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State estimation for advanced battery management: Key challenges and future trends

Xiaosong Hu[a,*], Fei Feng[a], Kailong Liu[b], Lei Zhang[c], Jiale Xie[d], Bo Liu[e]

[a] State Key Laboratory of Mechanical Transmissions, Department of Automotive Engineering, Chongqing University, Chongqing, 400044, China
[b] WMG, University of Warwick, CV4 7AL, United Kingdom
[c] National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology, Beijing, 100081, China
[d] School of Control and Computer Engineering, North China Electric Power University, Baoding, 071003, China
[e] Chongqing Chang'an New Energy Vehicle Technology Co., Ltd, Chongqing, 401120, China

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ABSTRACT

Batteries are presently pervasive in portable electronics, electrified vehicles, and renewable energy storage. These indispensable engineering applications are all safety-critical and energy efficiency-demanding such that batteries must be meticulously monitored and manipulated, where effectively estimating the internal battery states is a key enabler. The primary goal of this paper is to present a concise, understandable overview of existing methods, key issues, technical challenges, and future trends of the battery state estimation domain. More specifically, for the first time, the state of the art in State of Charge (SOC), State of Energy (SOE), State of Health (SOH), State of Power (SOP), State of Temperature (SOT), and State of Safety (SOS) estimation is all elucidated in a tutorial yet systematical way, along with existing issues exposed. In addition, from six different viewpoints, some future important research opportunities and evolving trends of this prosperous field are disclosed, in order to stimulate more technologically innovative breakthroughs in SOC/SOE/SOH/SOP/SOT/SOS estimation.

1. Introduction

Battery management is of paramount importance for operational efficiency, safety, reliability, and cost effectiveness of ubiquitous battery-powered energy systems, such as electrified vehicles and smart grids with renewables [1]. Owing to complicated electrochemical dynamics and multi-physics coupling, a trivial, black-box emulation of batteries that senses only voltage, current, and surface temperature obviously cannot result in high-performance battery management systems. How to accurately and robustly estimate and monitor critical internal states constitutes a key enabling technology for advanced battery management. Credible knowledge of State of Charge (SOC), State of Energy (SOE), State of Health (SOH), State of Power (SOP), State of Temperature (SOT), and State of Safety (SOS) is a prerequisite for effective charging, thermal, and health management of batteries.

Battery state estimation has already evolved as a vast field of research, with a large number of approaches reported in the literature. Instead of surveying all the existing methods by comprehensively listing relevant papers, this work, for the first time, intends to provide useful, inspirational insights into key issues, technical challenges, and future research directions of this area in a concise, tutorial way. Fig. 1 presents a schematic diagram highlighting the multi-timescale nature of SOC/SOE/SOH/SOP/SOT/SOS. Key battery dynamics can be often described precisely by a coupled electrochemical-thermal-aging model, each submodel of the coupling multi-physics model with its own timescale. Specifically, some battery states, such as SOC/SOP/SOE, generally change in real time, thanks to fast-changing microscopic electrochemical parameters. Macroscopic temperature distribution updates in an intermediate timescale, due to physical structures of batteries and heat transfer characteristics. Battery SOH of the slowest timescale, manifested by slow-changing parameters, such as internal impedance/resistance increase and capacity fade, varies slightly in a short period of time. Battery safety state can be overall determined by evaluating the aforementioned states. Taking the safety level requirements of battery systems into account, SOS-relevant system designs and management may alter.

2. Definitions of critical battery states

2.1. Definition of SOC

As one of the critical factors in battery management systems (BMSs),

* Corresponding author.
E-mail address: xiaosonghu@ieee.org (X. Hu).

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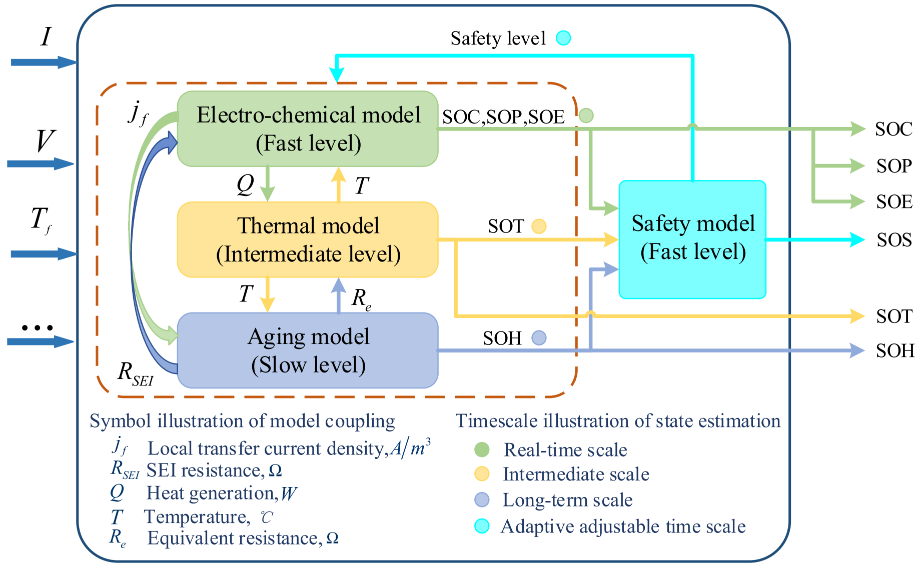

Fig. 1. The multi-timescale nature of multiple battery critical states (I, V, and T_f denote the current, voltage, and ambient temperature, respectively.).

State of Charge (SOC) can be expressed by various problem formulations [2]. In general, SOC refers to the available capacity (Q_a) expressed as a percentage of the nominal capacity (Q_n). Here Q_n stands for the maximum amount of charge that could be stored in the battery. Using the tank of a fuel vehicle as an analogy, SOC provides the same functionality as the fuel gauge. Assume that the current I is positive for charging and negative for discharging, one common definition of SOC can be given as follows:

$$SOC(t) = SOC(t_0) + \int_{t_0}^{t} \frac{I(t)\cdot\eta}{Q_n} dt \tag{1}$$

where $SOC(t)$ and $SOC(t_0)$ are the SOC values at the time t and the initial moment t_0, respectively, η is the coulombic efficiency that reflects the ratio of the fully discharged energy to the charged energy required to recover the original capacity.

Besides, from the perspective of battery electrochemistry, SOC refers to the charge contained in both anode and cathode electrode particles. Specifically, the SOC variation reflects the distribution of lithium concentration in the electrode particles. Because the amount of available charge is highly dependent on the amount of lithium stored in the electrodes, SOC can be directly calculated in terms of mean lithium concentration $\bar{C}_s$ by

$$SOC(t) = (\bar{C}_s(t) - C_{s,\min})/(C_{s,\max} - C_{s,\min}) \tag{2}$$

where $\bar{C}_s(t)$ is the mean surface lithium-ion concentration at the time t, $C_{s,\min}$ and $C_{s,\max}$ represent the surface lithium-ion concentrations when the battery is fully-discharged and fully-charged, respectively.

BMSs require accurate information of SOC, indicative of the remaining available energy inside a battery during operations. For the battery itself, such state information is applied to provide *a priori* knowledge for charging/discharging strategies, so as to ensure battery operations within safe and reliable conditions. In a laboratory condition, after knowing the initial SOC value, the reference values of SOC are generally obtained by a well-controlled coulomb counting method that accumulates the charge transferred [3]. However, due to the complicated electrochemical reactions and strong coupling characteristics, it is difficult to directly measure the battery SOC in real-world applications. Therefore, accurately estimating the SOC in real time becomes a critical functionality in BMSs, consequently attracting considerable research efforts.

