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A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems

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ABSTRACT

With the rapid development of new energy electric vehicles and smart grids, the demand for batteries is increasing. The battery management system (BMS) plays a crucial role in the battery-powered energy storage system. This paper presents a systematic review of the most commonly used battery modeling and state estimation approaches for BMSs. The models include the physics-based electrochemical models, the integral and fractional order equivalent circuit models, and data-driven models. The state estimation approaches are analyzed from the perspectives of remaining capacity and energy estimation, power capability prediction, lifespan and health prognoses, and other crucial indexes in BMS. This present paper, through the analysis of literature, includes almost all states in the BMS. The estimation approaches of state-of-charge (SOC), state-of-energy (SOE), state-of-power (SOP), state-of-function (SOF), state-of-health (SOH), remaining useful life (RUL), remaining discharge time (RDT), state-of-balance (SOB), and state-of-temperature (SOT) are reviewed and discussed in a systematical way. Moreover, the challenges and outlooks of the research on future battery management are disclosed, in the hope of providing some inspirations to the development and design of the next-generation BMSs.

1. Introduction

Energy storage technology is one of the most critical technology to the development of new energy electric vehicles and smart grids [1]. Benefit from the rapid expansion of new energy electric vehicle, the lithium-ion battery is the fastest developing one among all existed chemical and physical energy storage solutions [2]. In recent years, the frequent fire accidents of electric vehicles have pushed electric vehicles to the subject of public opinion, and also put forward high requirements and challenges for battery management technology [3]. As one of the key components of electric vehicles, the lithium-ion battery management system (BMS) is crucial to the industrialization and marketization of electric vehicles. Therefore, developing advanced and intelligent BMSs for the lithium-ion battery packs has become a hot research topic.

The main technical difficulties restricting the development of battery management technology can be concluded in the following three aspects: (1) the lithium battery system is highly nonlinear, with multi-spatial scale (such as nanometer active materials, millimeter cell, and meter battery pack, etc.) and multi-time scale aging, making it difficult to accurately modeling; (2) the internal states of the battery cannot be obtained by direct measurement approach and is easily affected by environmental temperature, noise, etc. The upsizing of power batteries reduces the representativeness of measured values, and reduces the predictability of battery states, which makes it hard to accurately estimate the internal states of the battery; (3) the inconsistencies of the battery cells directly influence the efficiency of the pack, which increases the hidden danger of the battery. Some effective safety measures on small battery systems have little effect on electric vehicles, and the efficient and accurate control of the battery pack is difficult. Therefore advanced BMSs should be designed to solve the above problems [4,5].

The functional structure diagram of an advanced BMS is shown in Fig. 1. The key features of the battery management system is shown in Fig. 2. The basic functions of a BMS include battery data acquisition, modeling and state estimations, charge and discharge control, fault diagnosis and alarm, thermal management, balance control, and communication. Battery modeling and state estimation are key functions of the advanced BMS. Accurate modeling and state estimation can ensure reliable operation, optimize the battery system and provide a basis for safety management [6].

In this paper, the hotspots of modeling and state estimation in battery

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management are selected to discuss. The basic theory and application methods of battery system modeling and state estimation are reviewed systematically. The most commonly used battery models including the physics-based electrochemical models, the integral and fractional-order equivalent circuit models, and the data-driven models are compared and discussed. The battery states including the state-of-charge (SOC), state-of-energy (SOE), state-of-power (SOP), state-of-function (SOF), state-of-health (SOH), remaining useful life (RUL), remaining discharge time (RDT), state-of-balance (SOB), and state-of-temperature (SOT) and their estimation approaches are reviewed and discussed. Moreover, the challenges and outlooks of the research on battery modeling and state estimation are proposed.

The remainder of the paper is organized as follows: Section 2 reviews the battery modeling techniques. Section 3 provides the state of the art of battery state estimation methods. The challenges and outlooks of the research on battery modeling and state estimation are presented in Section 4, and finally, Section 5 concludes the paper.

2. Battery modeling

The battery models presented in literature mainly fall into the following three main categories: the physics-based electrochemical models [7], the electrical equivalent circuit models (include the integral-order and fractional-order models) [8,9], and the data-driven models establish by artificial intelligence algorithms such as the neural network [10] and support vector machine [11].

2.1. Physics-based electrochemical models

The single-particle (SP) model is the most mature simplified model for the physics-based electrochemical models [12]. In the SP model, a single particle is used to represent the concentration distribution of lithium-ion in the electrode. The SP model can be used to investigate the primary performance and the effect of solid-phase diffusion of the electrodes. However, the accuracy of the SP model is relatively low. Grandjean et al. [13] established the SPMe model based on the SP model. The model considers the influence of electrolyte on the output voltage, and proposes a partial differential equation for liquid electrolyte material conservation and charge conservation, which improves the simulation accuracy. They also solved the problem of multi-parameter estimation in SPMe and conducted sensitivity analysis on these parameters.

Doyle and Newman et al. [14] presented the pseudo-two-dimensional (P2D) model. The P2D model treats the anode and cathode of the cell as porous electrodes composed of numerous spherical particles, and the spaces between particles are filled with the electrolyte. The concentration distribution and potential distribution of the lithium-ion in the electrolyte liquid phase and the solid phase of the electrode material particles are described by several coupled partial differential equations (PDEs), so as to comprehensively examine the main reaction and side reaction rates inside the cell. Since the P2D model contains several coupled PDEs, it is necessary to simplify the P2D model from the perspective of engineering practice [15,16]. Furthermore, some coupled battery models have been proposed to represent different features of battery. A P2D electrochemical-thermal-capacity fade coupled model was developed in Ref. [17]. Ref. [18] Proposed a fully coupled electro-chemo-mechanical model for thin-film battery, which accounted for several mechanical and electrochemical factors. One of the main reasons that the physics-based electrochemical models are difficult to apply in real-time applications is due to a large number of unknown variables need to be identified using global optimization methods. Inevitably, they are likely to run into over-fitting or local optimization problems. In the absence of accurate and detailed model parameters, the simulation results of the actual physics-based electrochemical models are often not ideal.

2.2. Electrical equivalent circuit models

The electrical equivalent circuit models have gained much interest in real-time applications due to their simplified model structure and easy to be identified. The electrical equivalent circuit models use electrical components to mimic the battery behavior. In literature, the equivalent circuit models can be divided into two groups: the integral-order models and fractional-order models.

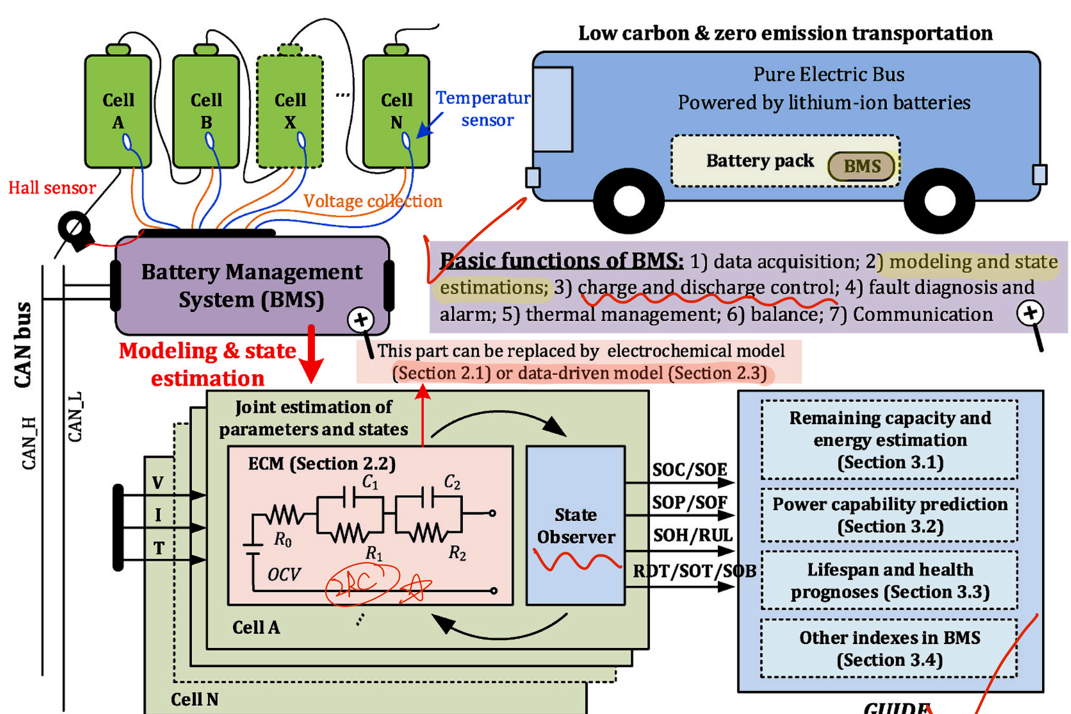

Fig. 1. Functional structure diagram of an advanced battery management system.

BMS

2.2.1. Integral-order equivalent circuit models

The simplest integral-order equivalent circuit model is the Rint model which is composed of an ideal voltage source in series with a resistor [19]. The model structure of the Rint model is simple, but the polarization and diffusion phenomena are not considered. Liaw et al. [20] presented the first-order resistor-capacitor (RC) model which is capable of simulating charge and discharge behavior of lithium-ion batteries by employing one RC network. This model can simulate the battery behavior with high fidelity as validated by experimental results. Xia et al. [21] utilized the second-order RC equivalent circuit model to approximate the battery dynamic performance and the voltage error is less than 40 mV. Andre and Sauer et al. [22,23] presented the ideal impedance spectrum of a lithium-ion cell and an equivalent circuit model with three RC networks was proposed. There is also literature considering the hysteresis behavior of the open-circuit voltage (OCV) to enhance the model accuracy [24].

