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Review

State Estimation Models of Lithium-Ion Batteries for Battery Management System: Status, Challenges, and Future Trends

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Abstract: The state estimation technology of lithium-ion batteries is one of the core functions elements of the battery management system (BMS), and it is an academic hotspot related to the functionality and safety of the battery for electric vehicles. This paper comprehensively reviews the research status, technical challenges, and development trends of state estimation of lithium-ion batteries. First, the key issues and technical challenges of battery state estimation are summarized from three aspects of characteristics, models, and algorithms, and the technical challenges in state estimation are deeply analyzed. Second, four typical battery states (state of health, state of charge, state of energy, and state of power) and their joint estimation methods are reviewed, and feasible estimation frameworks are proposed, respectively. Finally, the development trends of state estimation are prospected. Advanced technologies such as artificial intelligence and cloud networking have further reshaped battery state estimation, bringing new methods to estimate the state of the battery under complex and extreme operating conditions. The research results provide a valuable reference for battery state estimation in the next-generation battery management system.

Keywords: lithium-ion batteries; battery management system; electric vehicles; sustainable energy; state estimation technique

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1. Introduction

Environmental pollution and the shortage of fossil energy motivate the shift from fossil fuels to renewable energy [1,2]. Featured by the continuously decreasing cost, long lifespan, high power density, and high energy density, most electric vehicles (EVs) use LIBs as the main power source up to the paper submission [3–5]. With the worldwide transportation process, the total number of EVs is expected to exceed 300 million by 2030, and the required installed capacity of LIBs will reach 3000 GWh [6,7]. Due to the voltage and capacity limitations of a single cell, we tend to build a battery pack consisting of hundreds of cells in parallel or series to meet the high power and energy application scenarios demand [8,9]. To handle these high energy (>100 kWh) and high voltage (>300 V) packs, we need an excellent design BMS to safely and efficiently control, monitor, and optimize their use [10–12].

As the monitor of the power system, state estimation is one of the core key functions of a BMS. Commonly estimated battery states include the state-of-charge (SOC) [13], state-of-health (SOH) [14,15], state-of-power (SOP) [16], state-of-energy (SOE) [17], and state-of-safety (SOS) [18,19]. As is the case with most electrochemical energy storage systems, the internal battery states are unable to be measured directly and can only be estimated and predicted indirectly from limited signals such as voltage, current, and temperature signals [20,21]. Due to the complex electrochemical reaction inside the battery, the internal states exhibit a highly nonlinear relationship with the external measured signals, and this issue becomes severe under complex or extreme working conditions [22–24]. In addition, the battery degradation during the cycle affects the state estimation reliability and increases the difficulty of state estimation. Therefore, accurate battery state estimation is still a technical challenge, especially since the battery performances could change with aging, and a stable and exactitude estimation is required for the whole battery life.

By aiming at these issues, we here provide a timely and comprehensive review of the estimation strategies for commonly used battery states (SOC, SOH, SOE, and SOP), and the technical challenges and future trends are discussed. This study aims to contribute innovative ideas to solve the technical bottleneck for BMS. Potential contributions are as follows: (1) the research status and typical methods of battery state estimation are summarized and analyzed from more than 200 peer-reviewed journal papers; (2) the technical problems in battery state estimation are summarized, and the potential technical frameworks are given; (3) an innovative joint battery state estimation scheme is proposed; (4) and the development trend of battery state estimation is highlighted.

The rest of this article is organized as follows. In Section 2, the key issues and challenges of BMS and battery state are summarized. In Section 3, the estimation methods of typical battery states (SOC, SOH, SOE, and SOP) are outlined and analyzed. The future development trend of battery state estimation is highlighted in Section 4. Finally, in Section 5, some conclusions are provided.

2. Key Issues and Challenges of Battery State

2.1. Overview of the BMS

The primary function of BMS is to effectively control and manage the battery to ensure the durability, power, and safety of LIBs. Typical functions include signal measurement of the battery cell and battery pack, state estimation, battery pack consistency evaluation, battery pack balancing, safe charging, fault diagnosis, and thermal management [1,25–27]. H. Dai et al. [11] divided BMS into four stages: no, simple, advanced, and next-generation management. Currently, BMS is in the advanced management stage and is developing into the next-generation BMS. With the increasing number of batteries and the higher energy density of batteries, the battery state estimation method has poor adaptability under extreme conditions, and the safety issue of batteries becomes more and more prominent. Therefore, the development of the next generation BMS characterized by intelligence is imminent.