2.2. Definition of SOE

Since most battery chemistries characterize a pronounced voltage decline during the discharge process, an equal charge throughput at different SOC levels definitely provides/absorbs discrepant energy amounts, especially when approaching both end regions of voltage, as demonstrated in Fig. 2.

On the other side, high discharge rates may lead to significant internal energy losses in comparison to negligible capacity shrinks [4]. Consequently, the generic index of SOC can only represent the residual capacity (Ah) rather than the available energetic reserve (Wh). As a result, another practical concept of SOE is proposed and has been utilized to reliably forecast the driving mileage in electric vehicle (EV) applications [5,6]. The mathematic definition of SOE can be expressed as follows:

$$SOE(t) = SOE(t_0) + \frac{\int_{t_0}^{t} P(\tau)d\tau}{E_N} \tag{3}$$

where $SOE(t)$ and $SOE(t_0)$ are the SOE values at the time t and the initial moment (t_0), respectively, E_N represents the nominal energy amount, and $P(\tau)$ denotes the power at the time τ. Generally, the reference values in SOE estimation exercises are obtained by well-controlled power integration methods in a laboratory setting, which, however, would

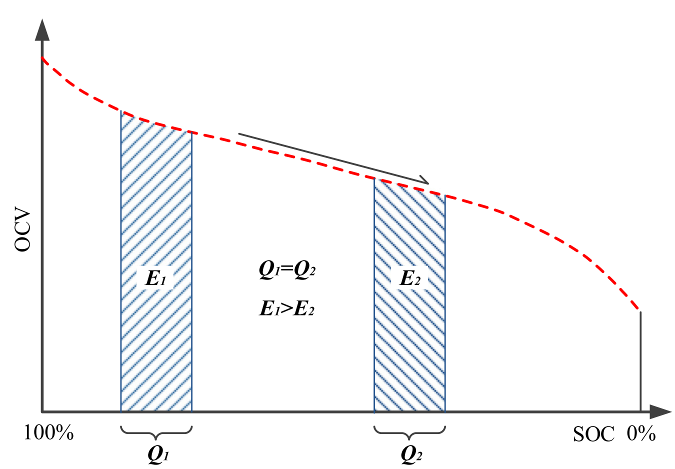

Fig. 2. An equal charge throughput at different SOC levels results in different energy amounts.

inevitably introduce a gradually deviating result caused by accumulative errors in practice. In contrast, a post-process based way that integrates the recorded power from the end moment backward to the initial moment proves to be more rational [7,8]. Physical probing means have also been explored as battery state indicators, e.g. mechanical and magnetic characteristic detection [9,10]. However, these techniques require signals that are unavailable unless additional expensive sensors are installed.

2.3. Definition of SOH

Electrochemical batteries inevitably experience gradual performance degradation during their service life, owing to side reactions [11]. This leads to the so-called aging phenomenon that causes losses of lithium inventory and active materials [12]. SOH is often used to quantitatively assess the level of battery aging in terms of capacity fade and internal resistance [13]. The definition of SOH can be mathematically expressed as

$$SOH = \frac{C_a}{C_r} \times 100\% \tag{4}$$

Or

$$SOH = \frac{R_a - R_r}{R_r} \times 100\% \tag{5}$$

where C_a and C_r denote the actual and rated capacity values, respectively, and R_r and R_a denote the actual and rated internal resistances, respectively.

A capacity fade of 20% and/or an internal resistance increase of 100% are often considered as the End-of-Life (EOL) of a battery in automotive applications. Battery SOH is a critical state that underlines safe, reliable and efficient operations of battery systems [14]. Timely and accurate SOH metering during vehicular operations is crucial for battery fault diagnosis, SOC/SOP estimation, and maintenance/replacement schedules. Currently, neither capacity nor internal resistance is directly measureable with commercially-available sensors. Thereby, the key for SOH acquisition is to develop estimation algorithms that enable online SOH metering based on the low-cost suite of sensors. To this end, substantial endeavors have been being made, giving rise to a rich literature in this regard. It is worth mentioning that the reference SOH should be precisely acquired in order to examine the performance of the proposed estimation algorithms. Usually, battery aging tests are performed in well-controlled environments, and the actual battery capacity or internal resistance is periodically measured with high-accuracy instruments. These collected experimental data can serve as the reference SOH for estimation algorithm validation.

2.4. Definition of SOP

As another key factor in BMSs, State of Power (SOP) generally refers to the available of power that a battery can supply to or absorb from the vehicle powertrain over a time horizon [15]. Battery SOP can be viewed as a product of the threshold current and the corresponding voltage, while various operational constraints should be explicitly considered and respected. Assume that the battery power is positive for discharging and negative for charging, a general definition of SOP is expressed by Ref. [16]:

$$\begin{cases} SOP^{ch\arg e}(t) = \max(P_{\min}, V(t+\Delta t)\cdot I_{\min}^{ch\arg e}) \\ SOP^{disch\arg e}(t) = \min(P_{\max}, V(t+\Delta t)\cdot I_{\max}^{disch\arg e}) \end{cases} \tag{6}$$

Subject to certain constraints.where $SOP^{ch\arg e}(t)$ and $SOP^{disch\arg e}(t)$ stand for the battery charging SOP and discharging SOP at the time t, respectively, $P_{\min}$ and $P_{\max}$ are the minimum and maximum battery power limitations, Δt represents a specific future time horizon, $V(t+\Delta t)$ is the terminal voltage at the $(t+\Delta t)$th sampling time, $I_{\min}^{ch\arg e}$ and $I_{\max}^{disch\arg e}$ stand for the minimum continuous charging current and maximum continuous discharging current from the tth sampling time to the $(t+\Delta t)$th sampling time, respectively. It should be known that $I_{\min}^{ch\arg e}$ and $I_{\max}^{disch\arg e}$ need to be obtained under conditions that certain constraints are not violated. These constraints generally include the battery voltage, current, SOC, and even temperature [17]. Moreover, key microscopic variables can be constrained if some physics-based models are utilized.

In the simulation conditions, the reference values of SOP are generally obtained through a high-fidelity battery model that considers various constraints [18]. In a laboratory condition, the battery SOP can be approximated by well-designed pulse tests that consider some modifications of applied current rate, duration time, etc. [15]. For EV applications, as energy-flow management, e.g., in terms of power split and battery charging during regenerative braking, is highly related to battery available power, accurate SOP estimation can be leveraged to not only regulate vehicular power flow more precisely, but also optimize overall powertrain efficiency [19]. In addition, for the battery itself, knowing the future SOP can make fast charging more feasible and benefit the battery performance, further improving its service life accordingly. To this end, it is vital to develop an accurate and efficient SOP estimation method that considers highly nonlinear battery dynamics and various key constraints.