For the integral-order equivalent circuit models, the input/output relationship of the cell is easy to derive and the models involve minor parameters. Therefore, the most widely used methods for on-line parameter identification are the recursive least-squares method. Wang et al. [25] proposed a co-estimator to estimate the model parameters and battery state. In Ref. [26], Zhang et al. proposed a novel parameter identification method considering the electrochemical properties. The presented method combines the electrochemical properties and equivalent circuit to study lithium-ion battery performance in different conditions, which better reflects the battery interior mechanism. Brand et al. [27] proposed a multi-objective genetic algorithm for parameter extraction of the equivalent circuit model. The results indicate that the method can accurately estimate the voltage of different types of batteries.

2.2.2. Fractional-order equivalent circuit models

The electrochemical impedance spectroscopy (EIS) [28] and the bode plot [29] are useful tools for analyzing the battery characteristics and establishing the model structure. Fig. 3 shows the EIS diagram for the impedance of a lithium-ion battery. In the middle-frequency, the battery's Nyquist curve is not a standard semicircle, which means that the standard RC network is not appropriate to simulate the battery characteristic on the whole frequency range. To overcome this problem, the constant phase elements (CPEs) can be used instead of the capacitors in RC networks. Therefore the fractional-order equivalent circuit models are proposed [30].

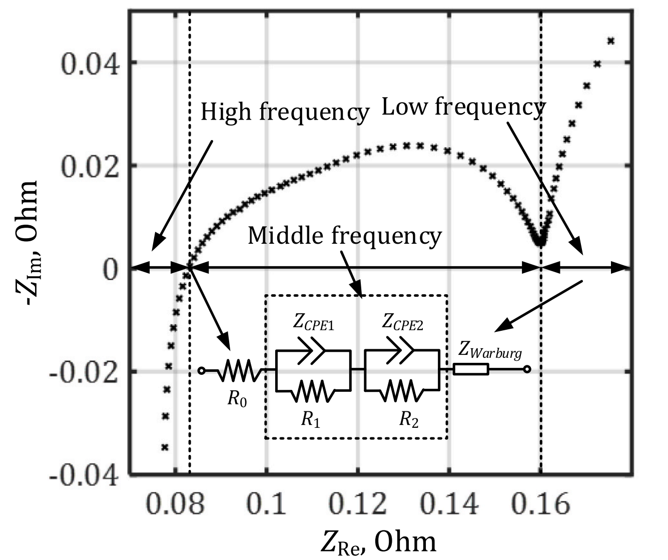

Fig. 3. Fractional-order equivalent circuit model and EIS diagram of a lithium-ion battery.

In Ref. [31], Yang et al. presented a simplified fractional order impedance model. The genetic algorithm is used to identify the model parameters and the voltage error is within 0.5%. Zou et al. [32] presented the non-integer order model derivatives and the particle swarm optimization algorithm was employed to identify the model parameters. The proposed fractional-order equivalent circuit model showed good accuracy and robustness. In recent years, the fractional-order models are widely used for battery state estimation and reliability analysis. Mu et al. [33] and Xiong et al. [34] employed the fractional-order equivalent

Fig. 2. Key features of the battery management system.

circuit model and Kalman filter to estimate the SOC of the lithium-ion batteries. Wang et al. [35] proposed the fractional-order models for a battery and supercapacitor hybrid system. Hu et al. [36] and Tian et al. [37] employed the fractional-order models to estimate the battery SOH and degradation state. In Ref. [38], the fractional-order model was used for the battery external short circuit fault diagnosis. A comparison of the benefits and drawbacks of the integral-order and fractional-order models is shown in Fig. 4.

2.3. Data-driven models

ref 39-43

The data-driven methods have been widely used in the development of battery models. Wang et al. [39] presented a thermal-electrical coupled model based on neural network. The effectiveness of the proposed approach was validated by different battery tests. Zhang et al. [40] proposed a data-driven state estimation approach by combining the neural network with particle filtering. Dong et al. [41] proposed a data-driven battery model based on wavelet-neural-network. In Ref. [42], the Stacked Denoising Autoencoders algorithm and the Extreme Learning Machine algorithm were combined to form a big data-driven lithium-ion battery model, which considered the impact of temperature. Although the data-driven approaches have good performance to nonlinear problems, they are easily influenced by training datasets and training methods. In addition, the dynamic simulation technology is also used in battery modeling. Vigneshwaran et al. [43] presented a three-dimensional kinetic Monte Carlo model to reveal the law of structural evolution of the dissolution/precipitation reaction of solid sulfur and lithium sulfide during the discharge of lithium-sulfur batteries. The kinetic Monte Carlo (kMC) model can approximate the dynamics of the battery at a longer time scale, so it can effectively predict the structural evolution of Li–O2, slurry redox flow batteries and other types of batteries.

3. Battery state estimation

The battery is a complex nonlinear system with multiple state variables, therefore the accurate estimation of battery states is the key to battery management and the basis of battery control. This section systematically summarizes the theoretical methods of battery state estimation from the following four aspects: remaining capacity & energy estimation, power capability prediction, lifespan & health prognoses, and other important indexes in BMS.

3.1. Remaining capacity and energy estimation

Physically, discharging a cell moves lithium from the negative electrode to the positive electrode, and the charging process does the opposite. Electrochemically, the cell state-of-charge (SOC) is positively related to the average concentration of lithium in the negative-electrode solid particles, and negatively related to the average concentration of lithium in the positive-electrode solid particles [44]. It should be noted that the cell voltage depends on electrode particle surface concentrations but SOC depends on average particle concentrations, which makes determining SOC using only voltage problematic. This is why the battery capacity is difficult to obtain and measure directly. Another question for the BMS to answer is how much energy is available in the battery pack. This question is most important for the electric vehicle because it is a fundamental input to vehicle range calculations which can tell the drivers how far they can drive. Therefore, the remaining energy or state-of-energy (SOE) estimation is crucial.

3.1.1. Review of state-of-charge estimation approaches

3.1.1.1. Look-up table method. The look-up table method is convenient and straightforward, which measures SOC based on the mapping relationship between characteristic parameters (such as impedance spectroscopy, internal resistance, OCV, etc.) and SOC [45].

- **Open-circuit voltage (OCV) look-up table method.** The OCV is the battery voltage after a long time of resting without load, which has a nonlinear relationship between SOC [46]. The detailed implementation process of the method is shown in Ref. [47]. The OCV is measured under different SOC conditions and made into the OCV-SOC table. In practice, the SOC is determined by measuring OCV and OCV-SOC table. The method is simple and easy, but the battery needs to be standing for a long time to ensure that the measured voltage is equal to OCV. Considering the influence of temperature, material, and aging on the relationship between OCV and SOC, these factors are added to the OCV-SOC table [48]. Pecht et al. [49] established an off-line OCV-SOC-Temperature table to infer battery SOC. Besides, the hysteresis effect of OCV is also an essential factor affecting the accuracy of OCV [50]. The hysteresis effect can be identified as the difference of OCV under the same SOC during charging and discharging, especially for $LiFePO_4$ batteries [51]. Therefore, an inaccurate OCV-SOC relationship without considering the hysteresis effect may lead to unacceptable SOC errors.

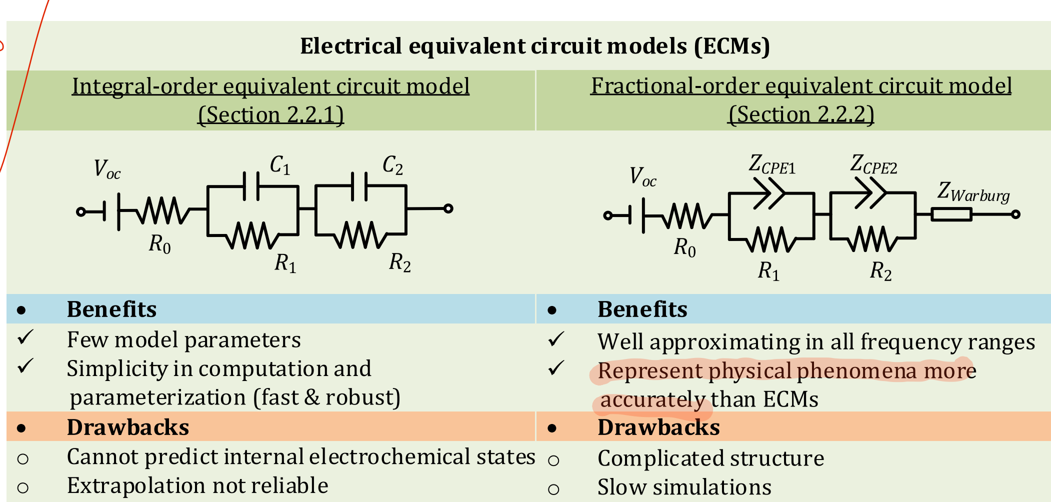

Fig. 4. Benefits and drawbacks of different electrical equivalent circuit models.

- **Impedance look-up table method.** There is a relationship between impedance and SOC. By applying a specific frequency of the current to the battery, several parameters related to SOC are identified by nonlinear fitting or parameter identification algorithm, then the impedance look-up table method is established [52]. The impedance parameters refer to internal ohmic resistance, polarization resistance, polarization capacitance, inductance, constant phase element, etc [53]. If the impedance amplitude is small, these methods may cause significant prediction errors. Ref. [54] indicated battery aging might affect the accuracy of SOC look-up table method. Besides, the current, ambient temperature and other factors may lead to non-linear changes in impedance and SOC [55]. To ensure the reliability of SOC estimation, the effects of current ratio, aging, and temperature on impedance need to be considered.