Figure 1 shows the development process and basic characteristics of BMS, which can be divided into the following four generations: (1) Zero management; this is mainly used for voltage detection and simple charge and discharge control of lead-acid batteries. (2) Simple management; the main feature is to monitor the battery data (such as current, voltage, and temperature) of a few LIBs and has a simple control algorithm to prevent overcharge and over-discharge. (3) Advanced management; it mainly manages the property and safety of a large number of batteries with a high intelligence level. It has the functions of state estimation [28], fault diagnosis [29,30], thermal management [31,32], and fast charging [32]. (4) Intelligent management; the intelligent BMS is being developed for the long-term and accurate management of large-scale batteries under complex conditions. It has the functions of the above-mentioned advanced BMS, ultrafast charging [33], active safety control [34], and strong interaction, such as vehicle-to-grid (V2G), vehicle-to-home/buildings (V2H/B), and vehicle-to-vehicle (V2V) [35,36]; personalization; flexibility; and customization. Some advanced technologies, such as intelligent sensing [37], big data [38], AI algorithm [39], digital twin [40], and blockchain [41], have been applied in BMS. In short, BMS will develop from passive and distributed management to active and cooperative management and from stage control to full life cycle control.

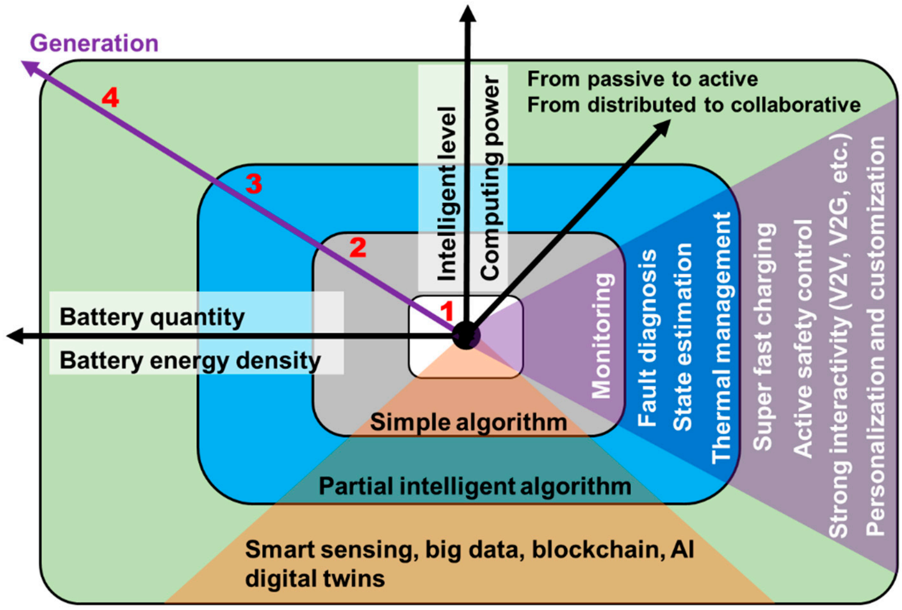

Figure 1. Development process and basic characteristics of BMS.

2.2. Key Technical Challenges of State Estimation

LIBs have a long-life cycle, during which their states have serious nonlinear characteristics. However, only the signals such as current, voltage, and temperature can be obtained directly in BMS. Therefore, the technical challenge of the battery state estimation is to estimate the complex internal state of the battery with limited external signals and predict the long-term state with short-time test signals. Specifically, the main technical challenges of battery state estimation lie in signals, models, and algorithms, which can be summarized as follows:

(1) Online and rapid extraction of key electrochemical characteristics of LIBs. The electrochemical characteristics of LIBs are the foundation of precise state estimation. At present, battery models are commonly used to reflect the electrochemical intrinsic characteristics of the battery. The common battery models include the integer-order equivalent circuit model (IOECM), fractional-order equivalent circuit model (FOECM), electrochemical model, and neural network model. Among them, the IOECM is extensively used because of its uncomplicated structure, easy implementation, and low computational load, but it cannot extract the hidden features inside the battery [42,43]. The FOECM is slightly stronger than the IOECM in electrochemical feature extraction but brings complicated computation [44–48]. The neural network model needs many training data to achieve satisfactory model accuracy [49]. The electrochemical model can accurately describe the electrochemical characteristics of the battery [50,51]. However, the aging of the battery will affect the parameters of the electrochemical model, resulting in the cycle dependence problem, and the complex electrochemical models are difficult to be applied online in actual scenarios [52]. Before the maturity and large-scale application of the built-in smart sensor in the battery, it is not easy to measure its internal state. The incremental capacity (IC) and electrochemical impedance spectroscopy (EIS) curves may be effective in characterizing internal electrochemical characteristics through external signal measurement [53–55]. However, the IC curve highly depends on the low noise constant current condition. The EIS curve is generally measured online by an electrochemical workstation, and the real part and imaginary part of impedance need to be recorded across dozens of frequency ranges, which seriously hinders the online application of EIS. Therefore, it may be a solution to develop a high-precision and low-cost method that can reconstruct the full frequency domain EIS curve by online measuring a few frequency points and an online extraction method of IC curve under dynamic conditions.

