^{-1}$)	Charging efficiency/%	Self-discharge rate /($\%\cdot month^{-1}$)	Charging temperature/°C	Discharging temperature/°C
Li-ion battery	600–3000	3.2–3.7	100–270	250–680	80–90	3–10	0 to 45	–20 to 60
Lead acid battery	200–300	2.0	30–50	180	50–95	5	–20 to 50	–20 to 50
NiCd battery	1000	1.2	50–80	150	70–90	20	0 to 45	–20 to 65
NiMH battery	300–600	1.2	60–120	250–1000	65	30	0 to 45	–20 to 65

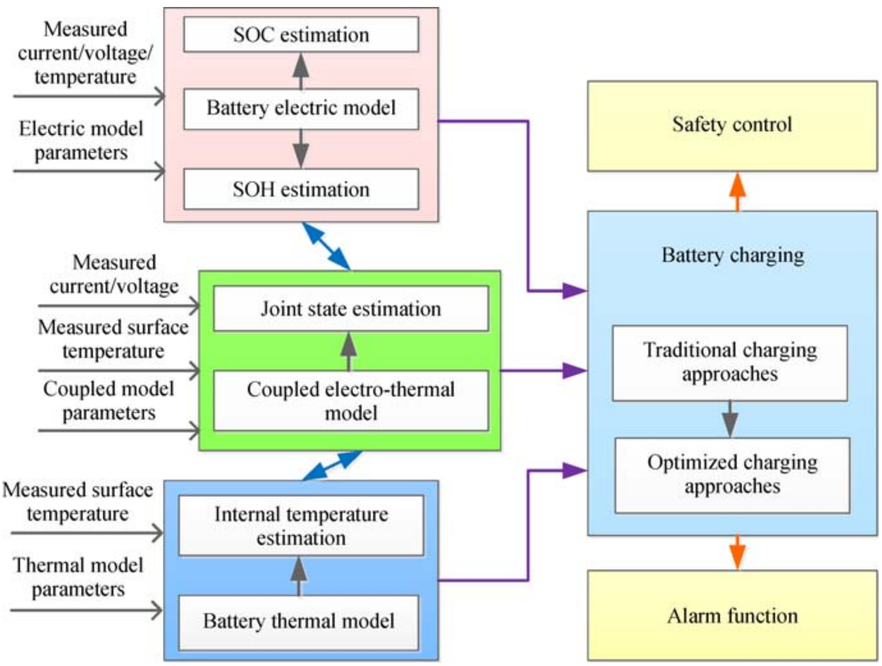

Fig. 1 The relation of key technologies in the BMS

these technologies become the thriving areas of research in the applications of BMS/EVs.

3 Battery modelling

Building a proper model is usually the starting point for BMS design, control and optimization. Over the years, numerous battery models with various levels of accuracy and complexity have been developed. These models can be primarily categorized as the battery electric model, battery thermal model, and battery coupled model, which are detailed in Fig. 2. Other model types such as battery kinetic models that are far less used in BMS are not covered in this paper.

3.1 Battery electric model

Battery electric models mainly include electrochemical model [6–9], reduced-order model [10–13], equivalent circuit model [14–17] and data-driven model [18–20]. For electrochemical model, Rahman et al. [6] claimed that the battery electrochemical model should have the abilities to capture the spatiotemporal dynamics of battery concentration, the electrode potential for each phase and the Bulter-Volmer kinetic to control intercalation reaction. Then an electrochemical model is established to describe battery electrochemical behaviours by using particle swarm optimization (PSO) method to optimize critical model parameters. Sung and Shin [7] showed that the electrochemical model presented a highly accurate prediction performance but required significant computation effort in model simulation. Then a model implementation scheme was developed to embed electrochemical model into the BMS. The main advantage of using electrochemical model is that a highly accurate description of electrochemical processes within the battery can be obtained. However, many parameters relating to the battery electrochemistry such as chemical compositions need to be identified, which is practically difficult to achieve in real-time applications. Besides, these electrochemical models usually involve many partial differential equations which need to be solved, resulting in large computational overheads. By making suitable assumptions, the full-order electrochemical models can be approximated by reduced-order models. For example, Han et al. [10] proposed an approximate method to capture the solid phase diffusion and electrolyte concentration distribution of battery, then a simplified physics-based electrochemical model is developed to estimate Li-ion battery SOC. Zou et al. [11] proposed a reduced-order electrochemical model for $LiFePO_4$ battery to predict discharging capacity under various conditions, then robust SOC estimation was achieved based on this reduced-order battery model. Although this approach leads to some information loss in the simplified reduced-order models, they are more desirable for real-time applications of batteries. The computational overheads become much lower for reduced-order models, and the corresponding parameters can be identified by the measured current and voltage signals. For equivalent circuit models, battery electric behaviours have been captured by a combination of circuit components, such as resistances, capacities,

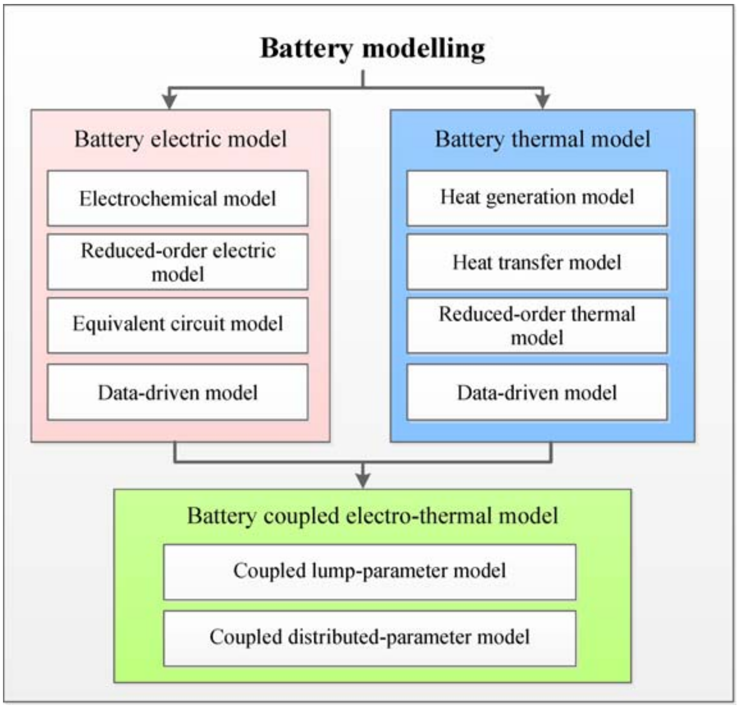

Fig. 2 Three classifications of battery modelling

voltage sources. Because of simple model structure and relatively small number of model parameters, equivalent circuit models have been widely adopted in battery real-time applications. A typical framework of battery equivalent circuit model is illustrated in Fig. 3. The resistor-capacitor (RC) networks in equivalent circuit model are related to the battery electric behaviours such as charge transfer or diffusion processes. The number of RC networks is treated as the model order, and need be carefully selected. It has been shown that the first and second order models are more popular, and higher order models in many cases are not necessary [14]. Nejad et al. [15] presented a critical review for commonly used battery lumped-parameter equivalent circuit model. Comparison results show that the RC network models have better dynamic performance especially for SOC and power predictions. Data-driven models try to capture the relation between input and output signals of batteries. Various data-driven models such as neural networks [18,19] and support vector machine (SVM) [20] have been adopted to describe battery electric behaviours without the prior knowledge. The performance of battery data-driven model is highly dependent on the test data as well as training approaches. To achieve acceptable model accuracy as well as good generalization ability, test data should cover enough battery operation ranges, and the parameters in the training approaches need to be effectively tuned. Besides, the adaptive data-driven approaches [21,22] can be used to achieve better battery modelling results.

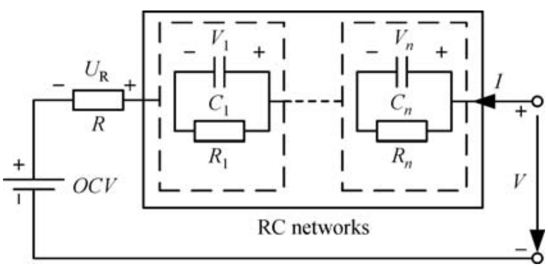

Fig. 3 Typical framework of a battery equivalent circuit model

3.2 Battery thermal model

Thermal behaviour such as temperature is also a key aspect in the BMS of EVs because temperature plays a vital role in battery performance and lifetime [23]. Various models such as heat generation model, heat transfer model, reduced-order thermal model and data-driven model have been developed to capture the thermal behaviours of batteries. For the heat generation model, a number of methods are introduced to describe the heat generation in battery, such as activation, concentration and ohmic losses, which distribute non-uniform inside the battery. Three popular approaches to assess the heat generation in the batteries are illustrated in Eq. (1), which have been widely applied in real-time applications [24–27].

$$\begin{cases} Q_1 = RI^2 \\ Q_2 = I(V - OCV) \\ Q_3 = I(V - OCV) + IT\dfrac{\mathrm{d}OCV}{\mathrm{d}T} \end{cases}, \tag{1}$$

where R is the battery internal resistance, I and V stand for the battery current and voltage, respectively, OCV is the battery open circuit voltage, Q_1 stands for the battery heat generation which is primarily caused by the large current crossing the battery internal resistance, Q_2 stands for the battery heat generation caused by the over-potentials across the RC network, Q_3 stands for the battery heat generation caused by both the entropy change and Joule's heating.