The primary defect of the look-up table method is that the battery requires to be rested for a long time to ensure the stability of internal electrochemistry so that the measured parameters can be relatively accurate. Besides, the reliability of SOC measurement dramatically depends on the accuracy of the SOC table. Therefore, the method is not suitable for the application of real-time and high accuracy of SOC estimation, such as aviation, aerospace, military industry, etc.

3.1.1.2. -hour integral method. Compared with the above methods, the ampere-hour integral method is more straightforward, where the SOC of the battery is calculated by current integration [56].

Although this method is simple, it has apparent shortcomings. Due to the open-loop calculation, the sensor error will be accumulated, which may generate more massive SOC error. Besides, aging and temperature can cause deviations in rated capacity and Coulomb efficiency, which affects the accuracy of SOC calculation. Moreover, the initial SOC is determined by the look-up table method so that any initial error may run through the whole SOC calculation process. Therefore, this method is usually combined with the model-based method or data-driven method to enhance its robustness.

3.1.1.3. Filter-based method. Typically, the filter-based method can be roughly grouped into two categories: the Gaussian process-based filter approaches (LKF, EKF, AEKF, SPKF, UKF, AUKF, CDKF, CKF) and the probability-based filter approaches (PF, UPF, CPF).

- **Liner Kalman Filter (LKF).** For the past few years, Kalman Filter (KF) is widely used for battery state estimation [57]. It can be seen as a recursive process that involves two steps: (1) predicting the system state and output, (2) updating the system state based on output errors [58]. Because the OCV function is nonlinear, KF cannot be used directly. In Ref. [59], a method of SOC estimation of LIB using a LKF based on local linearization was proposed. The OCV function is piecewise linearized, which makes LKF suitable for SOC estimation. Chen et al. [60] proposed a joint estimation method of SOC and SOF based on LKF. Wei et al. [61] put forward a joint estimation method of SOC and capacity. The SOC and capacity are estimated by LKF and the recursive least squares, respectively. In recent years, a variety of KF variants are used for battery SOC estimation.
- **Extended Kalman Filter (EKF).** The principle of EKF is to linearize the nonlinear system and perform Kalman filtering, so EKF is a suboptimal filter [62]. The EKF expands the nonlinear OCV function with partial derivatives based on the linearization principle of nonlinear functions [63]. Aiming at the problem that the model parameters are easily changed caused by the nonlinear behavior of the battery, the SOC estimation method based on a reduced-order battery model and EKF was proposed in Ref. [64]. Experimental results showed that SOC errors are within 2%. In Ref. [65], a SOC estimation method based on a dual-time scale EKF was developed for the battery pack. First, the average SOC was estimated, then the cell SOC was determined according to the difference between the average cell and single cell. The results showed that the pack SOC error is less than 2%. Whether the rated capacity is accurate directly affects the reliability of SOC estimation results. In Ref. [66], SOC and capacity were jointly estimated by EKF, SOC error was further reduced. In Ref. [67], a robust estimate SOC method using EKF was proposed for the battery. The modeling error was regarded as a constant bias state vector, which was used to correct SOC. The accuracy of the EKF depends not only on the linearization of the OCV function but also on model parameters [68]. Therefore, several improved methods have been proposed to estimate battery SOC, which can be divided into two categories: (1) model improvement; (2) algorithm improvement. In Ref. [69], the thermal-electrochemical model was developed for the battery. The model parameters are compensated by temperature and the SOC was estimated by EKF. In Ref. [70], an enhanced SOC estimation method based on EKF was developed, which considered the effects of different currents, SOCs and hysteresis effects on the model parameters. In Ref. [71], the cubic Hermite interpolation was used to correct the battery model, and the SOC was estimated by grey EKF. The proposed method can overcome the influence of truncation error. In Ref. [72], a multi time scale estimation algorithm based on EKF is proposed, which is applied to the joint estimation of SOC and SOH of battery. In order to reduce the error of SOC estimation, the filter with better performance than EKF is used to estimate SOC.
- **Adaptive Extended Kalman Filter (AEKF).** In AEKF, the covariance of process noise and observation noise are adaptive [73]. The adaptive covariance of process noise and measurement noise makes AEKF effectively avoid the divergence or bias of the algorithm [74]. In Ref. [75], an on-line OCV estimation method was established by using AEKF, and SOC was determined by looking up the OCV-SOC table. In Ref. [76], the relationship between SOC and the chemical composition of different types of batteries was analyzed. Then based on a multi-parameter closed-loop feedback system, the accurate estimation of SOC was estimated by AEKF. The results showed that the maximum SOC error is within 3%. Due to the aging of the battery, the accuracy of SOC estimation is challenged. A new method to estimate SOC of LIB based on AEKF was proposed in Ref. [77]. A simple optimization algorithm is applied to update the battery aging model, and the SOC with different aging batteries was estimated by AEKF. The results showed that the SOC error is less than 4%. Due to the fractional-order model has a better description of the battery behavior, the battery SOC was AEKF estimated by AEKF based on the fractional-order model [78]. In order to solve the problem of interference of current measurement offset to SOC estimation, a joint estimation method of SOC and capacity based on AEKF multi time scale framework is proposed in Ref. [79], which effectively improves the robustness and accuracy of SOC estimation.
- **Sigma-Point Kalman Filter (SPKF).** For EKF, the linearization of OCV-SOC function is expanded near the prior mean, and the nonlinear part is ignored, which leads to obvious SOC estimation error. Therefore, it is difficult for EKF to achieve satisfactory performance in applications requiring high SOC estimation accuracy. In Ref. [80], the SOC estimation methods based on SPKF ware proposed. The results indicated that SPKF could obtain higher SOC estimation accuracy than EKF. In Ref. [81], a SOC estimation method based on an electrochemical model was proposed, which uses an adaptive square root sigma point Kalman filter (ASRSPKF) with equality constraints. The results show that ASRSPKF has outstanding performance. Compared with AEKF, its accuracy is improved by 30%, and its convergence time is shortened by 88%.
- **Unscented Kalman Filter (UKF).** UKF is developed from the traceless transformation and standard KF. By traceless transformation, nonlinear system equations can be applied to the standard Kalman filter under linear assumption [82]. UKF does not ignore higher-order terms due to linearization, so it has high estimation

accuracy [83]. The parameters of the battery model are sensitive to temperature. In Ref. [84], model parameters were compensated by temperature, then SOC was estimated by UKF. To improve the performance of traditional UKF, several improved UKF algorithms were developed. In Ref. [85], the battery model was trained by the radial basis function (RBF) network, the SOC was estimated by SRUKF. The results showed that SRUKF has higher SOC estimation accuracy than EKF. To reduce the calculation requirements of unscented transformation in UKF, the square root unscented Kalman filter using spherical transform (Sqrt-UKFST) was developed to estimate battery SOC in Ref. [86]. Compared with EKF, RMSE and maximum error increased by 37% and 44%, respectively. The calculation requirement is reduced by 32% than UKF. To improve the robustness of UKF, the fuzzy inference system was applied to optimize UKF [87]. The improved UKF algorithm is more robust, and SOC error under the UDDS condition is within 1.76%.

- **Adaptive Unscented Kalman Filter (AUKF).** AUKF is an upgrade of UKF, which can automatically adjust the noise covariance in the SOC estimation [88]. The AUKF was employed for battery SOC estimation in Ref. [89]. The recursive least squares method identified model parameters on-line and updated the AUKF state model in real-time. The results showed that the joint estimation algorithm could reduce the SOC estimation error. Mara et al. [90] have compared the performance of AUKF, AEKF, UKF, and EKF in SOC estimation based on a 2nd order RC model. The results indicated that AUKF has the best performance. The absolute average error was only 0.028%. To calculate the error covariance adaptively, an improved AUKF based on Sage-Husa maximum posterior estimation was proposed for SOC estimation. In Ref. [91]. The experimental results showed that the accuracy of SOC estimation is higher than that of UKF and EKF.
- **Central Difference Kalman Filter (CDKF).** The CDKF assumes that the state variables of the system obey Gaussian distribution. For random Gaussian variables with known mean and covariance, CDKF estimates their mean and covariance after any nonlinear transformation. CDKF uses the Sterling interpolation formula to expand the nonlinear model according to the central difference, which does not need to calculate the partial derivative of the function [92]. The accuracy of EKF and CDKF in estimating SOC was compared in Ref. [93]. The results showed that CDKF has a higher performance in estimating SOC. The SOC absolute maximum error is less than 6%. To avoid the high-order Taylor series expansion in EKF calculation, an improved CDKF algorithm using second-order difference transformation to generate sigma points was proposed in Ref. [94]. The verification results showed that the SOC error is within 2%, which is better than EKF and UKF.
- **Cubature Kalman Filter (CKF).** The CKF was proposed by Canadian scholars Araararatnam and Haykin in 2009 [95]. Based on the third-order spherical radial volume criterion, the mean value of the nonlinear system state is approximated by CKF using a series of volume points, which can effectively solve the problem of nonlinear system state estimation. The most important two steps are to transform the integral form into the spherical radial integral form and the third-order spherical radial criterion. In Ref. [96], the performance of CKF and EKF in SOC estimation was compared. The experimental results show that the maximum absolute error of CKF-based SOC estimation of CKF is 1.78% lower than that of EKF. However, the calculation time of CKF is 8.8 times that of EKF. In Ref. [97], a SOC estimation method based on adaptive CKF (ACKF) was developed. The results showed that the robustness and convergence rate of ACKF are better than that of CKF. In Ref. [98], the improved cubature Kalman filter (ICKF) based on singular value decomposition (SVD) and Gauss-Newton iterative technique was used to estimate battery SOC, which reduces the SOC estimation error. To ensure the non-negativity of the covariance matrix and avoid filter divergence, the square root cubature Kalman filter (SRCKF) calculates the state covariance information by the Cholesky decomposition, which improves the performance of CKF in SOC estimation [99].