2.5. Definition of SOT

Up to date, there are few studies rigorously defining State of Temperature (SOT). Either internal temperature or temperature distribution has been reported in the existing literature [20,21]. In general, thermal dynamics of a battery are manifested macroscopically by temperature distribution, which arises from heat generation and dissipation inside a battery cell during normal operations. The heat dissipation is composed of heat conduction, convection, and radiation. Heat radiation is almost negligible, due to thermal properties of cells, configurations of battery systems, and common temperature regions for commercial battery operations [22,23]. In the case of large-format batteries, detailed temperature gradients inside a cell is necessary to capture for ensuring credible SOT estimation, since severe thermal inhomogeneity within a cell could result in rapid performance degradation. For control purposes and ease of implementation, core, average, and surface temperatures of a battery are often representative of SOT. For instance, the thermal dynamics of a battery are represented by its bulk temperature in a lumped-mass model [24], as formulated by

$$\rho C_p \frac{dT}{dt} = \dot{Q} + hA(T_\infty - T) \tag{7}$$

where ρ, C_p, h are the lumped density, specific heat capacity, and heat convective coefficient, respectively, T and T_∞ are the time-varying cell temperature and ambient temperature, respectively. Moreover, $\dot{Q}$ is the total heat generation rate, and A is the cell surface area. In the formula, a uniform heat generation is assumed. This representation and manipulation has been widely used for thermal modeling and controls of battery packs due to its computational efficiency. Some low-order or simplified thermal models were explored to capture the core and surface temperatures [21,25], which provides more accurate temperature information. The mathematical formulation of one example is expressed by Ref. [25].

$$C_c \dot{T}_c = \dot{Q} + \frac{T_s - T_c}{R_c} \tag{8}$$

$$C_s \dot{T}_s = \frac{T_\infty - T_s}{R_u} - \frac{T_s - T_c}{R_c} \tag{9}$$

where T_c and T_s are the core and surface temperatures, respectively, C_c and C_s are the core and surface capacitors, respectively, R_c and R_u are the conductive and convective resistances, respectively. The total heat

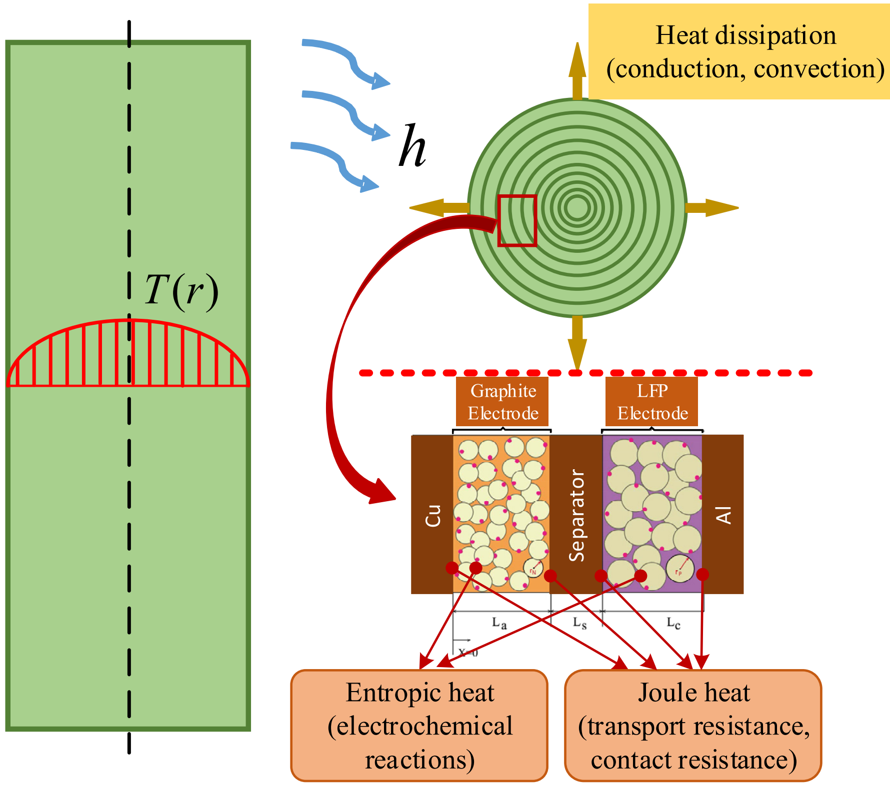

Fig. 3. A schematic representation of the temperature distribution and thermal dynamic principles.

source concentrates at the core, and heat dissipates outwards the battery. To obtain precise thermal dynamics, accurate model parameterization is indispensable. Thus, the reference values need to select meticulously. The reference temperatures (e.g., actual surface, core and/or volume-averaged temperatures) of thermal models are usually obtained directly or indirectly through experimental measurements.

From a perspective of microscopic mechanism, SOT is elaborated primarily from heat source and structural heat conduction. The thermal diffusion is mainly determined by battery material properties and the law of energy balance. The heat generation includes reversible heat (also called reaction heat or entropic heat) and irreversible heat. They originate from electrochemical reactions and energy losses, respectively. The irreversible losses are mainly caused by charge-transfer over-potential, mass transfer limitations, and contact resistance [24,26,27]. A schematic diagram in Fig. 3 shows the temperature distribution and thermal dynamic principles of a cylindrical Li-ion battery.

2.6. Definition of SOS

In the research area of battery safety, European Council for Automotive Research and Development (EUCAR) proposes the hazard levels for classifying the safety of a battery. Other organizations, such as Society of Automotive Engineers (SAE) and Sandia National Laboratory, also mention their own hazard level taxonomy. For example, in the SAE J2464 manual the rupture hazard is in the position 5 while flame is in the position 6. In the abuse test manual of the FreedomCAR (Cooperative Automotive Research) for electrical energy storage system (EESS), the above two levels are defined in an opposite way [28]. The hazard levels are also measured in a numerical way. For instance, hazard risk was defined as the product of hazard severity and hazard likelihood, as expressed by Ref. [29].

$$H_r = H_s \cdot H_l \tag{10}$$

where H_r, H_s, and H_l represent the hazard risk, hazard severity, and hazard likelihood, respectively. Furthermore, H_s can vary from 0 to 7, in the form of an integer, in accordance with the hazard level; H_l can take values from 1 to 10, describing the fault occurrence percentage; essentially, H_r utilizes two states (i.e., H_s and H_l) to find a safe operating region. However, state of function (SOF) was used to relate the SOC and SOH to the degradation of battery output power [30]. Given external stresses of battery operations, the safe operating area of a battery is defined, which considers voltage, temperature, and over-current protection. If the battery dynamics are further considered, the SOS can be formulated as the reciprocal of a probability function for possible abuses, including voltage, temperature, charging and discharging currents, internal impedance, battery expansion, and battery deformation, in the form [28]:

$$f_{sos}(x) = \frac{1}{f_{abuse}(x)} \tag{11}$$

where f_{sos} is the safety function, and f_{abuse} is the abuse function. Moreover, x represents all types of states and control variables that describe the battery dynamics, such as terminal voltage, load currents, operating temperature, internal impedance, and external deformation. Based on this definition, the state of safety will decrease as abuse function increases, and the investigation of this relationship still remains an open issue, while it can be described by a polynomial, exponential or logarithmic function. In order to limit SOS to be a reasonable value in the same numerical range as SOC, an abuse coefficient is often used in f_{abuse}, which limits SOS to be within a range from 0 to 1. Here, a general relationship between the safety function and abuse coefficient is shown in Fig. 4. Fig. 4(a) shows a general form of SOS trajectories with 3 different rates of decay, i.e., normal, 5 times decay, and 20 times decay, considering all states and variables that could affect a battery system. Specifically, the SOS traces accounting for abuse functions of current, voltage, and deformation are demonstrated in Fig. 4 (b).