For battery heat transfer, heat convection, heat conduction and heat radiation are the three main forms within and outside the battery. Guo et al. [28] developed a three-dimensional distributed-parameter heat transfer model for Li-ion battery to study the geometrical current and heat distribution inside the battery, which is illustrated as follows,

$$\frac{\partial \rho C_p T_{3C}}{\partial t} = -\nabla(k_{3C}\nabla T_{3C}) + Q, \tag{2}$$

it can be also expressed as [29],

$$\frac{\partial \rho C_p T_{3C}}{\partial t} = -\frac{\partial}{\partial x}\left(k_x\frac{\partial T_{3C}}{\partial x}\right) - \frac{\partial}{\partial y}\left(k_y\frac{\partial T_{3C}}{\partial y}\right) - \frac{\partial}{\partial z}\left(k_z\frac{\partial T_{3C}}{\partial z}\right) + Q, \tag{3}$$

where ρ stands for the battery density, C_p means battery heat capacity, k_{3C} is the coefficient of battery thermal conductivity (along three dimensions: k_x, k_y, k_z), Q means battery heat generation.

Assuming the battery temperature distribution within each layer plane is uniform, and only one dimension of battery heat conduction is considered (e.g., x dimension), then a simplified one-dimension heat conduction model can be developed [30] as follows,

$$\frac{\partial \rho C_p T_{1C}}{\partial t} = -\frac{\partial}{\partial x}\left(k_x\frac{\partial T_{1C}}{\partial x}\right) + Q, \tag{4}$$

The three-dimensional heat transfer models are capable of capturing temperature distribution inside the battery, which can be applied to detect possible hot spots, especially in high-heat generation applications. The one-dimensional heat transfer model can capture the temperature gradient along one direction. However, the computational overheads of these heat transfer models are often too large for real-time applications, and they are mainly used in offline simulations.

Supposing the heat conduction is the main heat transfer type, heat generation is evenly distributed within the battery, and further the temperatures of both battery surface and interior are uniform, then a popular two-stage thermal model for battery cell [31–33] can be derived as

$$\begin{cases} C_{q1}\mathrm{d}T_{\mathrm{in}}/\mathrm{d}t = k_1(T_{\mathrm{sh}} - T_{\mathrm{in}}) + Q \\ C_{q2}\mathrm{d}T_{\mathrm{sh}}/\mathrm{d}t = k_1(T_{\mathrm{in}} - T_{\mathrm{sh}}) + k_2(T_{\mathrm{amb}} - T_{\mathrm{sh}}) \end{cases}, \tag{5}$$

where T_{in} and T_{sh} stand for battery internal and surface temperature, respectively, T_{amb} means the ambient temperature around battery, C_{q1} and C_{q2} stand for the thermal capacities of battery interior and surface, respectively, k_1 stands for the heat conduction between battery surface and interior, k_2 stands for the heat conduction between ambiance and battery surface.

After defining battery heat generation and transfer parts, many battery reduced-order thermal models have been also developed to achieve control purpose for battery thermal management [34–36]. In Ref. [34], the order of a Li-ion battery model is reduced by converting the one-dimensional boundary-value problem into a low-order linear model in the frequency domain. The temperature prediction of the reduced order model matches closely with the experimental data and a three-dimensional finite-element simulation. Hu et al. [36] proposed a reduced-order state-space model of battery pack based on a computational fluid dynamics (CFD) model using the singular value decomposition method. The proposed model with much less computation costs is capable of providing similar results as those from the CFD model.

3.3 Battery coupled electro-thermal model

There is strong coupling between the battery electric and thermal behaviours. In order to capture battery electric behaviours (e.g., current, voltage, SOC) and thermal behaviours (e.g., surface and internal temperature) simultaneously, several coupled electro-thermal models have been developed in the literature, including both lump-parameter and distributed-parameter models [37–39]. Further, Goutam et al. [40] proposed a three-dimensional electro-thermal model to estimate battery SOC and calculate heat generation. This coupled model consists of a 2D potential distribution model and a 3D temperature distribution model. Then the battery SOC and temperature distribution under both constant and dynamic currents are effectively calculated based on this coupled model. In Ref. [41], a reduced low-temperature electro-thermal model was proposed and validated by batteries with three cathode materials. This reduced model is accurate enough to develop fast heating and optimal charging approach under low temperature condition. Basu et al. [42] presented a coupled three-dimensional electro-thermal model to analyse the influences of various battery operations such as coolant flow-rate and discharge current on the battery temperature. Contact resistance is verified to play a vital role in battery temperature based on the analysis of this coupled model.

4 Battery state estimation

This section gives a review of battery state estimation, while focus on battery key states including SOC, SOH, internal temperature and joint state estimation.

4.1 SOC estimation

SOC stands for the remaining battery capacity as a percentage to the total at the same situation. 100% stands for the battery is fully charged to its total capacity, and 0% stands for battery is fully discharged. Accurate SOC estimation plays a vital role in monitoring existing capacity state, to further guarantee the safe and healthy operation of battery [43]. Generally speaking, two approaches are developed for SOC estimation, which is categorized as direct estimation approach and model-based approach. For the direct estimation approach, based on the direct measurements of battery current and voltage, SOC is mainly calculated by two different ways named Ampere-hour (Ah) or coulomb counting method and open circuit voltage (OCV) based method. Ah method is a general and simple method to calculate SOC, which is illustrated as follows,

$$SOC(k) = SOC(k_0) + \int_{k_0}^{k} \eta I(t) \mathrm{d}t / C_\mathrm{n}, \tag{6}$$

where $SOC(k_0)$ is the known initial SOC, η stands for the efficiency of battery charging or discharging, C_n stands for the battery nominal capacity, $I(t)$ is the current value which is positive for charging and negative for discharging.

Since charging or discharging current can be easily measured, Ah method becomes a straightforward choice for SOC estimation. However, Ah method is highly dependent on the current measurements, error accumulation over the time will significantly affect the estimation accuracy. Besides, it is difficult to determine the initial SOC accurately in real-time applications especially when battery is only charged within a limited range, e.g., 10%–90%. Calibrations of initial SOC and current become the challenging issues to adopt Ah method for SOC estimation.

It has been proposed that there exists a one-to-one nonlinear relation between the battery SOC and OCV. Therefore, using OCV after enough resting to estimate battery SOC has become an effective and popular approach, which has been adopted in many applications [44,45]. Although high estimation accuracy of battery SOC can be achieved by the OCV method, the resting time has become a major limitation for OCV-based SOC estimation. It generally takes a long time to reach equilibrium after disconnecting the load current (for example for $LiFePO_4$ battery, duration time is always larger than two hours under low temperature condition). Further, the relation between OCV and SOC also changes along with battery aging and temperature changes.

The disadvantages of OCV method limit its wide applications in EVs. This problem can be addressed if the OCV can be obtained real-time to allow estimation of SOC during driving. Thus, the model-based approach has been developed to calculate OCV to further achieve on-line estimation of battery SOC. In the model-based approaches, a suitable battery model needs to be carefully designed. Battery equivalent circuit model [46] and electrochemical model [47,48] in the forms of standard state space are usually selected to estimate battery SOC, while SOC is one of the state variables in these battery models. Then various state observers are adopted for on-line SOC estimation [49–53], such as Kalman filter (KF), extended Kalman filter (EKF), adaptive Kalman filter (AKF), unscented Kalman filter (UKF), slide mode observer and $H\infty$ filter. The accuracy of these model-based approaches largely depends on the training of the battery models, the adopted state observers, and the parameter tuning such as the key parameters in model and the noise covariance matrix for KF observers. Besides, the performance of battery SOC estimation by these different observers is only validated under limited conditions of the test data, and a reliable confidence-zone is usually difficult to obtain. Therefore, the estimation performance under various practical conditions, which are different from the test conditions, cannot be guaranteed.

4.2 SOH estimation

There is no single definition for the battery SOH. A general description of battery SOH can be given as

$$SOH(t) = SOH(t_0) + \int_{\tau=t_0}^{t} \delta_\mathrm{func}(I, T, SOC, others) \mathrm{d}\tau, \tag{7}$$

where $SOH(t_0)$ represents the initial battery SOH, δ_func is an aging rate function, which strongly depends on several factors such as current, temperature, SOC, *others* represents some other stress factors such as the mechanical vibrations and over-potential.

For EV applications, battery aging will result in the degradation of battery capacity and the increase of battery internal resistance. Thus, the battery SOH can be estimated by the internal resistance or usable capacity as a kind of prediction regime changes in computer science field [54]. Numerous approaches have been proposed to estimate battery SOH, which are categorized into three groups, namely, model-free, model-based, and data mining methods.

For model-free method, given that the aged capacity C_{aged} or the increased internal resistance R_{inc}, battery SOH can be simply defined as

$$\begin{cases} SOH = C_{\text{aged}}/C_{\text{n}} \times 100\% \\ SOH = R_{\text{inc}}/R_{\text{n}} \times 100\% \end{cases}, \tag{8}$$

where C_{n} and R_{n} stand for the nominal capacity and internal resistance of the new battery without being used.

According to the definition of SOH in Eq. (8), one can apply the standard capacity test [55] or pulse current test [56] to measure the battery aged capacity and increased internal resistance. However, this direct method is inconvenient and not recommended because fully discharge using the controlled current and temperature will interrupt the normal EV operations. Compared with the direct measurements of C_{aged} and R_{inc}, the battery electrochemical impedance spectroscopy (EIS) can certainly offer much more information about the battery health condition. Therefore, researchers have proposed using battery EIS for health diagnosis [57–60]. However, the on-board measurement and application of battery EIS need specific instruments, which will limit its applicability. Further, a full EIS test also takes long time.