The Kalman filter and its distortion are limited by the Gaussian distribution condition, so it is difficult to obtain a satisfactory filtering effect for non-Gaussian distribution. At present, the more popular way to solve the generic filter is to use the particle filter (PF) [100,101]. Nowadays, the research of PF has made gratifying progress, and many deformations have been proposed used in battery state estimation.

- **Particle Filter (PF).** The core idea of PF is to generate a set of discrete sampling points in the state space according to the empirical distribution of the system state vector, then adjust the position and state of particles according to the observed values. Finally, the optimal particle state is estimated by adjusting the particle sets [102,103]. A method for estimating SOC and residual discharge time (RDT) of battery based on PF was developed in Ref. [104]. In Ref. [105], the PF was applied to estimate SOC and SOH. In Ref. [106], the performance of PF and EKF in SOC estimation was compared. The results showed that PF is better than EKF. To reduce SOC estimation error, a SOC estimation method based on dual PF was proposed in Ref. [107]. The numerical results indicated that the proposed method has higher accuracy then EKF and UKF.
- **Unscented Particle Filter (UPF).** The UPF is an improved form of PF. Its main idea is to use UKF to improve the sampling process of PF. The UKF calculates the mean and variance for each particle, then PF resamples the particle. UKF uses the function of approximate posterior filter density to calculate the mean and variance of particles. The latest observation information is included in the calculation results, so the PF sampling effect is improved [108]. Due to its superior performance, UPF has been widely used in SOC estimation. In Ref. [109], the author compared the algorithm performance of EKF, UKF and UPF in SOC estimation. The comparison results showed that the numerical indexes of UPF are optimal. In Ref. [110], a prediction framework of SOC and RDT based on UPF was proposed for the battery. The UPF improved the accuracy of SOC estimation and ensured the reliability of RDT prediction. For UPF, if the number of particles is too large, the convergence speed of the algorithm will slow down. To overcome this issue, a hybrid UPF algorithm was proposed in Ref. [111], which uses the normalized least mean square method to adapt the search range, so as to improve the efficiency of UPF. The results showed that the prediction SOC estimation error is within 2%, and the improved algorithm has better performance than the original algorithm.
- **Cubature Particle Filter (CPF).** CPF directly calculates the mean and variance of nonlinear random function by volume method and generates the suggested density function to get the weighted particles. Then, by calculating the mean value of the particles, the minimum mean square error estimation of the system state is obtained [112]. CPF algorithm uses the latest measurement information when generating particles, which improves the approximation degree of the posterior probability of system state [113]. The complexity, precision and robustness of three SOC estimation methods based on extended particle filter (EPF), CPF and UPF were compared in Ref. [114]. The experimental results indicated that the EPF algorithm is efficient, but SOC estimation error is high. On the contrary, CPF and UPF can improve the accuracy of SOC estimation, but require more running time. In Ref. [115], an adaptive weighted cubic particle filter (AWCPF) was proposed to estimate SOC. Aiming at the problem that the CKF algorithm is sensitive to noise, the proposed algorithm adaptively adjusts the sigma point weight according to the state and measurement residual vector iteratively. The algorithm was used to verify different operating conditions with various initial SOC. The results showed that AWCPF has high estimation accuracy, strong robustness, fast convergence speed, and the maximum SOC estimation error is within 1%.

3.1.1.4. Observer-based method. The state observer can obtain the estimated values of the state variables based on the measured values of the external variables of the system. In order to realize state feedback or other needs for control systems, Luenberg [116] proposed the concept and construction method of state observer. The appearance of the state observer not only provides a practical possibility for the realization of state feedback technology but also has been applied in many aspects of control engineering. In recent years, the observer-based methods such as the Luenberger observer (LO), the sliding mode observer (SMO), the proportional-integral observer (PIO), and the H-infinity/H_∞ observer (HIO) have been used extensively for battery state estimation.

- **Luenberger Observer (LO).** The LO is widely used in linear, nonlinear and time-varying systems [117]. Hu et al. [118] proposed an adaptive Luenberger observer (ALO) based method for online SOC estimation of a battery pack. The observer gain was adaptively adjusted through a stochastic gradient approach. Wang et al. [119] developed a LO for SOC estimation based on a nonlinear fractional battery model. The global asymptotic stability can be ensured through Lyapunov's direct method.
- **Sliding mode observer (SMO).** The SMO is developed from the sliding mode controller (SMC) and maintains robust tracking performance under the condition of model uncertainties and environmental interference. A switching gain is designed to ensure stability and convergence. To eliminate the chattering phenomenon, a second-order discrete-time SMO was developed in Ref. [120]. In Refs. [121,122], an adaptive gain SMO (AGSMO) was proposed to compensate model errors and minimize chattering levels. A grey prediction-based fuzzy SMO (GPFSMO) was proposed in Ref. [123] to both reduce chattering and solve the over-estimation problem. The value of battery voltage was predicted through grey prediction and the gains on SMO were tuned according to the prediction error through fuzzy inference system. Chen et al. [124] proposed a robust SMO (RSMO) for SOC estimation. The switching gain of RSMO was adjusted according to the upper bound of system uncertainty that is learned by a radial basis function neural network (RBFNN), and achieved the convergence of the SOC estimation errors. A fractional-order SMO based SOC estimation method was designed in Ref. [125]. Huang et al. [126] proposed a novel super-twisting SMO (STSMO) based SOC estimation method. The results indicated the STSMO can achieve faster convergence speed and higher robustness with less computation cost.
- **PI Observer (PIO).** The PIO is an efficient method to estimate the state of systems with unknown input disturbance. A PIO based SOC estimation method based on a simple RC battery model was proposed in Ref. [127]. Tang et al. [128] developed a dual-circuit based observer. The parameters-normalized PIO was designed to deal with the capacity error and initial error, and the current integrator was to restrain the influence of the drifting current. The experiment results showed that without matrix operation, this method had lower computation complexity but high accuracy, even when the initial SOC was unknown.
- **H-infinity/H_∞ Observer (HIO).** The HIO can ensure the robustness of the inaccurate initial system state and unknown disturbance from the inaccurate or unknown statistical characteristics of modeling and measurement errors. To accommodate the mode uncertainties from current, temperature, and aging, a methodology combined with an HIO and a hysteresis model was proposed in Ref. [129]. Zhu et al. [130,131] developed an HIO with dynamic gain for the SOC estimation of a battery pack, which can reduce the adverse influence of the non-Gaussian model and measurement errors. In addition, the observer design criterion was formed as the linear matrix inequality (LMI) for easy computation. Liu et al. [132] developed an HIO using a switched battery model to estimate the Electromotive force (EMF) for SOC. The switched model considered the relaxation effect and the relationship between EMF and SOC.
- **Other Observers.** Wei et al. [133] developed a recursive total least squares (RTLS) based observer to address the biased identification of model parameters resulting from the unexpected sensing of noises. A RTLS based on Rayleigh quotient (RQ) minimization was employed to minimize the influence of current and voltage sensing noises. A Frisch scheme based bias compensating recursive least squares (FBCRLS) based observer was proposed in Ref. [134]. The FBCRLS method was utilized to estimate online the noise variances and the unbiased model parameter. Then the FBCRLS was integrated with a SOC observer in a closed-loop feedback mechanism, namely FBCRLS based observer. Ma et al. [135] proposed an input-to-state stability (ISS) theory based nonlinear observer for the SOC estimation. Two nonlinear robust observers based on a reduced-order electrochemical model were presented in Ref. [136]. Both observers contained a Luenberger term for nominal error convergence and a variable structure term for the improvement of robustness of model uncertainties. Li et al. [137] proposed a discrete-time nonlinear observer for battery SOC estimation. Compared with the EKF and the discrete-time SMO algorithms, the computation cost was reduced and the estimation accuracy and convergence speed were improved. Xia et al. [138] applied a special nonlinear observer to verify the improved parameter identification method based on polarization depth.

3.1.1.5. Data-driven based method. The data-driven based methods consider the battery as a black box and learn the internal dynamics through large amounts of measurable input and output data. The commonly used data-driven based methods for SOC estimation include neural network (NN), fuzzy logic, genetic algorithm (GA), support vector machine (SVM), and so on.

- **Neural Network (NN) method.** The NN method has an excellent ability to form a non-linear map to demonstrate a complex nonlinear model. Dang et al. [139] proposed an OCV-based SOC estimation method on the basis of the dual NN fusion battery model. The linear NN battery model was used to identify parameters of the first-order or second-order electrochemical model, and the second back-propagation NN (BPNN) was utilized to capture the relationship between OCV and SOC. Sun et al. [140] developed a Radial Basis Function Neural Network (RBFNN) based uncertainty quantification algorithm to construct response surface approximate model (RSAM) of model bias function to estimate the SOC of multi-cell battery pack. Tong et al. [141] established a load-classifying NN model to estimate the SOC. The structure of the model and the post-processing improve the suppression of over fitting. Chemali et al. [142] developed a long short-term memory recurrent neural network (LSTM-RNN) based SOC estimation for Li-ion batteries. A BPNN based SOC estimation strategy was introduced in Ref. [143]. In addition, principal component analysis (PCA) and particle swarm optimization (PSO) were utilized to improve estimation accuracy and robustness. A novel method based on deep feed-forward NN was used for battery SOC estimation in Ref. [144] and the battery measurements can be directly mapped to SOC. Chen et al. [145] proposed a RBFNN based nonlinear observer using an inclusive equivalent circuit model to estimate SOC. An improved nonlinear autoregressive with exogenous input (NARX)-based NN (NARXNN) algorithm was developed to estimate the SOC of batteries [146]. The lighting search algorithm (LSA) was used to find the best value of input delays, feedback delays, and hidden layer neurons. Xia et al. [147] proposed a multi-hidden-layer wavelet NN (WNN) model optimized by Levenberg-Marquardt (L-M) algorithm. PSO algorithm was employed to optimized WNN for SOC estimation. Yang et al. [148] developed a RNN with gated recurrent units to estimate the battery SOC. A stacked LSTM network was proposed in Ref. [149] to model the dynamics of lithium iron phosphate batteries and estimate the

SOC. The proposed method presented quick convergence to the true SOC even if the initial SOCs were inaccurate.