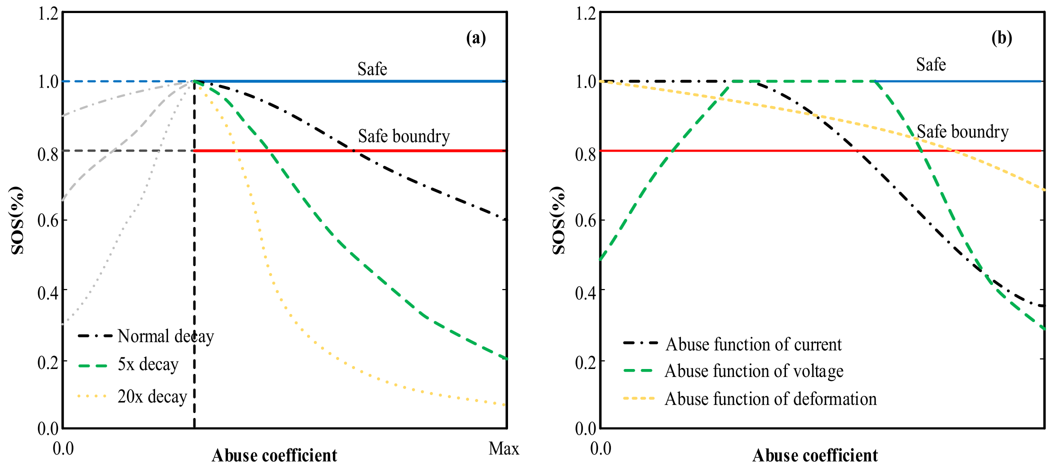

Fig. 4. SOS trajectories [28]: (a) with 3 different rates of decay, i.e., normal, 5x, and 20x. The vertical dashed line indicates the location of the maximum safe point and identifies the reasonable working range of SOS. The abuse coefficient represents the value of abuse function, given relevant states and control variables such as the terminal voltage, load current, operating temperature, internal impedance, and external deformation; (b) for 3 different abuse functions, namely, current, voltage, and deformation. The abuse coefficient varies with different abuse functions considered, and the safety function for the voltage abuse condition considers both overvoltage and undervoltage, the current abuse condition considers the maximal safe current, and the deformation abuse condition considers the slope of deformation.

3. Existing methods and key issues

3.1. SOC methods and key issues

To date, various approaches have been proposed to address SOC estimation challenges in the literature. Here, we divide these existing approaches into three principle categories, which are summarized in Fig. 5.

For the direct calculation approach, two common ways are noteworthy. First, due to an obvious mapping relationship between the SOC and several parameters such as open circuit voltage (OCV) and impedance, the battery SOC can be inferred through look-up tables that describe such a relationship [31]. Second, the change of SOC can be easily calculated through the coulomb counting method in cases that the battery nominal capacity and current profile are exactly known. These efforts seem easy to be implemented for the SOC estimation. However, precise online measurement of relevant parameters is still a daunting challenge, due to the facts that a rest period is required to obtain the OCV, and the battery capacity generally varies under different aging levels. Therefore, attempts have been made to estimate the SOC through other supporters such as battery models.

For the model-based approach, based upon suitable models as the dynamics equations, various estimation techniques e.g., with adaptive filtering, are employed to estimate the SOC. One widely-used model type is the electrochemical models (EMs) due to their strong abilities to capture both kinetic and charge transfers inside a battery, further resulting in a highly accurate SOC indication [32]. However, EMs-based approaches typically require intensive computational efforts due to many involved parameters and partial differential equations. Appropriate simplifications are necessary for facilitating a real-time implementation. Another popular model type is the equivalent circuit models (ECMs) that utilize the electrical circuit components to emulate battery dynamics. Due to the simple structure and reasonable expansibility, ECMs appear to be promising for the real-time SOC estimation [33]. However, considering that the parameters of ECMs would change over time, it is injudicious to utilize the invariant parameters under various temperature, SOC or aging levels [34]. Great efforts are needed to periodically recalibrate the parameters of ECMs, to ensure their extensibility. Also, it is vital to develop proper strategies, such as a joint parameter/SOC estimation tool, to adaptively adjust the model

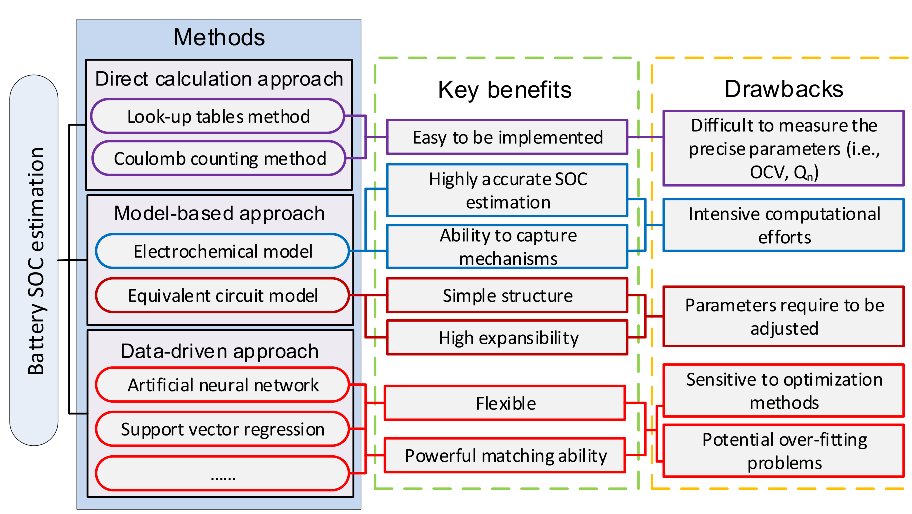

Fig. 5. SOC estimation methods in terms of key benefits and drawbacks.

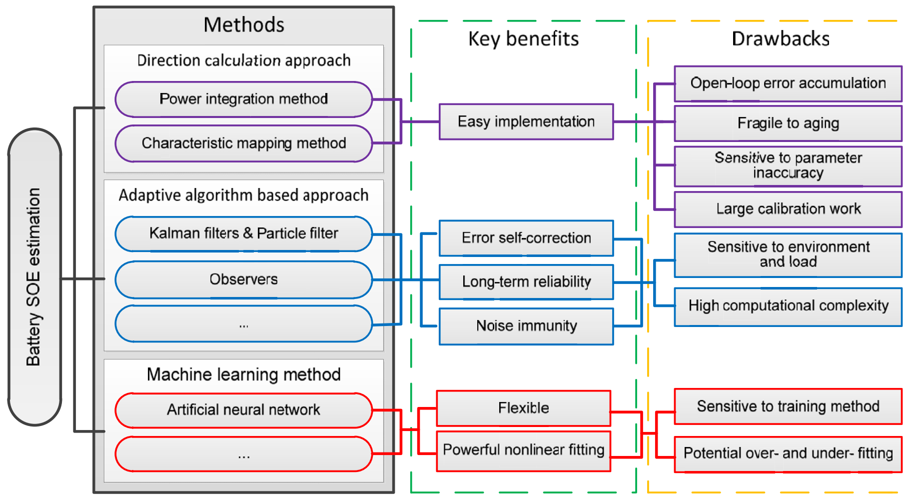

Fig. 6. SOE estimation methods in terms of key benefits and drawbacks.

parameters in practical applications.

The data-driven (DD) approach, free of capturing any physico-chemical mechanisms, has also been being exploited in the battery SOC estimation. Due to the potential advantages such as being flexible, highly nonlinear matching, and strong adaptability, diverse intelligent techniques, e.g., artificial neural network [35], support vector machine [36], have been utilized in the SOC estimation domain. However, these studies are very sensitive to their optimization methods and the quality of the data adopted. Moreover, potential over-fitting problems may occur when using improper training modes.

3.2. SOE methods and key issues

Owing to the consideration of nonlinear battery equilibrium potential, seeking accurate SOE estimates seems to be more complicated and challenging, in comparison with SOC estimation tasks [8,37]. Until now, extensive attempts (see Fig. 6) have been being made to continually improve the effectiveness of SOE estimation.

A common SOE estimation method is the power integration approach [38], which is able to effectively restrain the computational burden. However, cumbered by its open-loop nature, this type of approach inevitably results in accumulated errors subject to uncertain noises, limited sensor resolution, and measurement imperfection. As an improved solution, suitable characteristic mappings, such as the correlation among the discharge power, remaining energy, and SOE, are conducted [39]. Although these mapping-based methods exhibit performance improvements relative to the power integration method, expensive and time-consuming calibration and characterization tests are needed.