For model-based method, on the one hand, the battery capacity or internal resistance is taken as the time-varying parameters based on the battery equivalent circuit model [15] and electrochemical model [61]. Then various observers such as particle filters [62,63], Kalman filters [64–66] and sliding mode [67–69], are adopted to estimate the capacity and internal resistance during battery operations, thus the SOH can be obtained accordingly. On the other hand, in order to analyse the effects of stress factors on the battery degradation, some researchers focus on developing battery cycle-life models to predict battery capacity degradation. Defining the battery capacity loss C_{loss} as

$$C_{\text{loss}} = (C_{\text{n}} - C_{\text{aged}})/C_{\text{n}} \times 100\%. \tag{9}$$

Then C_{loss} can be further expressed as

$$C_{\text{loss}} = \delta_{\text{func}}(f)Ah^{z}, \tag{10}$$

where f stands for the stress factors to cause capacity degradation, Ah means the accumulated current throughput, z is a power law parameter, δ_{func} represents the effects of stress factors on the degraded battery capacity.

Considering battery capacity degradation is mainly associated with the battery current, temperature, SOC and charging methods, etc., numerous researches have been proposed to describe battery aging dynamics. For example, Wang et al. [70] adopted the power law equation to establish a generalized cycle-life model for $LiFePO_4$ cell. The life model was calibrated over wide current and temperature ranges without considering the depth of discharge. In Ref. [71], a similar cycle-life model was validated to predict battery capacity loss with constant temperature at low SOC level. Omar et al. [72] proposed a battery aging model to predict the degraded capacity in the situations of both discharging and fast charging. In Ref. [73], a cycle-life model was validated for the Li-ion battery based on the profiles proposed by the VDA (German association of the automotive industry). Suri and Onori [74] proposed a control-oriented cycle-life model to capture the battery capacity loss over data mimicking actual cycling conditions, the corresponding severity factor map was established to predict and control battery degradation. In Ref. [75], according to a mechanistic and prognostic model, a dynamic cycle-life model was proposed to capture the capacity degradation dynamics under the conditions of varying load for large-format Li-ion batteries. Gao et al. [76] analysed the battery aging under different charging conditions and concluded that charging current less than 1 C affects the active material loss, cut-off voltage less than 4.2 V affects the lithium loss respectively. Then an experiential life model was proposed to capture the relations of degraded battery capacity and charging stresses. These cycle-life models play important roles in optimizing the real-time operations to prolong the service life of battery. But current researches mainly focus on the specific working loads. Their accuracies cannot be guaranteed under real-time applications. Besides, as battery SOH changes at a much slower rate compared with the battery SOC, wider ranges of battery operation and more test data are required to train the battery cycle-life model, this inevitably increases the difficulty of engineering implementation.

Similar to battery SOC estimation, data mining methods have also been applied for battery SOH estimation [77–87]. Nuhic et al. [79] proposed a battery health diagnosis and prognosis method in an alternative power train using SVM, which relies only on on-board measurable data, e.g., battery terminal voltage and current and operating temperature. Klass et al. [80] also proposed an SVM method to estimate battery SOH. A new data-processing method is proposed using load collectives to generate the input and output vectors of the required SVM training data set. Hu et al. [81] proposed a data-driven classification method, i.e., the K-nearest neighbor (KNN) method, for battery capacity estimation. Again, only the on-board measurable signals, i.e., voltage and current, are needed. The characteristic features of the charge curve which are indicative of the battery SOH are identified, and then the KNN method is used to ‘learn’ from data the relationship between the battery SOH and these features. In Ref. [82], according to the historical distributions of sensible data such as battery current, voltage and temperature, a data mining approach was proposed to estimate the battery SOH by using clustering and neural network technologies. Under practical environment, the average error of estimated SOH can be within 2.2%. Liu et al. [85]

proposed a health indicator (HI) extraction and transformation framework to estimate the battery remaining useful life (RUL). The relevance vector machine (RVM) algorithm can achieve the satisfied RUL estimation with the optimized HI. Other data-driven methods, such as Naive Bayes [84], Bayesian learning [83,86], Bayesian Monte Carlo method [87] have also been applied for improved battery SOH estimation.

4.3 Internal temperature estimation

Battery temperature is another key factor to affect the battery performance in many ways such as lifetime, energy conversion efficiency, reliability and safety. Surface temperature is easy to be measured directly using suitable thermal sensors or thermocouples. But internal temperature of battery is an internal state which is difficult to be measured directly. The difference between battery surface and internal temperatures would be quite significant (e.g., sometimes greater than 12 °C [88] in high-power applications). Overheated internal temperature will accelerate battery aging and even lead safety problems such as fires and explosion [89]. Therefore, measuring battery surface temperature is insufficient to protect battery. Proper estimation approaches of internal temperature are capable of not only preventing battery against damages, but also allowing BMS to make reasonable strategies to save energy.

One simple method is to inject the proper micro-temperature sensors into the battery cell [90,91]. However, these methods are often of high cost and complexity due to the accessional manufacturing requirements and instrumentation challenges. A number of improved methods for battery temperature estimation have been proposed, including thermal model-based approaches which usually adopt battery distributed battery thermal model [92] or lumped-parameter battery thermal model [93,94]. The internal temperature is also selected as one of the state variables in battery thermal models, and various state observers are adopted for on-line internal temperature estimation. By combining the suitable state observers, these model-based approaches can be easily applied to estimate battery internal temperature on-line with good estimation results. Since the battery thermal models are mainly dependent on the information of heat generating properties and thermal boundary conditions, these model-based approaches also have the challenging issues such as tuning parameters and gaining useful thermal information.

Considering that the battery EIS measurements are also related to the variation of battery temperature [95], therefore battery internal temperature can be also estimated using the EIS measurements. Srinivasan et al. [96] discovered an intrinsic relationship between a cell's internal temperature and a readily measurable electrical parameter, namely the phase shift between an applied sinusoidal current and the induced voltage, which enables an instantaneous measurement of the battery internal temperature. The electrochemical cause of this observed relationship is analysed. One advantage of this method is that this observed relationship is almost completely independent of battery SOC. Further, the identified optimal frequency range of the sine excitation signal lies in 40–200 Hz, enabling a fast measurement, which is another merit for on-board applications. A four-probe measurement technique is later developed to monitor the dynamic temperature behaviour of the carbon anode in a Li-ion cell during charging and discharging operations [97]. Zhu et al. [98] also proposed estimating battery internal temperature using the measured EIS data. The effect of battery SOC, SOH and temperature on the EIS measurements is analysed, and the excitation signal frequency is selected so that the measured EIS is dominated by temperature, and independent of the battery SOC and SOH. Raijmakers et al. [99] also proposed battery sensorless temperature estimation methods using EIS measurements, and compared the performance of different EIS-based battery temperature estimation methods [100] under both thermal equilibrium states and dynamic load conditions. However, it is worth noting that those battery internal temperature estimation methods using the battery impedance measurement at a single frequency can only give an 'averaged' battery temperature, rather than the temperature distribution field or the peak internal temperature, under inhomogeneous or transient temperature distribution conditions.

Besides, data-driven methods such as neural networks can be adopted to estimate the battery internal temperature. Highly nonlinear performance of battery dynamic can be captured by the data-driven methods which are totally free of background knowledge. Liu et al. [101] proposed a hybrid data-driven method based on the linear neural network model to estimate Li-ion battery internal temperature. After EKF filtering, good estimation accuracy is achieved and this method can be extended to other types of batteries with minor modifications.

4.4 Joint state estimation

According to the coupled electro-thermal models which are capable of simultaneously describing battery electric and thermal behaviours, the joint state estimation of battery SOC and internal temperature can be achieved, which plays an important role in some control and equalization applications of batteries. The key step to achieve joint state estimation is to build a simple and accurate battery electro-thermal model firstly, then suitable estimation methods such as slide mode observer, Kalman filter observer can be applied accordingly. For example, Bizeray et al. [102] proposed a thermal-electrochemical model to achieve a joint estimation of Li-ion battery. After solving the partial differential equations of coupled model by orthogonal collocation approach, battery SOC and internal temperature can be estimated by a modified EKF. Zhang et al. [103] proposed a coupled thermoelectric model to capture battery electric and thermal behaviours. The interaction between battery resistance and internal temperature is simply described by a non-linear look-up table, then battery SOC and internal temperature can be estimated simultaneously.

5 Battery charging approach

When a battery energy source is exhausted or its terminal voltage drops below the cut-off voltage or SOC declines to 20% or lower, the discharging process should be stopped and the battery needs to be recharged. The charging performance for various batteries is shown in Table 2. Incorrect operations such as over-discharging, over-charging or improper charging will speed up the degradation process of the battery dramatically. Compared with other types of battery, the Li-ion battery has fairly stable performance but less cycle life at high-temperature conditions, while no permission is allowed for being charged below freezing. According to the enough accurate estimations of battery SOC, SOH and temperature, proper battery charging approaches can be effectively designed, further to charge battery from initial state to final SOC target value. Meanwhile, the charging approaches can also protect batteries from overheating, prolong the service life and improve the capacity utilization.

5.1 Traditional battery charging approach

There are some traditional but popular charging approaches to solve battery charging problem with numerous objectives and termination conditions. Four traditional charging approaches that have been widely utilized to charge batteries in EVs are listed in Fig. 4. These typical approaches can be mainly classified as constant-current (CC) charging, constant-voltage (CV) charging, constant-current-constant-voltage (CC-CV) charging and multi-stage constant-current (MCC) charging. In the following, a particular emphasis is place up on the CC-CV charging and MCC charging approaches.