- **Fuzzy Logic method.** A fuzzy NN (FNN) based battery model was established to capture the battery nonlinear dynamics [150,151]. Lee et al. [152] proposed a learning system that consists of learning controllers, FNNs, and cerebellar-model-articulation-controller networks to estimate the SOC. Li et al. [153] developed a simple-structure merge FNN for SOC estimation, where the soft computing approach combined the FNNs based on B-spline membership function (BMFs) and a reduced-form genetic algorithm (RGA).
- **Genetic Algorithm (GA).** The GA is usually used to identify the battery model parameters for further SOC estimation [154]. Chen et al. [155] developed a novel SOC estimation method on the basis of the grey model (GM) and genetic algorithms. The utilization of a genetic algorithm introduced higher accuracy and repeatability.
- **Support Vector Machine (SVM).** The SVMs are a cluster of related supervised learning methods that can universally approximate any multivariate function to any level of accuracy [156]. An optimized SVM for regression based SOC estimation method was proposed in Ref. [157]. The results verified this method was simpler and more accurate than that based on artificial neural networks (ANNs). Meng et al. [158] combined the adaptive unscented Kalman filters (AUKF) and least-square support vector machines (LSSVM) to estimate battery SOC. The battery model can be accurately established and updated even with limited training samples. Deng et al. [159] implemented a least squares SVM prediction algorithm to predict the battery available capacity.

The comparison of the above mentioned SOC estimation approaches in terms of computation accuracy, application scenarios, benefits and drawbacks, is summarized in Fig. 5. The look-up table method is simple and needs to establish the nonlinear relationship between SOC and OCV or impedance offline. Its main disadvantage is that it can not meet the real-time requirements and is sensitive to the accuracy of sensors. The ampere-hour integral method is simple and needs low computational cost. However, this approach is open-loop and the accuracy mainly relies on the initial SOC and the sensor accuracy. Thus, this method combined with other methods like OCV look-up table or model-based methods is a promising approach for better SOC estimation accuracy. The model-based methods, including filter-based and observer-based methods, can achieve high estimation accuracy and robust to noise. Nevertheless, the accuracy of the model-based methods usually depends on the model precision and more computing resources are required due to algorithm complexity. The KF family based methods are widely used in SOC estimation. The LKF-based method is only suitable for the linear systems. To overcome this drawback, the EKF-based method applies the linearization approximation to the nonlinear systems. The accuracy of EKF-based method depends on the linearization error. Thus, this is unsuitable for high order nonlinear systems. To avoid the complicated Jacobian matrix and Gaussian noise computation, the SPKF- and UKF-based methods are developed for SOC estimation, but more computing resources are required. Adaptive methods, such as AEKF and AUKF, are further developed to enhance robustness against the measurement noises and processing noises. To deal with the non-Gaussian noises, PF-based method is proposed and can achieve high accuracy. Furthermore, the UPF- and CPF-based methods are designed to improve particle sampling process and state probability approximation, but the convergence rate remains a challenge. The observer-based methods can also obtain satisfactory estimation accuracy against sensor or initial state errors. However, the appropriate gain determination is still a critical issue. Unlike the model-based methods, the data-driven based methods are insensitive to the model accuracy and environmental conditions. The main drawbacks are that these methods usually need high computational cost and long processing time, and the accuracy depends on the trained data to a great extent.

3.1.2. Review of state-of-energy estimation approaches

The state-of-energy (SOE) was first proposed by Mamadou et al. [160]. The SOE estimation approaches are similar to that of SOC estimation. The most commonly used approaches are data-driven based approaches and adaptive filter-based approaches. Liu et al. [161] used the SOE to estimate the remaining energy and considered the energy loss of internal resistance, chemical reaction, and OCV reduction. They also deeply explored the impacts of temperature and C-rate on SOE estimation and improved the accuracy of the estimation. Wang et al. [162] proposed a joint estimator of SOC and SOE based on particle filtering. They performed experiments on IFP1865140-type batteries under dynamic temperature and verified the robustness and accuracy of the method. He et al. [163] proposed a battery SOE estimator based on a Gaussian model. The results showed that the estimated SOE can guarantee high accuracy. Zhang et al. [164] proposed a joint estimator for SOE and SOP by using AUKF. The estimated error of battery SOE is less than 2%. Dong et al. [41] established a battery SOE estimator using PF. The battery state-space model was built based on a wavelet neural network. The superiority of this method was verified on $LiFePO_4$ batteries. Zhang et al. [165] proposed an adaptive H-infinity observer to estimate SOC and SOE of Li-ion batteries. The proposed method was verified to be more accurate than the EKF method. Zheng et al. [166] comprehensively analyzed the correlations between ambient temperature, C-rate, battery aging degree, and the maximum available energy of the battery. Dong et al. [167] proposed a dual filtering algorithm based on EKF and PF, and established an online SOE estimator. The estimated error was around 4%. Lin et al. [168] proposed a multi-model probabilistic estimation method, which combined the estimation results of different models according to the weights determined by Bayes theorem.

Method	Representativeness	Accuracy	Application	Benefits	Drawbacks
• Look-up table method	❖ OCV look-up table method[46]	MAE≤±1.2%	Parked EVs, Lab	√ Simple, easy to implement	× Off-line, long relaxing time required
	❖ Impedance look-up table method[53]	MAE≤±1.4%	Lab	√ Simple, easy to implement, online	× Sensitive to sensor accuracy
• Ampere-hour integral method	❖ Calculated by current integration[56]	MAE≤±4.0%	EVs, Lab	√ Simple, low computational cost	× Open-loop, rely on initial SOC and sensor accuracy
• Filter-based method	❖ Linear Kalman Filter (LKF)[60]	MAE≤±2.0%	EVs, Lab	√ Online, real-time	× Not suitable for nonlinear system
	❖ Extended Kalman Filter (EKF)[62]	MAE≤±1.4%	EVs, Implantable charger, Lab	√ Insensitive to uncertain initial state	× Depends on linearization error
	❖ Adaptive Extended Kalman Filter (AEKF)[75]	MAE≤±2.0%	EVs, Mobile robots, Lab	√ Robust to Gaussian noise	× Not suitable for non-Gaussian noise
	❖ Sigma-Point Kalman Filter (SPKF)[80]	ME≤±1.2%	EVs, Lab	√ No Jacobian matrix computation	× More computing resources required
	❖ Unscented Kalman Filter (UKF)[82]	ME≤±0.12%	EVs, Mobile robots, Lab	√ Suitable for high order nonlinear system, no Jacobian matrix required	× More computing resources Required, not suitable for non-Gaussian noise
	❖ Adaptive Unscented Kalman Filter (AUKF)[90]	ME≤±0.10%	EVs, Mobile robots, Lab	√ Robust to noise, high accuracy	× More computing resources required
	❖ Central Difference Kalman Filter (CDKF)[94]	MAE≤±1.42%	EVs, Spacecraft, Lab	√ No Jacobian matrix computation	× Limited to Gaussian noise
	❖ Cubature Kalman Filter (CKF)[96]	MAE≤±2.70%	EVs, Lab	√ Not limited to system type	× More computing resources required
	❖ Particle Filter (PF)[106]	MAE≤±0.863%	EVs, Lab	√ High accuracy, less computation time	× Need a complex mathematical tool
	❖ Unscented Particle Filter (UPF)[114]	MAE≤±0.9%	EVs, Lab	√ Better particle sampling	× Poor convergence rate
	❖ Cubature Particle Filter (CPF)[114]	MAE≤±1.1%	EVs, Lab	√ Better state probability approximation	× Poor convergence rate
• Observer-based method	❖ Luenberger Observer (LO)[118]	MAE≤±0.8794%	EVs, Lab	√ Fast convergence, high precision	× Difficult to determine observer gain
	❖ Sliding Mode Observer (SMO)[126]	ME≤±2%	EVs, Lab	√ Strong tracking, more stable	× Difficult to determine switching gain
	❖ PI Observer (PIO)[128]	ME≤±2.5%	EVs, Lab	√ Robust to sensor noise	× Difficult to determine PI gain
	❖ H-infinity/H_{-} Observer (HIO) [130]	ME≤±3.36%	EVs, Mobile robots, Lab	√ Robust to initial state	× More computing resources required
• Data-driven based method	❖ Neural Network (NN) method [141]	MAE≤±3.8%	EVs, Lab	√ Independent of battery model	× Dependent on training samples
	❖ Fuzzy Logic method[150]	ME≤±5.0%	EVs, Lab	√ Robust to operating conditions	× More computing resources required
	❖ Genetic Algorithm (GA)[33]	MAE≤±2.98%	EVs, Lab	√ Robust to system noise	× Complex calculation, slow response
	❖ Support Vector Machine (SVM)[156]	ME≤±6.0%	EVs, Lab	√ Better performs in nonlinear system	× More computing resources required

(Lab: Laboratory; EVs: Electrical vehicles; ME :Maximum error; MAE: Maximum absolute error)

Fig. 5. The comparison of different SOC estimation approaches.