To alleviate downsides of the foregoing methods, a diversity of model-based approaches, in combination with adaptive observers, are put forward to tackle the implications of internal interference, sensor noises, and accumulated errors. For instance, taking advantage of adaptive unscented Kalman filtering (AUKF) and extended Kalman filtering (EKF) algorithms to handle system nonlinearities, efficient SOE estimators have been built to obtain satisfactory estimation results [40,41]. In Ref. [42], based upon a predictive control technique, an optimization method is developed to acquire battery remaining energy through concurrent predictions of several future physical quantities. In order to accommodate parameter perturbations and suppress measurement noises, particle filtering (PF) was also exploited to establish robust SOE estimation frameworks [37,43]. With an attempt to resolve the cross-interference problem during a joint state/parameter estimation, a mixture of multiple filters, such as PF and EKF [44], or RLSF and AEKF [45], was employed to identify model parameters and estimate states in different time scales [46]. Considering energy losses resulting from battery internal impedance, a modified SOE governing equation was proposed by using electromotive-force-based imaginary power [8]. Based on in-depth research of fractional-order electrochemical modeling, an adaptive fractional-order EKF algorithm was devised to produce accurate SOE estimates in Ref. [47] as well. In order to overcome loading uncertainties and temperature fluctuations, several SOE values were pre-estimated using multiple models, and the final SOE was determined by a multi-state fusion technique [48]. Through an analytical model with an electrical model to track battery characteristics and capture rate-energy effects, a high-fidelity SOE estimator was constructed in Ref. [49]. Besides, on the basis of a Gaussian model, the genetic algorithm (GA) and the Akaike information criterion (AIC) were leveraged in Ref. [40] to identify model parameters and determine model complexity, and ultimately achieve credible SOE estimates. The modeling efficacy and proper treatments of parameter-state interactions are critical to the efficiency, applicability, and resilience of this type of model-based approach.

Meanwhile, machine learning techniques were also employed for battery SOE estimation [6]. For example, Back Propagation Neural Networks (NN) were utilized to capture the battery nonlinear and coupling characteristics with the consideration of irreversible energy losses from joule heating, electrochemical reactions, and phase shifts. Similarly, a wavelet-NN model was also applied to simulate battery electrical dynamics considering the impacts of temperature and discharge rate [50]. The extrapolation capability of this type of approach highly depends on the amount and quality of the training data, as well as the fitting algorithms.

3.3. SOH methods and key issues

A multitude of methods have been designed for estimating the battery SOH, which can be roughly assorted into four categories, i.e., physics-based models, empirical models, data-driven methods, and ICA (Incremental Capacity Analysis)-based approaches. A schematic of the available SOH estimation methods is illustrated in Fig. 7. Physical-based models use partial differential equations to depict the battery dynamics of internal physicochemical reactions that are closely related to battery degradation based on the first principles [51]. These models have clear physical meanings and very high accuracy. Nevertheless, they face great challenges in aspects of model simplification and parameter identification before being fully eligible for online implementation [52].

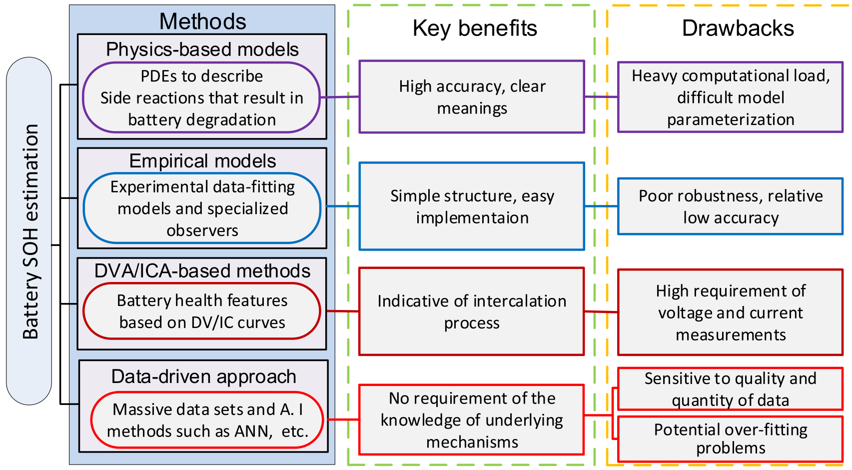

Fig. 7. SOH estimation methods in terms of key benefits and drawbacks.

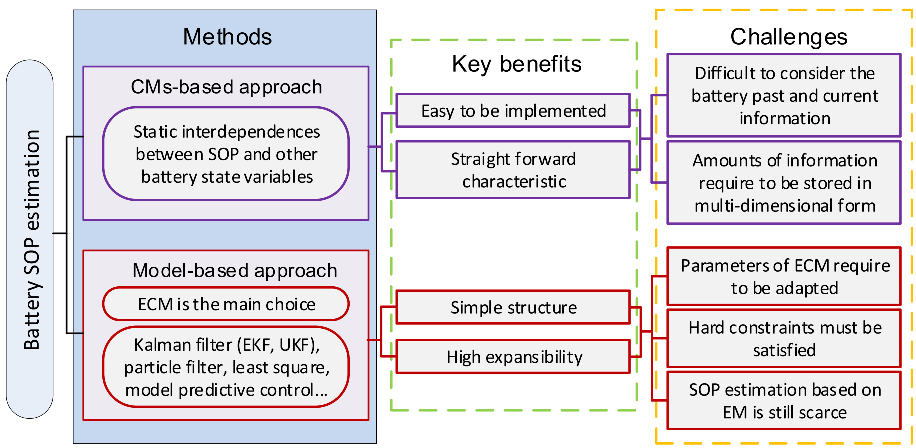

Fig. 8. SOP estimation methods in terms of key benefits and challenges.

Empirical models are derived by fitting experimental data collected under predefined experimental conditions [53,54]. They typically have high computational efficiency and can achieve acceptable validation accuracy when the battery is exposed to the similar operating conditions to the modeling case. In order to obtain an empirical SOH model, comprehensive aging tests need to be conducted, which are often labor-intensive and time-consuming. Moreover, the derived model may exhibit poor robustness to unseen operating conditions and lacks enough generalization to different battery chemistries or even dissimilar batches of the same chemistry. Hence, regular model recalibration is necessary, which in turn increases the development time and cost. In contrast, with fast-growing computational efficiency and memory of embedded systems, physics-based SOH estimation approaches are promising to be used in realistic BMSs (battery management systems) in the future. Model simplification and parameterization are the focus of intensive study in this regard. Attempts are also being made to develop enabling models to better simulate the battery degradation routes versus a spectrum of stressing factors.

Data-driven methods such as support vector machine and Gaussian process regression have received increasing attention, because of their model-free characteristics [55,56]. Specialized battery tests that incorporate all the SOH-influencing factors are first conducted, and a battery SOH model is then synthesized by associating these influencing factors with the battery SOH via data-driven methods. However, the effectiveness of these methods are heavily reliant on the quality and quantity of the test data, and the derived model is also often subject to heavy computational intensity [57].

Recently, incremental capacity analysis (ICA) emerges as an effective tool for battery SOH metering [58]. By differentiating the charged capacity over its voltage under a constant-current charging condition, the voltage plateaus on the voltage curves can be transformed into easily identifiable peaks on the IC curves [59]. Peak position, amplitude, and envelope area of the derived the IC curves at different cycles can be exploited to predict the battery SOH [12]. Signal filtering is needed to procure smooth IC curves [60]. This may compromise the estimation results since the peak amplitudes are heavily sensitive to the measurement noises. Besides, the voltage range of the voltage curve should cover the voltages that correspond to the peaks in IC curves, which may curtail its feasibility in real-world executions.