The CC charging is a simple but rough approach which adopts a small constant current rate to charge battery during the whole charging process. The CC charging is terminated when the time-to-charge reaches a predefined threshold. This charging approach is first introduced to charge NiCd or NiMH batteries [104], and is also widely used for Li-ion batteries [105]. However, the behaviours of batteries are highly dependent on the current rate in CC charging, hence the main challenge for CC charging approach is to search a suitable charging current rate which is capable of equilibrating battery charging speed and capacity utilization. For large current rate in CC charging, the charging speed is improved but the battery aging process will be aggravated accordingly. For small current rate in CC charging, high capacity utilization is achieved but too low current rate will slow down the battery charging speed and further have a negative effect on the convenience of EV usage.

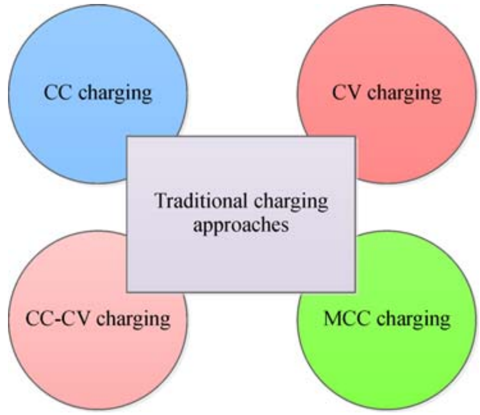

Fig. 4 Traditional charging approaches for battery in EVs

Another simple conventional charging approach is the CV charging which totally adopts a predefined constant voltage to charge batteries. The primary superiority of using CV charging is to avoid over-voltage and irreversible side reactions which may occur in the charging process, further to prolong battery cycle life. When the CV charging is applied, the charging current will gradually reduce due to the low acceptance with progressing recharge. This approach however needs a high current rate in order to keep constant terminal voltage at the early stage of the charging process, which is easy to cause the battery lattice collapse, and battery poles broken. The common problem of CV charging approach is also to select a proper value for

Table 2 Charging performance for various batteries

Battery type	Charging performance
Li-ion	1) High temperature can improve charging speed but damage to battery lifetime; 2) charging is dangerous at pretty low temperature, well below freezing
Lead acid	1) Higher temperature leads to lower V-threshold by 3 mV/°C; 2) charging at 0.3 C or less below freezing
NiMH, NiCd	1) Charging acceptance decreases from 70% at 45 °C to 45% at 60 °C, respectively; 2) 0.1 C charging rate between –17 °C and 0 °C; 3) 0.3 C charging between 0 °C and 6 °C

constant voltage to obtain a good trade-off among the charging speed, electrolyte decomposition and capacity utilization. Reference [106] summarizes the characteristic of CV charging, and it concludes that CV charging approach is capable of effectively improving the charging speed but bringing great damages to the battery capacity. This is primarily caused by the sharp increase of charging current when battery is charged from low SOC. The start current is far larger than the acceptable range of the battery, leading to the battery lattice frame collapses, and further aggravating the pulverization of the active substance in battery pole. But as battery capacity increases, the charging current will reduce dramatically. The charging speed for CV approach is relatively fast due to a high average battery current during the SOC interval from 0.15 to 0.8, and the charging current will reduce very slightly when SOC reaches 0.9.

By integrating CC charging and CV charging, a hybrid charging approach named CC-CV has been proposed, as shown in Fig. 5. In this approach, a battery is firstly charged by a predefined constant current in CC phase and the battery voltage will increase to the maximum safe threshold. Afterwards, the battery enters into the CV phase with a predefined constant voltage, entailing the continuous step-down of the charging current. This CV phase will end until a terminal value of the decreasing current or a goal capacity is reached. The standard CC-CV approach is first utilized to charge lead acid battery with the preset values of constant current as well as constant voltage which are recommended by battery manufacturers, and is also extended to charge Li-ion battery with some modifications. Because of higher terminal voltage and charging acceptance for Li-ion battery, constant current in the applications of Li-ion battery CC-CV charging should be much larger than that of lead acid battery, which is usually chosen from 0.5 to 3.0 C [107]. In CC-CV charging process, CC stage and CV stage can be complementary in some way [108], the capacity loss caused by the large electrochemical polarization in CC stage will be effectively compensated by CV stage. Hence the CC-CV charging approach is superior to the sole CC as well as sole CV charging in the applications of EVs, and has been selected as a benchmark to compare with the performance of other newly developed battery charging approaches [109,110]. Although standard CC-CV charging approach is easy to apply, the challenging issue is to set the appropriate constant current rate at the CC stage and constant voltage value at the CV stage. Battery charging speed of CC-CV approach is primarily determined by the constant current rate, while the capacity utilization of battery charging is mainly affected by the values of constant voltage and termination. For constant current rate in CC-CV, on the one hand, high value of current rate may cause lithium plating, further to cause low efficiency of energy conversion, and battery temperature may exceed permissible levels especially in high power applications. On the other hand, low charging current may decrease battery charging speed and affect the convenience of EVs usage. Therefore, it is vital to design a proper CC-CV approach to improve the overall charging performance and guarantee the operation safety of battery.

Another popular traditional charging approach is the MCC charging, as shown in Fig. 6. This approach has been successfully developed to charge numerous types of battery such as lead acid battery [111], NiMH battery [112] and Li-ion battery [113]. The mainly difference between MCC charging and CC-CV charging is that in MCC charging, the multi-stage series of monotonic charging currents are injected into battery during total charging process. This series of charging currents should be gradually reduced as the form of various constant currents stages ($I_{CC1}>I_{CC2}>...>I_{CCN}$). When terminal voltage goes up to a default voltage threshold by the constant current in one stage, charging procedure will turn into another constant current stage and then a new less constant current rate will be utilized accordingly. This decrease process of charging current will continue until battery terminal voltage reaches the last default voltage threshold under the condition of minimum current. The charging speed for standard MCC approach will be usually a bit slower than the standard CC-CV approach with the same initial current.

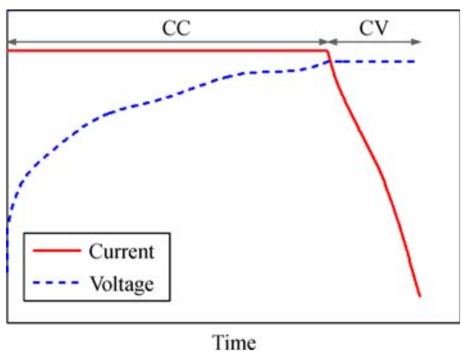

Fig. 5 Battery current and voltage of CC-CV charging approach

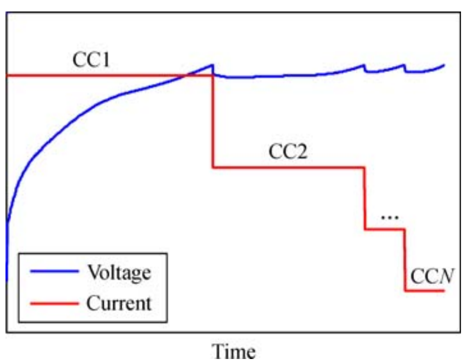

Fig. 6 Battery current and voltage of MCC charging approach

Table 3 Comparison of traditional battery charging approaches in EVs

Approach	Advantages	Disadvantages	Key elements
CC	Easy to implement	Capacity utilization is low	1) Charging constant current rate; 2) terminal condition
CV	1) Easy to implement; 2) stable terminal voltage	Easy to cause the lattice collapse of battery	1) Charging constant voltage; 2) terminal condition
CC-CV	1) Capacity utilization is high; 2) stable terminal voltage	Difficult to balance objectives such as charging speed, energy loss, temperature variation	1) Constant current rate in CC phase; 2) constant voltage in CV phase; 3) terminal condition
MCC	1) Easy to implement; 2) easy to achieve fast charging	Difficult to balance objectives such as charging speed, capacity utilization and battery lifetime	1) The number of CC stages; 2) constant current rates for each stage

Table 3 gives a brief comparison of the traditional charging approaches mentioned above, while the advantages, disadvantages and key elements to design these approaches are summarized. All in all, for rough charging approaches including sole CC charging and CV charging, the implementation costs are relatively low with just a few parameters need to be considered. However, these simple charging approaches would cause many charging problems such as battery lattice collapse, and battery poles broken. It is significantly difficult to equilibrate battery capacity utilization and charging speed by using just sole CC or CV charging approach. In order to further improve charging performance such as avoiding over-voltage, enhancing capacity utilization and achieving fast charging, some hybrid charging approaches including CC-CV and MCC are developed. The open problem for using these hybrid approaches is to search the proper current and voltage values to efficiently equilibrate conflicting objectives such as charging speed, energy loss, temperature variation and battery lifetime. Besides, the analysis of electrochemical reaction such as lithium plating during these charging process are still at its primitive stage and will be a thriving area of research in the field of EV applications.

5.2 Optimization of battery charging approach

On the basis of the standard traditional charging, many optimized charging approaches have been developed to improve the charging performance of batteries in EVs recently. These optimizations of charging approach can be categorized as four fields, which are detailed in Fig. 7.

The first field is the optimization of CV charging. Some approaches have been adopted to enhance the charging performance of standard CV charging. Objectives such as charging speed and temperature variation are considered in these approaches. In Ref. [114], a constant voltage with various restricting current approach is presented to limit the variation of battery temperature. Low battery temperature rise in total charging process is achieved by modulating the current rate of proposed approach. Lee and Park [115] proposed a fast charging control scheme in CV stage based on the battery internal impedance. In comparison with standard CV charging, battery charging speed becomes faster by using the developed control scheme.