3.2. Power capability prediction

The prediction of power capability is also crucial in battery management which shows users how much power is available in the immediate future. The power capability is the rate at which energy can be moved from the battery pack to the loads without exceeding cell or electronics design limits and is an instantaneous quantity. Generally, the state-of-power (SOP) or state-of-function (SOF) is used to evaluate the power capability of a battery. The SOP can be defined as the percentage of peak power relative to rated power, where the peak power is the maximum continuous power over a short period of time that does not exceed the thresholds [169]. According to the available literature, the common SOP calculation methods can be divided into three types: experimental testing approach, multiple constraints estimation approach, and data-driven approach.

3.2.1. Experimental testing approach

The measurement approach for battery power capability evaluation based on the hybrid pulse power characterization (HPPC) test is proposed in Ref. [170]. The experimental testing approach is the most commonly used approach for static peak power measurement. It can estimate the instantaneous available power. However, it needs a static test environment resulting that it is impractical in practical applications.

3.2.2. Multiple constraints estimation approach

In order to overcome the drawback of the experimental testing approach, Plett et al. [171] proposed a voltage-constraint method to improve the HPPC method which can estimate the continuous useable power. Feng et al. [172] proposed a SOP prediction algorithm based on an equivalent circuit model, considering both the voltage and current limits. However, it may cause over-charge or over-discharge without SOC as a constraint when the batteries are nearly saturated or hungry. Dong et al. [173] analyzed the influenced factors of SOP based on statistical data. Moreover, they proposed a joint estimator for SOC and SOF of LIB based on KF. The SOF in this paper indicated the power capability of the battery, which was consistent with the content expressed by the SOP. The methods use only one constraint to estimate the SOP of the battery would give over-optimistic results, due to the peak current would not be allowed to be used under a large-scale SOC [174]. Hence, a multi-constraints (voltage, current, power, SOC, etc.) SOP prediction algorithm was proposed to obtain a more precise result in Ref. [175]. The advantages and disadvantages of the single-constraint methods were deeply analyzed in this paper. Furthermore, the results indicated that the multi-constraints method could overcome the drawbacks of the single-constraint methods and improve the precision and robustness of their model. Wei et al. [176] established an adaptive peak power estimator for vanadium redox battery by combining voltage, SOC and current design constraints. Experiments verified that the method has good performance in modeling accuracy, convergence, and computational complexity. Zhang et al. [177] proposed an adaptive UKF joint estimator to jointly estimate the SOE and SOP of the battery. The effectiveness of the method at different temperatures and different aging degrees was verified on lithium iron phosphate batteries. Sun et al. [178] proposed a joint estimator of AEKF algorithm to jointly estimate battery SOC and SOP. Wang et al. [179] estimated the power and energy of lithium-ion batteries and ultra-capacitor hybrid systems. They carried out a detailed analysis of power capacity and maximum charge/discharge energy prediction under multiple constraints. Experiments and discussions on the prediction of charge and discharge energy are conducted on different timescales. Tang et al. [180] proposed a high-fidelity migration model for SOC and SOP estimation. An efficient numerical search algorithm is used to calculate the value of the SOP, and it is constrained by multiple conditions such as current, SOC, and voltage. Zou et al. [181] for the first time formulates battery power prediction and management as an economic model predictive control. The algorithm will be extended in this application for battery management where more factors will be considered, such as physics-based battery models and associate state constraints.

3.2.3. Data-driven approach

In the data-driven approach, the battery is regarded as a black box, and the reaction mechanism and characteristics inside the battery are not considered. The SOP is taken as output of a model by means of data analysis and machine learning, and influence factors such as voltage, temperature, and SOC are taken as inputs. Fleischer et al. [182] presented a method to estimate SOP by an adaptive neuro-fuzzy inference system (ANFIS).

3.3. Lifespan and health prognoses

The state-of-health (SOH) is a critical index for lifespan and health prognoses, which can reflect the current life condition of batteries [183]. The definition of SOH can be expressed as shown in Eq. (1).

$$SOH = Q_{\max}/Q_{\text{new}} \quad (1)$$

In Eq. (1), $Q_{\max}$ is the maximum available capacity of the battery, Q_{new} is the available capacity of a new battery. The SOH/RUL estimation approaches can be divided into the following groups: measurement & analysis approach, Bayesian-based estimation approach, empirical fitting approach, and machine learning-based approach.

3.3.1. Measurement & analysis approach

3.3.1.1. Direct measurement approach. The battery internal resistance and available capacity are critical parameters for the battery SOH assessment. The Coulomb counting method is a useful method for capacity estimation. In Ref. [184], the Coulomb counting method employed to estimate the SOH is evaluated by the maximum releasable capacity. Kim et al. [185] developed an enhanced Coulomb counting algorithm that can get robust and accurate SOC and SOH estimation. The internal resistance is an important indicator of battery degradation. Blanke et al. [186] presented an overview of methods used to estimate the SOH based on impedance measurements. The EIS technique is employed to determine the SOH through the change of the impedance spectrum at a particular peak [187].

3.3.1.2. Indirect analysis approach. In Refs. [188], the indirect analysis of the battery charging and discharging curves are employed for battery SOH estimation. In Ref. [189], incremental capacity analysis method is used to obtain the battery aging level. The support vector regression is employed to extract the aging level and the results show that this method can predict the SOH within 1% error bound. Merla et al. [190] proposed a novel technique called differential thermal voltammetry (DTV) to determine the SOH of batteries. The peak parameters of DTV which represent the particular chemical reaction can be used to explore the aging process [191,192]. In Ref. [193], the differential voltage (DV) curve is used to quantify the aging mechanisms. Ref. [194] Presented the center least squares method to obtain the DV curve. The inflection point location and the transformation parameters can be used in battery SOH estimation. The differential mechanical parameter (DMP) analysis is a complementary approach to the existing SOH estimation techniques [195,196]. Cannarella et al. [197] developed a DMP-based approach to estimate SOH by using the stress measurement.

3.3.2. Bayesian-based estimation approach

3.3.2.1. Kalman filters family. The KF can be applied to a linear system with Gaussian noise [198,199]. In Ref. [200], the KF is used to predict the capacity of batteries using a two-phase service model. Wassiliadis et al. [201] used two EKF to obtain the battery states and model parameters synchronously. However, this method will deviate from the real value at the end of battery life. To solve this problem, Xue et al. [202] proposed an AUKF realize the multi-step prediction of SOH and RUL by updating the noise covariance. In Refs. [203,204], the EKF is compared with the knowledge-based algorithm. The result shows that the EKF and the knowledge-based algorithm can obtain similar results.

3.3.2.2. Particle filters family. The PF also can be used in battery lifespan and health prognoses, which is suitable for nonlinear systems with non-Gaussian noise [205–207]. To deal with the aging fluctuations in the uncontrolled environments, Tang et al. [206] proposed a model-oriented gradient-correction particle filter (GC-PF) based method to predict the aging process of Lithium-ion batteries. Miao et al. [208] used the UPF to estimate the remaining useful life (RUL) of batteries with an error of less than 5%. In Ref. [209], the Gauss Hermite PF technique is proposed to predict the battery capacity fading based on a state projection scheme method. Zhang et al. [210] proposed a RUL prediction method that combined the PF with the exponential degradation model due to the nonlinear and non-Gaussian fading phenomenon. The results show that this method has better prediction accuracy than the regularized PF according to the accuracy index. Wang et al. [211] developed a prognostic technology using the spherical cubature PF (SCPF) based on the state-space model to predict the RUL of batteries. For PF method, the importance function and the degradation of the sampling particles influenced the estimation accuracy [212]. Therefore Zhang et al. [213] proposed the UPF to predict the RUL based on linear optimizing combination resampling (LOCR), which uses UKF to generate a distribution as the importance function and use LOCR to improve the diversity of sampling particles.

3.3.3. Empirical fitting approach

The empirical fitting method is usually based on battery models that relate to the degradation of one or more performance parameters. In Ref. [214], a memory-less degradation model is developed, which allows the degradation rate to depend on both the stress level and SOH. The results showed that this model can describe a broader range of battery fading behavior. Wang et al. [215] established a generalized battery life model considered the using time, C-rate, and temperature. In Ref. [216], the calendar aging test and cycle aging test are conduct to analyze different aging factors. An aging model is developed with impedance-based model that based on the electric-thermal kinetics to obtain the mathematical description of degradation. Smiley et al. [217] proposed a method to estimate the parameters of the aging model and select the most representative model from a set of pre-aged models using the interacting multiple-model KF and the Viterbi algorithms. Zhang et al. [218] developed a capacity loss model which is coupled with the aging mechanisms of solid electrolyte interface layer growth and active material loss. The recursive least squares method is applied to estimate the model parameters. The result shows that the estimated capacity loss has less than 1% error. Zou et al. [72,181] proposed a multi-time-scale estimation algorithm to predict the SOH and formulate an economic predictive model for battery health management. The algorithm will be extended in this application for battery management, where more factors will be considered, such as physics-based battery models and associated state constraints.