3.4. SOP methods and key issues

In comparison with the SOC or SOH estimation that has involved a plethora of techniques, research on the battery SOP estimation is relatively scarce. According to a comprehensive survey in Ref. [15], SOP estimation methods can be primarily classified into two groups, as illustrated in Fig. 8.

For the characteristic maps (CMs)-based methods, the static interdependences between SOP and battery state variables (i.e., SOC, temperature, voltage, and power pulse duration) are established offline. To improve the estimation accuracy of CM-based methods, the difference between measured battery power and estimated value is calculated. Then the reference points in CMs would be adapted in the case that a huge deviation occurs [61]. Due to a straightforward treatment, CMs-based methods can be readily implemented. However, many key issues have not been addressed thoroughly. First, it is difficult to consider the past and current information of batteries in CMs. Because the battery power strongly depends on its operating conditions, the accuracy of SOP estimation would be severely influenced. Second, constructing a satisfactory CM under various conditions generally requires a large amount of information to be stored in multi-dimensional forms, further resulting in a huge computational cost on micro-controllers. In light of this, real-time SOP estimation methods based on battery models with different complexity levels are explored and exploited.

For the model-based methods, ECM and its variants are generally employed in the SOP estimation domain. After formulating the ECMs as their discrete-time state space forms, numerous techniques such as Kalman filter [62], particle filter [63], least square-based method [64], model predictive control [65], have been successfully utilized to achieve reasonable SOP estimation. However, in order to improve estimation accuracy, an ECM that can not only capture the battery overall dynamics but also owns a suitable structure and parameters becomes necessary. In this regard, ECM parameters require to be adapted based on different operating SOC, temperature, and aging levels. Additionally, to ensure safe battery operations, the SOP estimation also requires to satisfy hard constraints on current, voltage, SOC, and/or even internal temperature. Up to now these constraints have not been optimally addressed. Moreover, ECM-based methods are most likely unable to depict the inside electrochemical process of a battery, further resulting in a poor generalization ability. Unfortunately, EM-based methods are still rather scarce for real-time SOP estimation.

3.5. SOT methods and key issues

Since batteries are highly complex electrochemical systems [66], it is difficult to directly noninvasively measure the temperature inside a battery. Although thermocouples or other devices can be utilized to measure the surface temperature of a battery, the core temperature is highly possible to significantly differ from the surface temperature (e.g., 10 °C or more) in high power applications, bringing tremendous challenges for efficient thermal management of battery systems [21,67]. Moreover, recyclability, reliability, power and energy performances of batteries also strongly depend on their operating temperatures [25]. As a result, credible SOT estimation becomes indispensable and is of extreme importance.

Based on measurable temperatures (i.e., the surface temperature and ambient temperature) and/or electrochemical impedance spectroscopy (EIS), on-line estimation of the battery temperature distribution can be implemented via various observers, in conjunction with simplified thermal models or empirical impedance models. Besides, physics-based thermal simulation is also carried out by using numerical techniques such as the finite element method (FEM) to transform partial differential equations (PDEs) into a coupling set of ordinary differential equations (ODEs). Without appropriate simplifications, such a method may be difficult for online SOT estimation, due to its inherently computational complexity [20].

Fig. 9 illustrates a taxonomy of SOT estimation methods. Based on EIS measurement, the impedance-temperature detection (ITD) [21] is mainly used to establish empirical correspondences between the imaginary part [68], real part [69,70], phase change [69,70] or intercept frequency [70] of impedance and the battery temperature. Then the bulk temperature of a battery could be captured by real-time measurement of EIS and proper data processing. Another type of method is based on simplified thermal models, which are applied to establish a quantitative relationship of the battery temperatures (e.g., the core, surface, and/or average temperatures) with respect to measurable quantities (e.g., the current, voltage, and/or ambient temperature). Suitable observers building on these models can then be synthesized to estimate the internal battery temperature distribution [20,21,71]. Moreover, by means of combining the ITD and model-based methods, an integrated approach was proposed in Ref. [72] to reproduce the battery internal temperature. The simplified thermal models could be mainly classified into the lumped-mass model (also called the zero-dimensional model), the one-dimensional model, and the two-dimensional model. Moreover, the one-dimensional model can be grouped into the concentrated heat generation model and the distributed heat generation model. Most studies have focuses on the cell level's SOT estimation. Due to complicated interactions of adjacent cells and thermal conductions, there is still a lack of efficient SOT estimation for a battery module or pack. In addition, how to develop an improved thermal model that strikes a desirable balance between accuracy and computational efficiency is worthy of further explorations and investigations.

3.6. SOS methods and key issues

Safety assessment of battery systems based on hazard levels is a nontrivial task. A variety of interpretations and classifications of hazard levels may also make the evaluation results contaminated by uncertainties [28]. In general, hazard risk is calculated by the product of hazard severity and hazard likelihood. According to the hazard level, hazard severity can be selected from 0 to 7 [73,74]. In order to reflect the rate of occurrence, hazard likelihood can take values from 1 to 10 [29]. After defining the SOS as a probability function that comprehensively considers the effects of an arbitrary number of sub-functions [75], the numerical value of SOS could be calculated as the product distribution of all the individual sub-functions. Here each sub-function describes a particular case of abuse condition, such as the voltage, temperature, or mechanical deformation.

The SOS estimation is a most recently emerging topic in the research field of battery state estimation, with a number of key issues that need to be further addressed (see Fig. 10). Hazard levels in the literature are qualitative in nature without a suitable numerical quantification of the safety of a battery system [28]. The fidelity and practicability of the SOS implementation is still challenging to guarantee. By defining more sub-functions and adjusting the existing sub-functions, the accuracy and dependability of SOS estimation can be further improved. Moreover, it is also necessary to study properties of individual sub-functions, such as the failure probabilities of individual components (i.e., electrodes, separators, and electrolytes). Besides, since many battery safety tests have been being conducted, it is highly possible to use more statistics and big-data techniques, in order to better define the probability function of abuse.

4. Future directions

Battery state estimation, featured by its salient cyber-physical design and multidisciplinary nature, is definitely a rapidly evolving area of research, as there are increasingly stringent regulations on battery safety for large-scale automotive and grid applications. Considering potential scientific importance and engineering application requirements, we outline some research directions and trends of this field, from the following six perspectives (see Fig. 11), with an overarching target of stimulating more technical innovations and transformative breakthroughs.