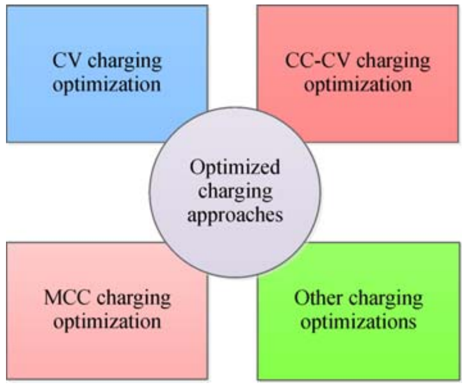

Fig. 7 Optimizations of battery charging approach in EVs

Given that CC-CV charging and MCC charging are two simple and efficient charging approaches, numerous researches have been developed to improve battery charging performance on the basis of CC-CV or MCC approach. The framework to improve the CC-CV/MCC charging approach can be summarized in Fig. 8.

For CC-CV charging optimization, the key optimal elements are the current rate in CC phase and constant voltage value in CV phase. A number of researches to improve the CC-CV charging approach have been developed recently. In Ref. [116], a cycle control algorithm associated with the zero computational method is proposed to optimize the CC-CV profile of Li-ion battery. This improved battery charger is validated to drive the CC-CV process accurately and smoothly. In Ref. [117], a closed-form approach to search the optimal charging strategy for a Li-ion battery is proposed. A cost function which considers the charging time, energy loss and temperature rise is used to acquire the optimal CC-CV charging profile. Hsieh et al. [118] designed a controller to improve the performance of Li-ion battery in CC-CV charging. The general CV mode is replaced by two modes: Sense and charge. Then the

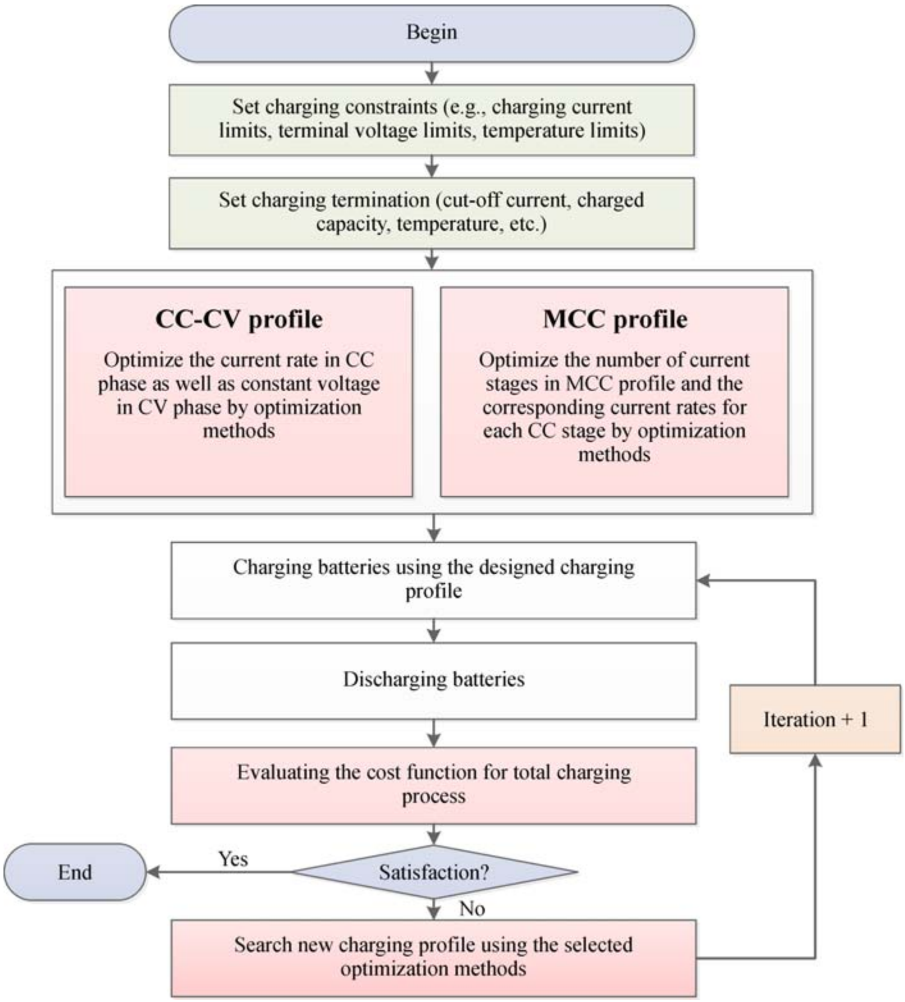

Fig. 8 Summary of improvements to the CC-CV/MCC charging approach

faster charging trajectory can be achieved. In Ref. [119], a battery charging cost function with three objectives including charging time, energy loss and temperature rise especially the battery internal temperature is presented based on a coupled thermoelectric model. Then the teaching learning-based optimization (TLBO) method is applied to balance three conflicting objectives, further to obtain an optimal CC-CV pattern for Li-ion battery. In Ref. [120], a model-based strategy was proposed to optimize the CC-CV charging pattern for Li-ion battery management. The desirable trade-offs among charging speed, energy conversion efficiency and temperature variation can be achieved based on the multi-objective biogeography-based optimization (M-BBO) approach. Then the current regions to efficiently equilibrate these key objectives are also identified. He et al. [121] presented a user-cell aware charging strategy to maximize the charged Li-ion battery capacity. The charging strategy is an extended version of standard CC-CV which starts with CC charging until the battery voltage reaches a predefined voltage, and then the battery will be charged with another different predefined voltage until the charging current falls to cut-off current. The phase-locked loop (PLL) control [122] is also adopted to improve CC-CV charging performance. In Ref. [123], a current-pumped battery charger (CPBC) based on PLL-CC-CV is presented to improve the performance of Li-ion battery charging. Results illustrate that the battery capacity and efficiency are improved.

For MCC charging optimization, the main and challenging target is to determine the number of current stages in MCC profile and the corresponding current rates for each CC stage. One popular approach to improve MCC charging performance is the fuzzy logic technology. In Refs. [124,125], the fuzzy logic controller is utilized to convert the charging quality characteristics (charging time and normalized discharged capacity) into a single fuzzy dual-response performance index, and a five-stage MCC charging pattern is optimized to improve charging efficiency. In Refs. [126,127], the fuzzy logic control is adopted to regulate the weights within the fitness function of Li-ion charging process. Then the optimal MCC charging patterns can be optimized by the PSO algorithm based on the designed fuzzy-logic fitness function. The Taguchi-based method is another effective approach to search the optimal MCC charging pattern. Liu et al. [128] presented a Taguchi-based approach to accelerate charging speed and prolong cycle life for a Li-ion battery. A five-stage MCC charging pattern is optimized by the consecutive orthogonal array technique. According to the Taguchi approach together with the SOC estimation, Vo et al. [129] proposed a four-stage MCC charging pattern to equilibrate battery temperature variation, charging speed and energy conversion efficiency. Besides, some other technologies such as ant colony system, function or model-based methods are also applied to improve the MCC charging performance. Liu et al. [130] proposed an MCC charging approach with various weights in each stage based on an internal-DC-resistance (DC: Direct current) model to balance the conflicts between charging speed and energy loss during charging process. Khan et al. [131] presented a unique approach to search the optimal MCC charging pattern by using equivalent circuit model for Li-ion battery. The three and five CC stages are both discussed based on the optimal pattern to improve the charging speed and efficiency. In summary, charging objectives such as charging speed, energy loss and capacity utilization of the total MCC charging process are primarily determined by the number of CC stages and the current values in each stage. The implementation cost of MCC charging is reduced because of no regulations of voltage are required.

In addition to the optimizations of traditional charging approaches, a number of other charging approaches, obtained by using computational intelligent technologies such as dynamic programming (DP), model predictive control (MPC), evolutionary algorithms and pseudo-spectral optimization, have been also reported. The DP method is generally adopted to optimize battery charging profiles based on the proper battery models [132,133]. Since DP method is capable of examining sub-problems and combining the decisions to further obtain the best solution, both non-linear and time varying parameters in battery models can be accepted by DP method, thus DP becomes one of the most flexible methods to search battery charging profiles. However, often a large quantity of information needs to be stored by using DP, which leads to large computation cost especially in high dimension charging problems. The MPC-based charging approaches also need to design a suitable battery model firstly [134–136]. Then the charging behaviours such as current, voltage, and even temperature can be predicted directly by the designed electric model or thermal model. Hard battery constraints in total charging process can be also effectively solved by MPC. Nevertheless, influences of battery temperature and aging on the parameters of battery model need to be further studied to improve prediction accuracy. For evolutionary algorithm [137,138], it can effectively search the charging profiles especially in the situations that some charging problems have no theoretical foundations. But the computation cost in evolutionary algorithm is usually too large. Researchers need to select the suitable evolutionary algorithm and the parameters empirically. Charging battery based on the pseudo-spectral optimization is also a popular and effective method in the real battery charging applications [139,140]. Many complicated charging conditions can be considered by pseudo-spectral optimization. However, strong theoretical foundations and much battery information are required by using pseudo-spectral optimization, which will bring large challenges in real-world applications of EVs with growing requirements for battery charging.