3.3.4. Machine learning-based approach

With the development of big data and artificial intelligence industry, machine learning methods have been applied to predict battery SOH and RUL [219]. Chang et al. [220] developed a RUL prediction method composed of relevance vector machine (RVM), UKF and complete ensemble empirical mode decomposition (CEEMD). The RVM is used to correct the prognostic results obtained by UKF. For the estimation of SOH and RUL, the SVM is a well-known machine learning method. Nuhic et al. [221] proposed an on-board SOH and RUL monitoring method using SVM. In order to handle the uncertain external conditions and the complex internal electrochemical process, Dai et al. [222] proposed a novel SOH estimation method by using prior knowledge-based neural network (PKNN) and Markov chain. Fen224g et al. [223] developed a predictive diagnosis method by comparing partial charging curves with the stored SVMs. The Gaussian process regression (GPR) is a type of Bayesian non-parametric machine learning method, which can handle uncertainty in a complex model. Ref. [224] capture the mapping among capacity, temperature, and SOC by using GPR with an automatic relevance determination structure. Ref. [225] consider the electrochemical knowledge to the understanding of the covariance functions within the GPR. In Ref. [226] the long short term memory (LSTM) model is applied to predict the residual of GPR. Richardson and Howey et al. [227] proposed a GPR method for forecasting battery SOH, which showed good performance than other data-driven approaches.

The key benefits, drawbacks, accuracy, and application scenarios of different approaches are summarized in Fig. 6. The measurement and analysis approach is the simplest and direct method, which need to calculate and analyze the measured external characteristics of batteries. This method is open-loop, so the accuracy is affected by noise and environmental disturbance. The empirical fitting approaches need to establish the aging model bade on experience and electrochemical knowledge. A large number of battery aging test data are needed to fit the model. Therefore, specific models are often only effective for the specific type of battery and the specific aging condition. The Bayesian-based approaches are developed from the previous methods. These methods estimate the key parameters to evaluate the battery health state by the closed-up filtering algorithm, which are robust to the modeling and measurement error. The machine learning-based approaches are the black box model, which is intelligent and flexible, but the estimation and prediction result is sensitive to the training data set.

3.4. Other indexes in battery management system

3.4.1. Review of remaining discharge time prediction approaches

The remaining discharge time (RDT) indicates the continuous operation time until the voltage of the battery reaches its lower threshold, which is helpful to solve the range anxiety issues. Although the SOC and SOE can reflect the residual capacity and energy of the battery, they cannot give the driver an exact endurance time directly. The crucial issues for RDT prediction are the modeling of the battery system and the forecast of future information such as discharge current and terminal voltage profile [104]. The Markov transition probability model can be used for battery current discharge profile prediction. In Ref. [228], Pola et al. employed a PF-based method considering the battery current transition probabilities for a two-state Markov chain. Wang et al. [35] established fractional-order models and proposed a Bayes Monte Carlo estimator for RDT prediction with future load trajectory information obtained by a Markov probability model. For known past dynamics of input currents, a discrete wavelet transform technique was employed to extract future battery currents [229]. The recursive method also can be used to predict a future constant-current by introducing forgetting factors. Quiñones et al. [230] employed the Lambert function together with an electrochemical reduced-order model for RDT prediction. Wang et al. [110] proposed a prediction framework for SOC and RDT based on an equivalent circuit model considering hysteresis. In Ref. [231], a Dirichlet process mixture model was established to identify the voltage trajectory which can be utilized for RDT prognostic. Considering the dynamic uncertainties in the RDT prediction process, Zhang et al. [232] quantified the uncertainty of state estimation and future loads with the probabilistic method.

3.4.2. Review of state-of-temperature estimation approaches

Thermal management is a key part of the BMS, and accurate state-of-temperature (SOT) estimation is a high priority of thermal management. High temperatures would adversely affect the performance and lifespan of batteries, resulting in thermal runaway, e.g., fire and explosion [233].

Method	Representativeness	Accuracy	Scenario	Benefits	Drawbacks
• Measurement & analysis approach	❖ Enhanced coulomb counting method [184]	ME≤1%	Portable devices, EVs	√ Simple, easy to implement √ Less computation √ Online applications	× Depend on test equipment accuracy × Some parameters are difficult to measure × Sensitive to initial state
	❖ Impedance measurement[186]	Not Provided	Lab		
	❖ Charging and discharging curves analysis[188]	Not Provided	Lab		
	❖ Incremental capacity analysis[189]	ME≤1%	EVs, Lab		
	❖ Differential voltage analysis[193]	ME≤1.5%	EVs, Lab		
	❖ Differential thermal voltammetry[190]	Not Provided	Lab		
	❖ Differential mechanical parameter[197]	Not Provided	Lab		
• Bayesian-based estimation approach	❖ Kalman FIlter[200]	RMSE≤2%	EVs, Lab	√ Close-loop/adaptive √ Strong robustness & Scalability √ Estimation of internal parameters √ High estimation accuracy	× Sensitive to model accuracy × Heavy calculation burden
	❖ Extended Kalman filter[201]	Not Provided	EVs, Lab		
	❖ Adaptive Unscented Kalman Filter[202]	MAE≤3.5%	Lab		
	❖ Unscented Particle Filter[208]	ME≤5%	Lab		
	❖ Improved Unscented Particle Filter [213]	RMSE≤3%	Lab		
	❖ Gauss Hermite Particle Filter[209]	ME≤0.7%	Lab		
	❖ Spherical Cubature Particle Filter[211]	ME≤5%	Lab		
• Empirical fitting approach	❖ Memory-less degradation model[214]	Not Provided	EVs, Lab	√ Ability to capture mechanisms	× Sensitive to datasets × Sensitive to method × Long time cost
	❖ Cycle life model[215]	Not Provided	EVs, Lab		
	❖ Impedance-based model[216]	Not Provided	EVs, Lab		
	❖ Capacity loss model[218]	ME≤1%	EVs, Lab		
• Machine learning-based approach	❖ Relevance vector machine[220]	Not Provided	Satellite, Lab	√ Intelligent & flexible √ Powerful approximating ability	× Sensitive to training datasets × Required offline training × Potential over-fitting problems
	❖ Support vector mechine[221][223]	ME≤3%	Lab		
	❖ Prior knowledge-based neural network [222]	ME≤1.7%	Lab		
	❖ Gaussian process regression[224-227]	ME≤5%	EVs, Lab		

Fig. 6. Key benefits and drawbacks of different SOH/RUL estimation approaches.

The surface temperature of battery can be measured easily with some conventional measurement methods such as thermocouples. However, the internal cell temperature during transients differs significantly (in the experimental study of Ref. [234] more than 20%) from temperatures measured by external sensors located on the cell surface [235]. Therefore, monitoring the internal temperature of battery is more crucial and challenging for thermal management. The SOT estimation approaches can be divided into the following groups: direct measurement approach, model-based estimation approach, electrochemical impedance-based approach, and data-driven approach.

3.4.2.1. Direct measurement approach. Researchers have proposed methods of battery internal temperature measurement by integrating temperature micro-sensors into the battery cell internal layers [236]. For battery internal temperature indication, the commonly used sensors are thermocouples [237] and resistance thermometers [238]. The traditional temperature measurement methods and several recently introduced methods such as fiber Bragg-grating techniques are reviewed in Ref. [239]. Although battery internal temperature can be obtained directly by inserting sensors, this approach would bring additional manufacturing costs and potential safety threats.

3.4.2.2. Model-based estimation approach. Numerical thermoelectric and thermal models are widely used in internal temperature estimation [240]. In order to establish thermoelectric and thermal models such as lumped-parameter battery model [241] and distributed battery thermal model [242], the knowledge of heat generation, conduction, dissipation, balance, and thermal boundary conditions are indispensable. Basing on the thermal model established, Kim et al. [243] and Dai et al. [244] applied the adaptive KF method for the estimation of the battery core temperature. Ref. [245] Presented an experimental method based on thermal conduction analysis to determine the core temperature of a Li-ion cell during thermal runaway. The battery internal temperature may be well estimated based on the established thermal or thermoelectric model and state estimation approach, but during actual operation of electric vehicles, various complex situations should be taken into account, which is quite different from lab environment.

3.4.2.3. Electrochemical impedance-based approach. Without establishing a thermal model, some other methods for battery temperature estimation have been proposed based on EIS measurements [246]. Impedance indicators obtained from EIS, such as phase shift, real part amplitude, and imaginary part amplitude, can map to temperature. For instance, the phase shift was utilized to estimate internal temperature in Refs. [247]. Since the impedance is a composite function of SOC, SOH, and temperature, the impedance indicators should be chosen at special frequency where the indicators are not sensitive to SOC and SOH [248]. Schindler et al. [249] and Barai et al. [250] studied the battery impedance with different relaxation processes. Considering the impact of injecting excitation signal for EIS test, Wang et al. [251] proposed a fast impedance calculation method based on wavelet transform. In battery pack application, Beelen et al. [252] took crosstalk interference in surrounding cells and influence of currents flowing through the pack into account. The robust estimation of battery system temperature under sparse sensing and uncertainty was studied in Ref. [253]. By using indicators of electrochemical impedance, internal temperature can be mapped uniquely. But there are temperature gradients in battery, and large difference exists between the maximum temperature and the mean temperature. Richardson et al. [254] presented a promising new approach for estimating the internal temperature distribution in cylindrical cells by combining measured electrochemical impedance and thermal model.

3.4.2.4. Data-driven approach. The data-driven approaches have been used in estimating the internal temperature of the battery. In Ref. [255], a data-driven approach combining the RBF neural network and the EKF is proposed to estimate the internal temperature for lithium-ion battery thermal management.

3.4.3. Review of state-of-balance estimation approaches

The state-of-balance (SOB) is a novel concept for the consistency evaluation which is designed for the purpose of the balance state characterization and regulation. SOB characterized not only the cell capacity balance, but also the balance state for the LIB pack. The factors of cell voltage, pack voltage, temperature, maintenance current, and internal resistance are considered to estimate SOB [256]. In Ref. [256], the SOB estimation was realized with the detailed deduction, in which a dual filter consisting of the UKF was used in order to predict the balance state of the battery pack. In order to characterize the cell-to-cell battery consistency, Wang et al. [257] proposed an iterative SOB evaluation method by conducting the improved variation coefficient calculation. The SOB and aging process correction were considered.