4.1. Advanced sensing technologies

With the rapid development of sensing technologies, the physicochemical reactions inside a battery are likely to be preciously measured using advanced sensors. It is straightforward that the most accurate and direct way to obtain battery states is to directly measure them, provided that feasible sensors exist. For example, a novel monitoring approach of SOC and SOH with acousto-ultrasonic stress waves has been introduced [76]. By using built-in piezoelectric sensors [77,78], the implicit correlation between waveform signal parameters and battery SOC/SOH can be captured by a time-domain analysis, such as electrochemical acoustic time of flight analysis [79,80]. Considering the cell expansion

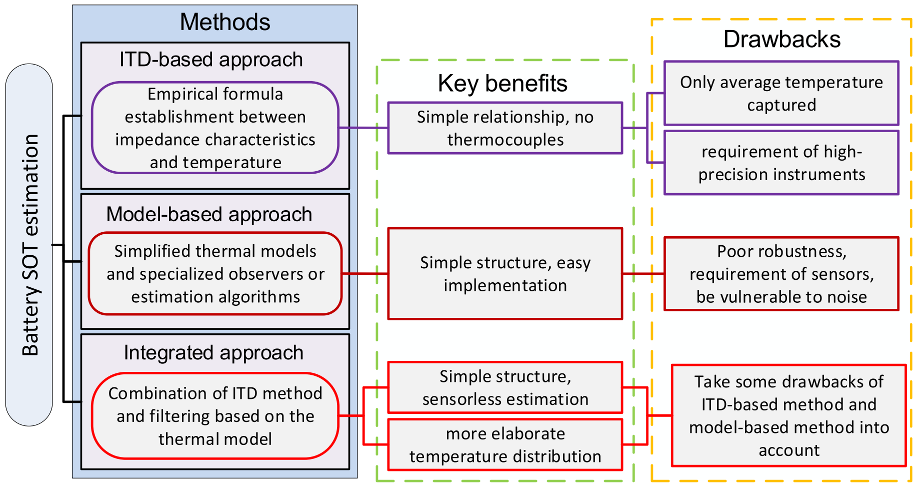

Fig. 9. SOT estimation methods in terms of key benefits and drawbacks.

caused by swelling of the electrode active material during charging [81], high-precision contact-type displacement sensors, such as Omega load cell sensors (strain gauge type) [82], have been also applied to measure the force generated by expansion of battery cells. Moreover, they have been employed by the incremental capacity analysis (ICA), based on the measured force instead of the voltage [83]. Fiber optic sensors are also typical advanced sensors with advantages such as selective sensitivity to various parameters, light weight, robustness to electromagnetic interference. In comparison to measurement using conventional electrical sensors, they can monitor additional informative cell parameters, such as strain and temperature [84].

In the medium and/or long run, advanced sensing technologies are critical to next-generation battery management. Future improvements could be focused on both fast and accurate access to key internal information and deeper insights into the internal structure and mechanisms. Moreover, low-cost sensing technologies, attempting to address the entrenched complications arising from battery degradation, rate dependency, external interference, etc., will be conducive to a new, realistic implementation of efficient battery monitoring and health management.

4.2. Multi-state joint estimation

There is a rich library of battery single state estimation methods reported in the literature, whereas the research of multi-state joint estimation, denoting the co-estimation of at least two cell states, are still few. Battery states are coupled and interact with each other. To estimate one state independently while ignoring others can only obtain relatively satisfactory results under certain constraints. The multi-state joint estimation and prediction, considering a multi-field coupling of the internal electro-thermal-aging-mechanical conditions of a battery, is a promising but still challenging research direction.

To date, only a few of studies focus on two-state joint estimations. Among the existing literature, the SOC and SOH joint estimation seems to occupy a dominant position. This is mainly due to that periodical updates of SOH (capacity or resistance) play vital roles in improving the accuracy of SOC estimation. Kalman filtering (KF) [14,85], particle filtering (PF) [86], nonlinear predictive filtering [87], and adaptive filtering [88], as well as their variants, such as extended Kalman filtering (EKF) [89], dual fractional-order extended Kalman filtering (DFOEKF) [14], exemplify extensive endeavors to leverage advanced observer technologies with different ECMs for jointly estimating the battery SOC and SOH. In addition to the co-estimation of SOC and SOH, a few of papers also work on other dual-state estimation, such as the joint estimation of SOC and SOP [90], co-estimation of SOC and SOT [91,92], as well as the combined estimation of SOE and SOP [40,93]. Although effective dual-state estimation has been attained for the above research, two-state estimation still has its own limitations, because there generally exist strong coupling relationships among three or more battery states in real applications. Till now, it is rare in the relevant literature for researchers to achieve a joint estimation scheme with more than three battery states [94,95]. Therefore, it is meaningful and valuable to elevate state-of-the-art joint estimation techniques one step beyond, achieving powerful co-estimation techniques of more than three states, by sufficiently examining the hierarchy and coupling of states in different spatial and temporal scales. An ultimate objective for next-generation battery management is to develop a holistic, hierarchical algorithm framework to credibly estimate SOC/SOE/SOH/SOP/SOT/SOS, as highlighted in Fig. 1.

Additionally, in comparison with applications of just one state

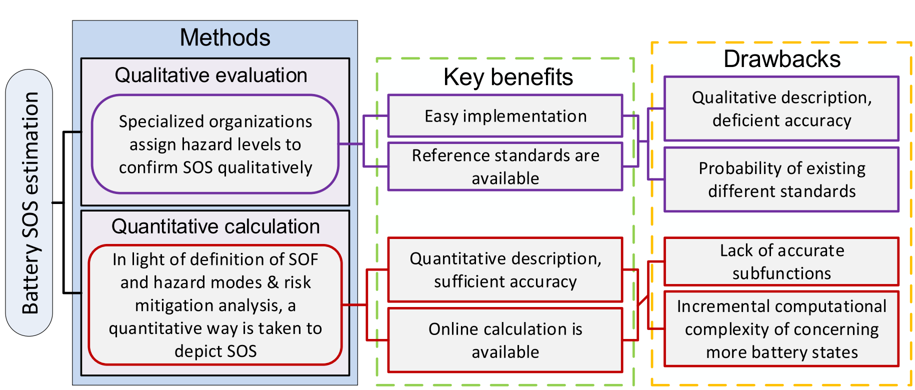

Fig. 10. SOS estimation methods in terms of key benefits and challenges.

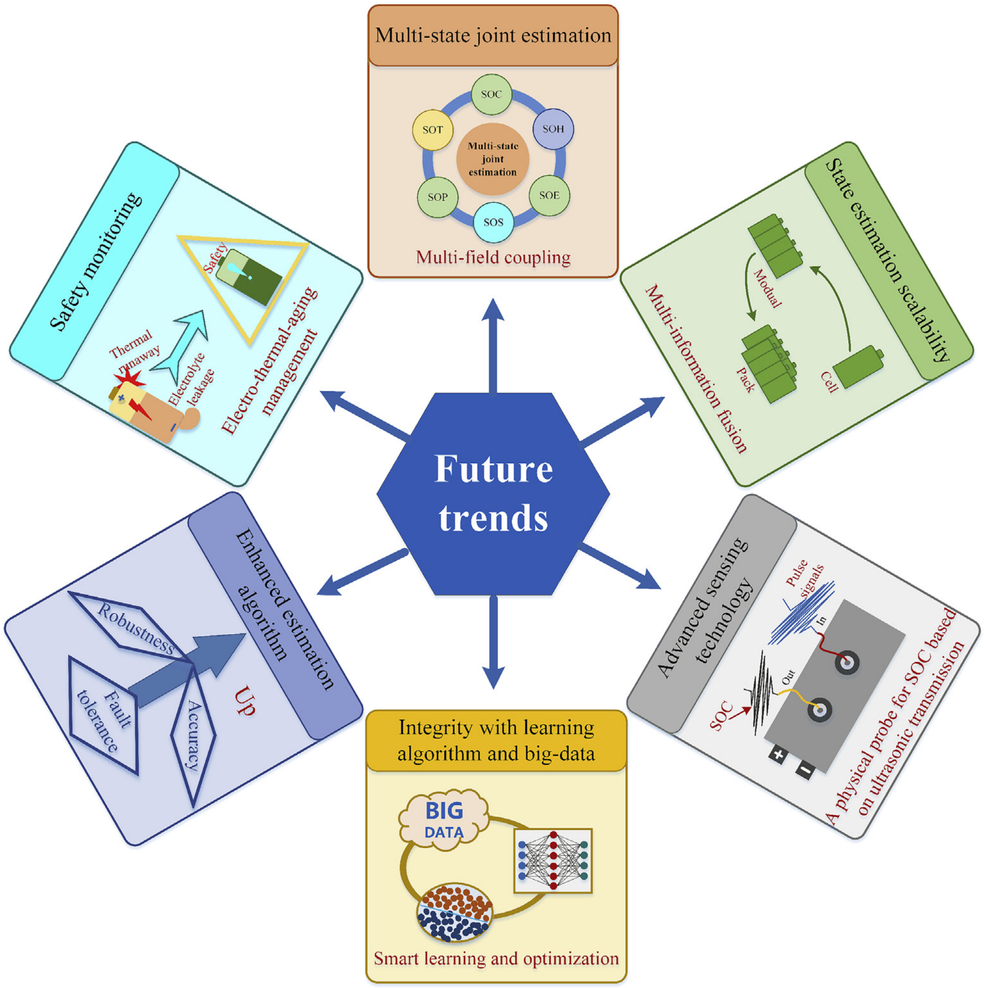

Fig. 11. Future trends of state estimation for advanced battery management.