6 Conclusions

Key technologies in the BMS of EVs have been reviewed in this paper, especially in the fields of battery modelling, state estimation and battery charging. Battery modelling together with the estimations of battery internal states and parameters play a vital role in revealing a hologram of battery operating status in the applications of EVs firstly. After capturing these key states, suitable battery charging approach can be designed to protect battery against damages, improve efficiency of energy conversion, and prolong the battery lifetime. However, most of the key technologies in the BMS are achieved and validated in specific test conditions. The modelling, estimation and charging performance in real-world applications that would be different from the test conditions, or in a worse-case scenario, is difficult to guarantee. Therefore, to explore the limitations or to develop a confidence interval of the presented algorithms and approaches are required to tackle this challenging issue.

Acknowledgements This work was financially supported by UK EPSRC under the ‘Intelligent Grid Interfaced Vehicle Eco-charging (iGIVE) project EP/L001063/1 and NSFC under grants Nos. 61673256, 61533010 and 61640316. Kailong Liu would like to thank the EPSRC for sponsoring his research.

References

1. Abada S, Marlair G, Lecocq A, et al. Safety focused modeling of lithium-ion batteries: A review. Journal of Power Sources, 2016, 306: 178–192
2. Rao Z, Wang S. A review of power battery thermal energy management. Renewable & Sustainable Energy Reviews, 2011, 15 (9): 4554–4571

3. Park B, Lee C H, Xia C, et al. Characterization of gel polymer electrolyte for suppressing deterioration of cathode electrodes of Li ion batteries on high-rate cycling at elevated temperature. Electrochimica Acta, 2016, 188: 78–84
4. Li J, Han Y, Zhou S. Advances in Battery Manufacturing, Services, and Management Systems. Hoboken: John Wiley-IEEE Press, 2016
5. Lu L, Han X, Li J, et al. A review on the key issues for lithium-ion battery management in electric vehicles. Journal of Power Sources, 2013, 226: 272–288
6. Rahman M A, Anwar S, Izadian A. Electrochemical model parameter identification of a lithium-ion battery using particle swarm optimization method. Journal of Power Sources, 2016, 307: 86–97
7. Sung W, Shin C B. Electrochemical model of a lithium-ion battery implemented into an automotive battery management system. Computers & Chemical Engineering, 2015, 76: 87–97
8. Shen W J, Li H X. Parameter identification for the electrochemical model of Li-ion battery. In: Proceedings of 2016 International Conference on System Science and Engineering (ICSSE). Puli: IEEE, 2016, 1–4
9. Mastali M, Samadani E, Farhad S, et al. Three-dimensional multi-particle electrochemical model of $LiFePO_4$ cells based on a resistor network methodology. Electrochimica Acta, 2016, 190: 574–587
10. Han X, Ouyang M, Lu L, et al. Simplification of physics-based electrochemical model for lithium ion battery on electric vehicle. Part I: Diffusion simplification and single particle model. Journal of Power Sources, 2015, 278: 802–813
11. Zou C, Manzie C, Nešić D. A framework for simplification of PDE-based lithium-ion battery models. IEEE Transactions on Control Systems Technology, 2016, 24(5): 1594–1609
12. Yuan S, Jiang L, Yin C, et al. A transfer function type of simplified electrochemical model with modified boundary conditions and Padé approximation for Li-ion battery: Part 2. Modeling and parameter estimation. Journal of Power Sources, 2017, 352: 258–271
13. Bartlett A, Marcicki J, Onori S, et al. Electrochemical model-based state of charge and capacity estimation for a composite electrode lithium-ion battery. IEEE Transactions on Control Systems Technology, 2016, 24(2): 384–399
14. Zhang L, Wang Z, Hu X, et al. A comparative study of equivalent circuit models of ultracapacitors for electric vehicles. Journal of Power Sources, 2015, 274: 899–906
15. Nejad S, Gladwin D T, Stone D A. A systematic review of lumped-parameter equivalent circuit models for real-time estimation of lithium-ion battery states. Journal of Power Sources, 2016, 316: 183–196
16. Zhang X, Lu J, Yuan S, et al. A novel method for identification of lithium-ion battery equivalent circuit model parameters considering electrochemical properties. Journal of Power Sources, 2017, 345: 21–29
17. Widanage W D, Barai A, Chouchelamane G H, et al. Design and use of multisine signals for Li-ion battery equivalent circuit modelling. Part 1: Signal design. Journal of Power Sources, 2016, 324: 70–78
18. Gong X, Xiong R, Mi C C. A data-driven bias-correction-method-based lithium-ion battery modeling approach for electric vehicle applications. IEEE Transactions on Industry Applications, 2016, 52(2): 1759–1765
19. Wang Q K, He Y J, Shen J N, et al. A unified modeling framework for lithium-ion batteries: An artificial neural network based thermal coupled equivalent circuit model approach. Energy, 2017, 138: 118–132
20. Deng Z, Yang L, Cai Y, et al. Online available capacity prediction and state of charge estimation based on advanced data-driven algorithms for lithium iron phosphate battery. Energy, 2016, 112: 469–480
21. Sbarufatti C, Corbetta M, Giglio M, et al. Adaptive prognosis of lithium-ion batteries based on the combination of particle filters and radial basis function neural networks. Journal of Power Sources, 2017, 344: 128–140
22. Li Y, Chattopadhyay P, Xiong S, et al. Dynamic data-driven and model-based recursive analysis for estimation of battery state-of-charge. Applied Energy, 2016, 184: 266–275
23. Richter F, Kjelstrup S, Vie P J, et al. Thermal conductivity and internal temperature profiles of Li-ion secondary batteries. Journal of Power Sources, 2017, 359: 592–600
24. Dai H, Zhu L, Zhu J, et al. Adaptive Kalman filtering based internal temperature estimation with an equivalent electrical network thermal model for hard-cased batteries. Journal of Power Sources, 2015, 293: 351–365
25. Raijmakers L H, Danilov D L, van Lammeren J P, et al. Non-zero intercept frequency: An accurate method to determine the integral temperature of Li-ion batteries. IEEE Transactions on Industrial Electronics, 2016, 63(5): 3168–3178
26. Lee K T, Dai M J, Chuang C C. Temperature-compensated model for lithium-ion polymer batteries with extended Kalman filter state-of-charge estimation for an implantable charger. IEEE Transactions on Industrial Electronics, 2018, 65(1): 589–596
27. Mehne J, Nowak W. Improving temperature predictions for Li-ion batteries: Data assimilation with a stochastic extension of a physically-based, thermo-electrochemical model. Journal of Energy Storage, 2017, 12: 288–296
28. Guo M, Kim G H, White R E. A three-dimensional multi-physics model for a Li-ion battery. Journal of Power Sources, 2013, 240: 80–94
29. Jeon D H, Baek S M. Thermal modeling of cylindrical lithium ion battery during discharge cycle. Energy Conversion and Management, 2011, 52(8–9): 2973–2981
30. Jaguemont J, Omar N, Martel F, et al. Streamline three-dimensional thermal model of a lithium titanate pouch cell battery in extreme temperature conditions with module simulation. Journal of Power Sources, 2017, 367: 24–33
31. Lin X, Perez H E, Siegel J B, et al. Online parameterization of lumped thermal dynamics in cylindrical lithium ion batteries for core temperature estimation and health monitoring. IEEE Transactions on Control Systems Technology, 2013, 21(5): 1745–1755
32. Shah K, Vishwakarma V, Jain A. Measurement of multiscale thermal transport phenomena in Li-ion cells: A review. Journal of Electrochemical Energy Conversion and Storage, 2016, 13(3): 030801
33. Chen D, Jiang J, Li X, et al. Modeling of a pouch lithium ion

battery using a distributed parameter equivalent circuit for internal non-uniformity analysis. Energies, 2016, 9(11): 865