4. Challenges and outlooks

With the popularization of energy storage technology, the development of advanced battery management technology has attracted more and more attention. The battery itself is a kind of complex electrochemical system. It is difficult to accurately model the battery system, and estimate the battery states, which seriously influences the reliability and effectiveness of the BMS. Therefore, we outline some research directions and trends in this field from the following aspects.

4.1. Advanced sensing

The inside of the battery is a closed space, so the internal multiple states and parameters are hard to be directly measured. Thus, many researchers have studied the battery state estimation algorithms and parameter identification methods. However, these indirect approaches will inevitably bring estimation or identification errors. The more accurate way to obtain internal multiple states and parameters is to use advanced sensors to directly measure them. For example, fiber-optic sensing technology has been introduced to monitor the internal battery states. Fiber optic sensors can be embedded into the Li-ion battery pouch cells to monitor the internal strain and temperature [258–260], and then these signals can be used for high-accuracy cell state estimation. A buckled membrane sensor has been developed for in situ, simultaneous characterization of stress and microstructure evolutions in the lithium-ion battery [261]. A new ultrasonic transmission based probe for the SOC has been introduced in Ref. [262]. Besides, acousto-ultrasonic guided waves have been used to monitor SOC and SOH of Lithium-ion pouch batteries with built-in piezoelectric sensors [263]. In addition, high-precision contact-type displacement sensors can be used to measure the swelling of the battery [264], which can be used to estimate SOC imbalance of batteries. Based on the mechanical rather than electrical signal, incremental capacity analysis method can be used to estimate the battery capacity fading [265]. In the long run, advanced sensing technologies are expected to improve battery management. The future development direction is to develop real-time, accurate and robust sensors, combined with multi-sensor information fusion technology, to obtain the deeper understanding of the internal structure and mechanism of the battery.

4.2. Full life cycle modeling and aging behavior expression

The current battery modeling and state estimation approaches have made great progress. In terms of modeling, the most commonly used ECMs lack chemical significance, which can't describe the dynamic characteristics inside the battery. Therefore, it is recommended to establish physics-based models considering electrochemical processes [266,267]. The data-driven models are obtained under certain training conditions, and there will be robustness problems in actual vehicle operation. This requires model training under comprehensive aging conditions. The training data sets should consider the effects of battery aging, hysteresis, different charge and discharge rates, temperature, etc. Another important issue in battery modeling is the match of computing complexity and computing resources. Therefore, future research direction will also focus on battery model reduction and simplification.

4.3. Thermal field prediction and thermal behavior characteristic analysis

Simultaneously, some problems remain in terms of thermal field prediction and thermal characteristic analysis. On the one hand, the inside of the cell is a closed space. In addition, the internal components are sensitive to the environment. On the other hand, battery aging is affected by multiple stresses, and the interactions of the stresses are not clear. Most of the current research only focus on partial stresses under ideal cycle conditions, and have not established a quantitative description of the aging mechanism. The thermal field prediction and thermal characteristic analysis are crucial to thermal management. Currently, there are some researches focus on the development of the electrochemical-thermal coupling model and thermal abuse model of battery [268]. However, the research methods for the distribution of current density in the electrodes inside the battery and the situation of the battery thermal runaway caused by side reactions at high temperatures are still in the simulation stage. The mechanism analysis and research methods of thermal failure and thermal abuse still have limitations.

4.4. Multi-states joint estimation

At present, the method of single state estimation is very rich, but in the process of automobile operation, there is a coupling relationship between the battery states, and the states may affect the model parameters. There are also many studies on joint estimation of the two states. Song et al. [269] proposed a data-driven least squares support vector machine and model-based UPF method for joint estimation of SOC and SOH of lithium-ion batteries. Feng et al. [270] designed an accurate joint estimator of SOC and SOT. The temperature range of their experiment is from -10 °C to 40 °C, the temperature change rate is as high as 10 °C. In this verification process, their method still showed good performance. There are other joint state estimates, such as SOC and SOP, and SOC and RUL. However, researches on the joint estimation of three or more types still need to be deepened. Hu et al. [271] designed a new co-estimation hierarchy, which can jointly estimate the SOC, SOH and SOP of lithium-ion batteries. Their method significantly improves the estimation accuracy of SOC, voltage and capacity. In general, the joint state estimation can improve the state estimation accuracy. Many scholars have begun to pay attention to this aspect of research, and believe it is a popular research direction in the future.

4.5. Fault diagnosis and health management

Fault diagnosis is one of the key functions of BMS. The traditional BMS is mainly based on the threshold method to detect the battery overvoltage, over-current, over temperature and conventional faults. The simple fault strategy cannot realize the high-level functions of fault tracing, early warning, etc. The traditional BMS mainly focuses on the simple fault, which seldom involves the fault detection of thermal fault and sensor fault. Therefore, in the future, BMS fault diagnosis mainly has the following development directions: first, based on artificial intelligence algorithm to achieve battery system fault detection, location, traceability, prediction, etc. The second is to establish a comprehensive fault diagnosis system for large-scale battery array, including battery thermal fault, electrical fault, sensor fault, BMS fault, etc. There are some challenging problems in the health management of electric vehicles, such as modifying the battery parameters in the whole life cycle, determine the battery safe charging and discharging constraints, and achieve fast and efficient charging [272,273]. Accurate state estimation and fault diagnosis algorithms are the basis of battery health management. The management strategy that considering the optimization of battery health, battery charging and discharging speed and battery temperature protection can prevent the battery from overheating, prolong the cycle life and improve the energy conversion efficiency [274]. With the development of electrochemical models and advanced state estimation methods, future battery health state estimation methods will be more applied in online applications and more integrated with battery management strategies.

4.6. Advanced BMS architecture with 5G

The conventional BMS calibrates parameters based on laboratory data, which is difficult to meet the requirements of high accuracy and real-time performance. Moreover, with the development of the vehicle to grid (V2G) technology and the advent of 5G high-speed information age, the bandwidth requirements of BMS have also put forward new requirements. Therefore data-driven personalized battery management scheme based on platform of big data and cloud computing will become the future trend as shown in Fig. 7. It will break through the resource limitation of traditional embedded hardware terminals, make full use of immense computing power and information storage, and upgrade the battery from traditional offline management to active online management. With the application of 5G technology in the fields of automotive electronics and industrial control, it can be expected that the on-line management scheme based on cloud computing will become the future direction.

5. Conclusions

In this paper, the current literature on battery modeling and state estimation were reviewed systematically. Over 200 highly relevant

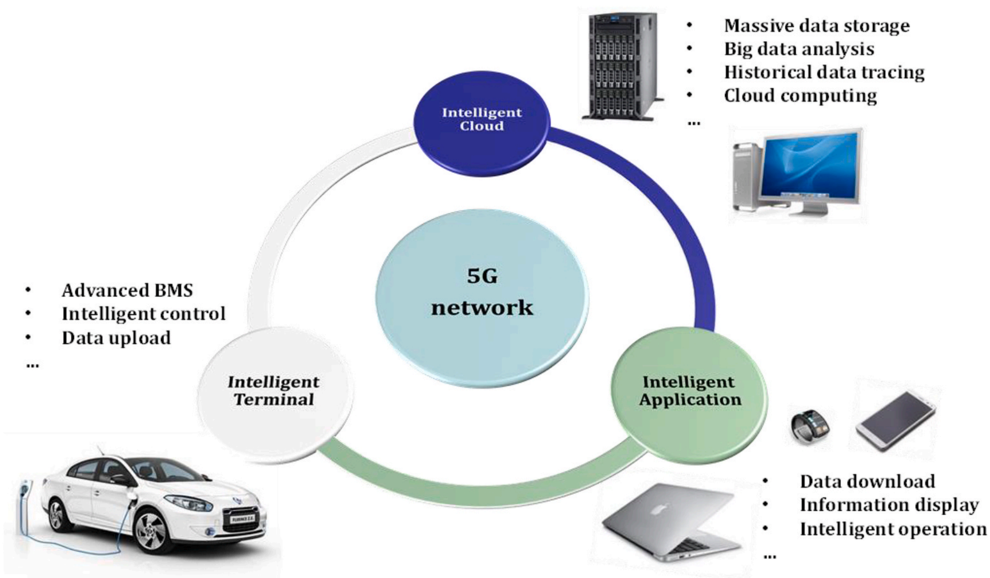

Fig. 7. Advanced BMS architecture with 5G.

journal and conference articles were selected and reviewed in this survey. The battery models including the physics-based electrochemical models, the integral and fractional-order equivalent circuit models, and the data-driven models were summarized. Battery state estimation approaches were introduced from the perspectives of remaining capacity and energy estimation, power capability prediction, lifespan and health prognoses and other important indicators relating to battery equalization and thermal management. Finally, the challenges and outlooks of the research on battery modeling and state estimation were discussed. Technologies include advanced sensing, full life cycle modeling and aging behavior expression, thermal field prediction and thermal behavior characteristic analysis, multi-states joint estimation, fault diagnosis and health management are expected to be hotspot topics of research in the future. The data-driven battery management scheme based on platform of big data and cloud computing is expected to be the future trend.

Credit author statement

Yujie Wang: Conceptualization; Formal analysis; Investigation; Data curation; Methodology; Supervision; Validation; Visualization; Writing - original draft; Writing - review & editing. Jiaqiang Tian, Zhendong Sun, Li Wang, Ruilong Xu and Mince Li: Conceptualization; Formal analysis; Investigation; Writing - original draft. Zonghai Chen: Idea; Project administration; Resources; Writing - review & editing; Supervision; Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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