estimation, more computational efforts would be required for multi-state estimation scenarios. In light of this, devising advanced approaches such as fractional-order calculus [14] and multi-timescale estimator [96] to effectively improving the accuracy of multi-state estimation, with an acceptable computational efficiency, becomes another essential future direction.

4.3. Scalability

With the continual advancement of state estimation algorithms themselves, more attention should be paid to scalability issues of state estimation, from cell to module, or even pack levels. Most existing studies focused on the cell level. In the case of a battery module, or pack, how should the estimation scheme adapt, in order to ensure a reasonable balance among accuracy, computational cost, and safety? Put another way, different estimation configurations should be sufficiently examined, including distributed and lumped configurations, to accommodate system-level estimation requirements [97,98]. In a distributed configuration, a state estimator can be built for each individual cell or for several adjacent cells, resulting in an array of estimators for a module or pack. In this way, different model parameters are applied to dissimilar cells or cell groups, to seek precise estimates at the cost of modeling and algorithmic efficiencies. As for a lumped configuration, the whole battery system could be considered as a big battery cell, and accordingly only a single state estimator is utilized to seek minimal computational burden, without any capture of cell interactions and inconsistency. Extensive research efforts are still needed to better address the scalability of state estimation to battery module and pack levels.

4.4. Holistic SOS monitoring and safety management

In the past, safety was mainly studied as an attribute of a system, rather than a system state. Only measuring the thermal safety of a battery system is unsatisfying, due to a relatively narrow operating temperature range, which merely exemplifies an attribute. Instead, the safety of a battery system has been researched as a state, SOS, similar to other common states, like SOC and SOH. And increasing attention from both academia and industry has been paid to the operational safety of batteries involving various aspects. Many authoritative organizations, such as EUCAR [74], SAE [99], and Sandia National Laboratory (SNL) [73] have developed their abuse test manuals and assigned hazard levels for electrified vehicle battery applications. The thermal, electrical, and mechanical abuse tests have been being carried out to develop technical standards for guideline.

Due to the requirements for the accurate numerical calculation of SOS, the SOS monitoring of a battery in various physical fields and conditions, such as mechanical, electrical, thermal, and electrochemical, will become a significant research direction for life-cycle battery prognosis and health management. For example, if the actual operating temperature of a battery exceeds the upper allowable temperature, the decomposition of SEI layer and active materials might take place, resulting in potential drastic exothermic reactions, thermal runaway [30,100], and even explosion [101]. Therefore, the probability function construction as a sub-function of calculating SOS relating to thermal reactions is of particular importance. Nowadays, enough accuracy and practicability of the SOS implementation is still tremendously challenging to obtain. By defining more sub-functions and recalibrating existing sub-functions based on investigations in various physical fields and conditions, the overall performance of SOS estimation can be further improved [28]. Moreover, individual sub-function that could affect the SOS of a battery system is necessary to be further studied in depth, such as the failure probabilities of individual components (such as electrodes, separators, and electrolytes). In addition, more statistical knowledge could be introduced, when defining the probability function of abuse, by means of abundant abuse tests.

4.5. Artificial intelligence

Artificial intelligence algorithms can complement traditional mathematical algorithms with strong capabilities of classification and linear/nonlinear regression. With the increasing integrity and accuracy of battery system big-data, integrated state estimation and prediction, combined with intelligent optimization algorithms, such as deep learning and reinforcement learning, will become growingly popular in the community of battery management and integration.

Artificial intelligence-based methods have been increasingly used in battery state estimation. For instance, support vector machine (SVM) [102], relevance vector machine (RVM) [103], fuzzy logic (FL) [104], artificial neural network [105] and fuzzy C-means (FCM) clustering [106] were explored. For battery health state estimation, apart from SOH that evaluates the current health status, the remaining useful life (RUL) estimation is also essential for practical applications. It is worth noting that battery capacity/power capabilities gradually degrade over real-world operations until its end of life (EOL). How to use a small sample of early aging phase to construct a reliable artificial intelligence-based approach for precise battery RUL or aging-path estimation is of extreme importance for advanced battery management [107]. Besides, exterior characteristic parameters such as the current, voltage, and temperature, are often selected as training input. Consequently, the trained artificial intelligence-based methods are unable to describe the internal electrochemical behaviors of a battery, which limits their applications under varying operating conditions. More importantly, artificial intelligence-based methods often need a large amount of data for training, and the training process is time-consuming. Therefore, studying the estimation of various state variables, incorporating internal electrochemical parameters into the algorithm training, and improving computational efficiency constitute major challenges in improving the performance of artificial intelligence-based methods.

4.6. Comprehensive evaluation with multiple metrics

The apparent variability and complexity in operating conditions, such as strong electromagnetic interference, wide temperature and current ranges, are representative of an electrified vehicle application scenario. Improvements of the robustness, precision, and fault tolerance of optimization algorithms for battery state estimation is an imperative research direction, which determines whether estimation algorithms can be really applied in practice well.

In the available literature, pertinent methods were often validated by experimental tests, so the original signals have a high quality in such laboratory conditions. In realistic electrified vehicle applications, there exist random measurement noises and electromagnetic interference [108], which requires better robustness and fault tolerance for battery state estimation. For instance, some studies investigated the theoretical analysis of a fundamental relationship between state estimation accuracy and the measurement data by utilizing Cramer-Rao bounds, with the consideration of sensor noise and measurement uncertainty [109–111]. Such an analysis can guide the experimental design for system identification and data selection for online estimation. Besides, considering the bus communication delay in BMSs, sensors will inevitably do sampling at different times, which is defined as asynchronous sampling [112]. In addition to adopting modified sampling strategies (e.g., the voltage is first sampled and the current later), improvements of state estimation algorithms are needed accordingly. Also, the parameters of battery models may vary frequently due to changing driving conditions, in terms of SOC, temperature, and current profiles, etc. Thus, the online learning abilities of state estimation methods, which can update model parameters dynamically, are of prominent importance to some battery operational scenarios, like electrified vehicle applications.

5. Conclusions

This article provides some beneficial insights into recent research progress of the area of battery state estimation. Existing methods and associated issues/challenges are overviewed regarding State of Charge (SOC), State of Energy (SOE), State of Health (SOH), State of Power (SOP), State of Temperature (SOT), and State of Safety (SOS) estimation. From six different standpoints, a number of key research directions and trends are presented, aiming to incent more researchers and practitioner in this field to contribute innovative ideas and tools for SOC/SOE/SOH/SOP/SOT/SOS estimation, which is critical to the research, design, and development of next-generation battery management systems.

Declarations of interest

As Xiaosong Hu, a co-author on this paper, is an Associate Editor of RSER, he was blinded to this paper during review, and the paper was independently handled by Aoife M. Foley.

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