34. Muratori M, Canova M, Guezennec Y, et al. A reduced-order model for the thermal dynamics of Li-ion battery cells. IFAC Proceedings Volumes, 2010, 43(7): 192–197
35. Kim Y, Mohan S, Siegel S J, et al. The estimation of temperature distribution in cylindrical battery cells under unknown cooling conditions. IEEE Transactions on Control Systems Technology, 2014, 22(6): 2277–2286
36. Hu X, Asgari S, Yavuz I, et al. A transient reduced order model for battery thermal management based on singular value decomposition. In: Proceedings of 2014 IEEE Energy Conversion Congress and Exposition (ECCE). Pittsburgh: IEEE, 2014, 3971–3976
37. Lin X, Perez H E, Mohan S, et al. A lumped-parameter electro-thermal model for cylindrical batteries. Journal of Power Sources, 2014, 257: 1–11
38. Perez H, Hu X, Dey S, et al. Optimal charging of Li-ion batteries with coupled electro-thermal-aging dynamics. IEEE Transactions on Vehicular Technology, 2017, 66(9): 7761–7770
39. Dey S, Ayalew B. Real-time estimation of lithium-ion concentration in both electrodes of a lithium-ion battery cell utilizing electrochemical-thermal coupling. Journal of Dynamic Systems, Measurement, and Control, 2017, 139(3): 031007
40. Goutam S, Nikolian A, Jaguemont J, et al. Three-dimensional electro-thermal model of Li-ion pouch cell: Analysis and comparison of cell design factors and model assumptions. Applied Thermal Engineering, 2017, 126: 796–808
41. Jiang J, Ruan H, Sun B, et al. A reduced low-temperature electro-thermal coupled model for lithium-ion batteries. Applied Energy, 2016, 177: 804–816
42. Basu S, Hariharan K S, Kolake S M, et al. Coupled electrochemical thermal modelling of a novel Li-ion battery pack thermal management system. Applied Energy, 2016, 181: 1–13
43. Xiong R, Cao J, Yu Q, et al. Critical review on the battery state of charge estimation methods for electric vehicles. IEEE Access: Practical Innovations, Open Solutions, 2017, PP(99): 1
44. Baccouche I, Jemmali S, Manai B, et al. Improved OCV model of a Li-ion NMC battery for online SOC estimation using the extended Kalman filter. Energies, 2017, 10(6): 764
45. Lin C, Yu Q, Xiong R, et al. A study on the impact of open circuit voltage tests on state of charge estimation for lithium-ion batteries. Applied Energy, 2017, 205: 892–902
46. Grandjean T R, McGordon A, Jennings P A. Structural identifiability of equivalent circuit models for Li-ion batteries. Energies, 2017, 10(1): 90
47. Tang S X, Camacho-Solorio L, Wang Y, et al. State-of-charge estimation from a thermal-electrochemical model of lithium-ion batteries. Automatica, 2017, 83: 206–219
48. Li J, Wang L, Lyu C, et al. State of charge estimation based on a simplified electrochemical model for a single $LiCoO_2$ battery and battery pack. Energy, 2017, 133: 572–583
49. Wang Y, Zhang C, Chen Z. On-line battery state-of-charge estimation based on an integrated estimator. Applied Energy, 2017, 185: 2026–2032
50. Acuña D E, Orchard M E. Particle-filtering-based failure prognosis via sigma-points: Application to lithium-ion battery state-of-charge monitoring. Mechanical Systems and Signal Processing, 2017, 85: 827–848
51. Zou C, Manzie C, Nešić D, et al. Multi-time-scale observer design for state-of-charge and state-of-health of a lithium-ion battery. Journal of Power Sources, 2016, 335: 121–130
52. Xiong B, Zhao J, Su Y, et al. State of charge estimation of vanadium redox flow battery based on sliding mode observer and dynamic model including capacity fading factor. IEEE Transactions on Sustainable Energy, 2017, 8(4): 1658–1667
53. Ye M, Guo H, Cao B. A model-based adaptive state of charge estimator for a lithium-ion battery using an improved adaptive particle filter. Applied Energy, 2017, 190: 740–748
54. Arabmakki E, Kantardzic M. SOM-based partial labeling of imbalanced data stream. Neurocomputing, 2017, 262: 120–133
55. Roscher M A, Assfalg J, Bohlen O S. Detection of utilizable capacity deterioration in battery systems. IEEE Transactions on Vehicular Technology, 2011, 60(1): 98–103
56. Coleman M, Hurley W G, Lee C K. An improved battery characterization method using a two-pulse load test. IEEE Transactions on Energy Conversion, 2008, 23(2): 708–713
57. Zhang J, Lee J. A review on prognostics and health monitoring of Li-ion battery. Journal of Power Sources, 2011, 196(15): 6007–6014
58. Jiang J, Lin Z, Ju Q, et al. Electrochemical impedance spectra for lithium-ion battery ageing considering the rate of discharge ability. Energy Procedia, 2017, 105: 844–849
59. Mingant R, Bernard J, Sauvant-Moynot V. Novel state-of-health diagnostic method for Li-ion battery in service. Applied Energy, 2016, 183: 390–398
60. Xiong R, Tian J, Mu H, et al. A systematic model-based degradation behavior recognition and health monitoring method for lithium-ion batteries. Applied Energy, 2017, 207: 372–383
61. Berecibar M, Gandiaga I, Villarreal I, et al. Critical review of state of health estimation methods of Li-ion batteries for real applications. Renewable & Sustainable Energy Reviews, 2016, 56: 572–587
62. Bi J, Zhang T, Yu H, et al. State-of-health estimation of lithium-ion battery packs in electric vehicles based on genetic resampling particle filter. Applied Energy, 2016, 182: 558–568
63. Wang D, Yang F, Tsui K L, et al. Remaining useful life prediction of lithium-ion batteries based on spherical cubature particle filter. IEEE Transactions on Instrumentation and Measurement, 2016, 65 (6): 1282–1291
64. Gholizadeh M, Salmasi F R. Estimation of state of charge, unknown nonlinearities, and state of health of a lithium-ion battery based on a comprehensive unobservable model. IEEE Transactions on Industrial Electronics, 2014, 61(3): 1335–1344
65. Plett G L. Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 1: Introduction and state estimation. Journal of Power Sources, 2006, 161(2): 1356–1368
66. Remmlinger J, Buchholz M, Soczka-Guth T, et al. On-board state-of-health monitoring of lithium-ion batteries using linear parameter-varying models. Journal of Power Sources, 2013, 239: 689–695
67. Kim I S. A technique for estimating the state of health of lithium

batteries through a dual-sliding-mode observer. IEEE Transactions on Power Electronics, 2010, 25(4): 1013–1022
68. Hu C, Youn B D, Chung J. A multiscale framework with extended Kalman filter for lithium-ion battery SOC and capacity estimation. Applied Energy, 2012, 92: 694–704
69. Du J, Liu Z, Wang Y, et al. An adaptive sliding mode observer for lithium-ion battery state of charge and state of health estimation in electric vehicles. Control Engineering Practice, 2016, 54: 81–90
70. Wang J, Liu P, Hicks-Garner J, et al. Cycle-life model for graphite-$LiFePO_4$ cells. Journal of Power Sources, 2011, 196(8): 3942–3948
71. Todeschini F, Onori S, Rizzoni G. An experimentally validated capacity degradation model for Li-ion batteries in PHEVs applications. IFAC Proceedings Volumes, 2012, 45(20): 456–461
72. Omar N, Monem M A, Firouz Y, et al. Lithium iron phosphate based battery—Assessment of the aging parameters and development of cycle life model. Applied Energy, 2014, 113: 1575–1585
73. Ecker M, Gerschler J B, Vogel J, et al. Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test data. Journal of Power Sources, 2012, 215: 248–257
74. Suri G, Onori S. A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries. Energy, 2016, 96: 644–653
75. Ouyang M, Feng X, Han X, et al. A dynamic capacity degradation model and its applications considering varying load for a large format Li-ion battery. Applied Energy, 2016, 165(C): 48–59
76. Gao Y, Jiang J, Zhang C, et al. Lithium-ion battery aging mechanisms and life model under different charging stresses. Journal of Power Sources, 2017, 356: 103–114
77. Wu L, Fu X, Guan Y. Review of the remaining useful life prognostics of vehicle lithium-ion batteries using data-driven methodologies. Applied Sciences, 2016, 6(6): 166
78. Rezvanizaniani S M, Liu Z, Chen Y, et al. Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility. Journal of Power Sources, 2014, 256: 110–124
79. Nuhic A, Terzimehic T, Soczka-Guth T, et al. Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. Journal of Power Sources, 2013, 239: 680–688
80. Klass V, Behm M, Lindbergh G. A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation. Journal of Power Sources, 2014, 270: 262–272
81. Hu C, Jain G, Zhang P, et al. Data-driven method based on particle swarm optimization and k-nearest neighbor regression for estimating capacity of lithium-ion battery. Applied Energy, 2014, 129: 49–55
82. You G, Park S, Oh D. Real-time state-of-health estimation for electric vehicle batteries: A data-driven approach. Applied Energy, 2016, 176: 92–103
83. Hu C, Jain G, Schmidt C, et al. Online estimation of lithium-ion battery capacity using sparse Bayesian learning. Journal of Power Sources, 2015, 289: 105–113
84. Ng S S Y, Xing Y, Tsui K L. A naive Bayes model for robust remaining useful life prediction of lithium-ion battery. Applied Energy, 2014, 118: 114–123
85. Liu D, Zhou J, Liao H, et al. A health indicator extraction and optimization framework for lithium-ion battery degradation modeling and prognostics. IEEE Transactions on Systems, Man, and Cybernetics. Systems, 2015, 45(6): 915–928
86. Saha B, Goebel K, Poll S, et al. Prognostics methods for battery health monitoring using a Bayesian framework. IEEE Transactions on Instrumentation and Measurement, 2009, 58(2): 291–296
87. He W, Williard N, Osterman M, et al. Prognostics of lithium-ion batteries based on Dempster-Shafer theory and the Bayesian Monte Carlo method. Journal of Power Sources, 2011, 196(23): 10314–10321
88. Zhang G, Ge S, Xu T, et al. Rapid self-heating and internal temperature sensing of lithium-ion batteries at low temperatures. Electrochimica Acta, 2016, 218: 149–155
89. Martinez-Cisneros C, Antonelli C, Levenfeld B, et al. Evaluation of polyolefin-based macroporous separators for high temperature Li-ion batteries. Electrochimica Acta, 2016, 216: 68–78
90. Li Z, Zhang J, Wu B, et al. Examining temporal and spatial variations of internal temperature in large-format laminated battery with embedded thermocouples. Journal of Power Sources, 2013, 241: 536–553
91. Lee C Y, Lee S J, Tang M S, et al. *In situ* monitoring of temperature inside lithium-ion batteries by flexible micro temperature sensors. Sensors (Basel), 2011, 11(12): 9942–9950
92. Kim Y, Mohan S, Siegel J B, et al. The estimation of temperature distribution in cylindrical battery cells under unknown cooling conditions. IEEE Transactions on Control Systems Technology, 2014, 22(6): 2277–2286
93. Lin X, Perez H E, Mohan S, et al. A lumped-parameter electro-thermal model for cylindrical batteries. Journal of Power Sources, 2014, 257: 1–11
94. Lin X, Perez H E, Siegel J B, et al. Online parameterization of lumped thermal dynamics in cylindrical lithium ion batteries for core temperature estimation and health monitoring. IEEE Transactions on Control Systems Technology, 2013, 21(5): 1745–1755
95. Samadani E, Farhad S, Scott W, et al. Empirical modeling of lithium-ion batteries based on electrochemical impedance spectroscopy tests. Electrochimica Acta, 2015, 160: 169–177
96. Srinivasan R, Carkhuff B G, Butler M H, et al. Instantaneous measurement of the internal temperature in lithium-ion rechargeable cells. Electrochimica Acta, 2011, 56(17): 6198–6204
97. Srinivasan R. Monitoring dynamic thermal behavior of the carbon anode in a lithium-ion cell using a four-probe technique. Journal of Power Sources, 2012, 198: 351–358
98. Zhu J G, Sun Z C, Wei X Z, et al. A new lithium-ion battery internal temperature on-line estimate method based on electrochemical impedance spectroscopy measurement. Journal of Power Sources, 2015, 274: 990–1004
99. Raijmakers L H, Danilov D L, van Lammeren J P M, et al. Non-zero intercept frequency: An accurate method to determine the integral temperature of Li-ion batteries. IEEE Transactions on Industrial Electronics, 2016, 63(5): 3168–3178
100. Beelen H, Raijmakers L, Donkers M, et al. A comparison and accuracy analysis of impedance-based temperature estimation methods for Li-ion batteries. Applied Energy, 2016, 175: 128–140

101. Liu K, Li K, Deng J. A novel hybrid data-driven method for Li-ion battery internal temperature estimation. In: Proceedings of 2016 UKACC 11th International Conference on Control (CONTROL). Belfast: IEEE, 2016
102. Bizeray A, Zhao S, Duncan S, et al. Lithium-ion battery thermal-electrochemical model-based state estimation using orthogonal collocation and a modified extended Kalman filter. Journal of Power Sources, 2015, 296: 400–412
103. Zhang C, Li K, Deng J. Real-time estimation of battery internal temperature based on a simplified thermoelectric model. Journal of Power Sources, 2016, 302: 146–154
104. Berndt D. Maintenance-free Batteries: Lead-acid, Nickel-cadmium, Nickel-metal Hydride. Taunton: Research Studies Press, 1997
105. Hua A C C, Syue B Z W. Charge and discharge characteristics of lead-acid battery and $LiFePO_4$ battery. In: Proceedings of 2010 International Power Electronics Conference (IPEC). Sapporo: IEEE, 2010, 1478–1483
106. Notten P, Veld J H G O, Beek J R G. Boostcharging Li-ion batteries: A challenging new charging concept. Journal of Power Sources, 2005, 145(1): 89–94
107. Kim T H, Park J S, Chang S K, et al. The current move of lithium ion batteries towards the next phase. Advanced Energy Materials, 2012, 2(7): 860–872
108. Li L, Tang X, Qu Y, et al. CC-CV charge protocol based on spherical diffusion model. Journal of Central South University of Technology, 2011, 18(2): 319–322
109. Liu K, Li K, Yang Z, et al. Battery optimal charging strategy based on a coupled thermoelectric model. In: Proceedings of 2016 IEEE Congress on Evolutionary Computation (CEC). Vancouver: IEEE, 2016, 5084–5091
110. Cope R C, Podrazhansky Y. The art of battery charging. In: Proceedings of the Fourteenth Annual Battery Conference on Applications and Advances. Long Beach: IEEE, 1999, 233–235
111. Ikeya T, Sawada N, Takagi S, et al. Multi-step constant-current charging method for electric vehicle, valve-regulated, lead/acid batteries during night time for load-levelling. Journal of Power Sources, 1998, 75(1): 101–107
112. Ikeya T, Sawada N, Murakami J, et al. Multi-step constant-current charging method for an electric vehicle nickel/metal hydride battery with high-energy efficiency and long cycle life. Journal of Power Sources, 2002, 105(1): 6–12
113. Al-Haj Hussein A, Batarseh I. A review of charging algorithms for nickel and lithium battery chargers. IEEE Transactions on Vehicular Technology, 2011, 60(3): 830–838
114. Lee K T, Chuang C C, Wang Y H, et al. A low temperature increase transcutaneous battery charger for implantable medical devices. Journal of Mechanics in Medicine and Biology, 2016, 16(5): 1650069
115. Lee Y D, Park S Y. Rapid charging strategy in the constant voltage mode for a high power Li-ion battery. In: Proceedings of 2013 IEEE Energy Conversion Congress and Exposition. Denver: IEEE, 2013, 4725–4731
116. Yong S O, Rahim N A. Development of on-off duty cycle control with zero computational algorithm for CC-CV Li ion battery charger. In: Proceedings of IEEE Conference on Clean Energy and Technology (CEAT). Langkgkawi: IEEE, 2013, 422–426
117. Abdollahi A, Han X, Avvari G V, et al. Optimal battery charging, Part I: Minimizing time-to-charge, energy loss, and temperature rise for OCV-resistance battery model. Journal of Power Sources, 2016, 303: 388–398
118. Hsieh G C, Chen L R, Huang K S. Fuzzy-controlled Li-ion battery charge system with active state-of-charge controller. IEEE Transactions on Industrial Electronics, 2001, 48(3): 585–593
119. Liu K, Li K, Yang Z, et al. An advanced lithium-ion battery optimal charging strategy based on a coupled thermoelectric model. Electrochimica Acta, 2017, 225: 330–344
120. Liu K, Li K, Ma H, et al. Multi-objective optimization of charging patterns for lithium-ion battery management. Energy Conversion and Management, 2018, 159: 151–162
121. He L, Kim E, Shin K G. Aware charging of lithium-ion battery cells. In: Proceedings of 2016 ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS). Vienna: IEEE, 2016, 1–10
122. Chen L R. PLL-based battery charge circuit topology. IEEE Transactions on Industrial Electronics, 2004, 51(6): 1344–1346
123. Chen L R, Chen J J, Chu N Y, et al. Current-pumped battery charger. IEEE Transactions on Industrial Electronics, 2008, 55(6): 2482–2488
124. Asadi H, Kaboli S H A, Mohammadi A, et al. Fuzzy-control-based five-step Li-ion battery charger by using AC impedance technique. In: Proceedings of Fourth International Conference on Machine Vision (ICMV 11). SPIE, 2012, 834939
125. Wang S C, Chen Y L, Liu Y H, et al. A fast-charging pattern search for Li-ion batteries with fuzzy-logic-based Taguchi method. In: Proceedings of 2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA). Auckland: IEEE, 2015, 855–859
126. Liu C L, Wang S C, Chiang S S, et al. PSO-based fuzzy logic optimization of dual performance characteristic indices for fast charging of lithium-ion batteries. In: Proceedings of 2013 IEEE 10th International Conference on Power Electronics and Drive Systems (PEDS). IEEE, 2013, 474–479
127. Wang S C, Liu Y H. A PSO-based fuzzy-controlled searching for the optimal charge pattern of Li-ion batteries. IEEE Transactions on Industrial Electronics, 2015, 62(5): 2983–2993
128. Liu Y H, Hsieh C H, Luo Y F. Search for an optimal five-step charging pattern for Li-ion batteries using consecutive orthogonal arrays. IEEE Transactions on Energy Conversion, 2011, 26(2): 654–661
129. Vo T T, Chen X, Shen W, et al. New charging strategy for lithium-ion batteries based on the integration of Taguchi method and state of charge estimation. Journal of Power Sources, 2015, 273: 413–422
130. Liu W, Sun X, Wu H, et al. A multistage current charging method for Li-ion battery bank considering balance of internal consumption and charging speed. In: Proceedings of IEEE 8th International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia). Hefei: IEEE, 2016, 1401–1406
131. Khan A B, Pham V L, Nguyen T T, et al. Multistage constant-current charging method for Li-ion batteries. In: Proceedings of IEEE Conference and Expo on Transportation Electrification Asia-

Pacific (ITEC Asia-Pacific). Busan: IEEE, 2016, 381–385

132. Chen Z, Xia B, Mi C C, et al. Loss-minimization-based charging strategy for lithium-ion battery. IEEE Transactions on Industry Applications, 2015, 51(5): 4121–4129
133. Wu X, Shi W, Du J. Multi-objective optimal charging method for lithium-ion batteries. Energies, 2017, 10(9): 1271
134. Liu K, Li K, Zhang C. Constrained generalized predictive control of battery charging process based on a coupled thermoelectric model. Journal of Power Sources, 2017, 347: 145–158
135. Xavier M A, Trimboli M S. Lithium-ion battery cell-level control using constrained model predictive control and equivalent circuit models. Journal of Power Sources, 2015, 285: 374–384
136. Zou C, Hu X, Wei Z, et al. Electrochemical estimation and control for lithium-ion battery health-aware fast charging. IEEE Transactions on Industrial Electronics, 2017, PP(99): 1
137. Zhang C, Jiang J, Gao Y, et al. Charging optimization in lithium-ion batteries based on temperature rise and charge time. Applied Energy, 2017, 194: 569–577
138. Ma H, You P, Liu K, et al. Optimal battery charging strategy based on complex system optimization. In: Li K, Xue Y, Cui S, et al., eds. Advanced Computational Methods in Energy, Power, Electric Vehicles, and Their Integration. LSMS 2017, ICSEE 2017. Communications in Computer and Information Science, Vol. 763. Singapore: Springer, 2017, 371–378
139. Hu X, Li S, Peng H, et al. Charging time and loss optimization for LiNMC and $LiFePO_4$ batteries based on equivalent circuit models. Journal of Power Sources, 2013, 239: 449–457
140. Perez H, Hu X, Dey S, et al. Optimal charging of Li-ion batteries with coupled electro-thermal-aging dynamics. IEEE Transactions on Vehicular Technology, 2017, 66(9): 7761–7770