(2) Online identification of battery aging pattern and enhancement of aging model. The online identification and quantification of typical aging mode can essentially consider the aging mechanism inside the battery. It plays an important role in the high-accuracy prediction of the SOH estimation and the remaining life of the battery (especially for the accelerated aging and capacity diving), and the online diagnosis of battery faults [56,57]. However, the existing online aging process evaluation of batteries mostly focuses on the online evaluation of battery capacity and internal resistance [58,59], where it is difficult to go deep into the battery and touch the essence of aging. The aging mode is mainly characterized and analyzed by the offline aging mechanism of the battery [60,61]. Due to the cumbersome test process or the need for special instruments, it is not easy to quantify and apply the aging mode online. Moreover, the aging model is prone to parameter mismatch during the degenerative process of the battery, and the description and mapping of the long-term electrochemical characteristics of the battery are insufficient [62,63]. Therefore, innovative methods are urgently needed to enhance the long-term and hidden characteristics of the aging model.

(3) Accurate prediction of battery life-cycle aging trajectory. Battery aging is a long-term evolution process with high path dependence [64]. The traditional scheme of predicting battery trajectory by machine learning has the common problems of insufficient data in the early stage, mismatching of model parameters in the medium stage, and distortion of characteristics in the later stage. The training data available in the early stage are insufficient, and the mapping of electrochemical characteristics is limited, resulting in low global accuracy in predicting aging trajectories. In the medium stage of battery aging, the parameters of the aging model may be mismatched with the battery aging [65]. At the later stage of battery aging, the nonlinearity of battery aging is very prominent, resulting in distortion in predicting some hidden characteristics (such as the knee point effect [66–68]).

3. Status of State Estimation

3.1. SOC Estimation Methods

Battery SOC is generally defined as the proportion of the current remaining capacity of the battery to the rated capacity of the battery under a specific discharge rate [69], and its expression is:

$$SOC = \frac{Q}{C_N} \times 100\% \quad (1)$$

where Q is the current remaining battery capacity, and C_N is the rated battery capacity. In the standard charge and discharge mode, when the battery is completely discharged to empty, the SOC is 0; when the battery is fully charged, the SOC is 100%.

Battery SOC is the basis of other state estimations, and it is influenced by several factors, such as charge and discharge rate, cycle times, temperature, and battery aging [70]. It presents obvious nonlinear characteristics, making high-precision SOC estimation a great technical challenge. SOC estimation has been widely studied [71,72], and the main methods can be summarized as follows:

(1) Discharge test method. The method can accurately and reliably estimate SOC [73]. In this method, the battery is discharged with a constant current until the discharge cutoff voltage, and the value obtained by multiplying the current by the time is the battery SOC. This method needs a long time and is unsuitable for dynamic working conditions. Therefore, it is generally used in the laboratory.

(2) Impedance method. The battery SOC affects the impedance of the battery, and there is a certain mapping relationship between them [71,74]. Therefore, SOC can be estimated by using the battery impedance in theory. The impedance method has the following two obvious disadvantages: (1) The battery impedance needs special instruments to measure, which is difficult to apply online; (2) AC impedance is very sensitive to temperature and SOH. Once the temperature fluctuates greatly, the accuracy of the impedance method decreases [75].

(3) Ampere-hour (AH) method. The method is to integrate the battery charge and discharge current, and then the current SOC value is estimated by the initial SOC. The expression of the AH method is shown in Equation (2). The AH method is simple and easy to implement, so it is widely used in early BMS [76–78]. However, its disadvantages are obvious and can be summarized as follows: (a) The AH method is very dependent on the initial SOC, and the initial SOC accuracy directly affects the estimation results. (b) The measure errors of the battery current sensors will cause cumulative errors in the SOC estimation results. (c) For calculation simplicity, the coulomb efficiency is generally taken as 1. However, it is closely related to temperature and battery aging. Therefore, the precision of the method is not exact under complex conditions, and the current SOC algorithm usually combines the AH method with other algorithms.

$$SOC(t) = SOC(t_0) - \int_{t_0}^{t} \frac{\eta \cdot I}{C_N} dt \tag{2}$$

where $SOC(t_0)$ is the SOC at the initial time, I is current, and η is coulomb efficiency.

(4) Open circuit voltage (OCV) method. There is a clear mapping relationship between OCV and battery SOC [79], and the OCV-SOC can be obtained by the hybrid pulse power characteristic (HPPC) [80]. Therefore, SOC can be estimated by measuring OCV. The OCV method is simple and easy to realize with high accuracy. However, before the OCV measure, the battery needs to be rested for more than two hours, which cannot be used online and only for offline SOC estimation.

(5) SOC estimation method based on equivalent circuit model (ECM). This method can be divided into two types: direct estimation based on the battery model and model-based adaptive filter. The former is an open-loop method, which uses the analog voltage obtained by the battery model to replace the actual voltage. It overcomes the disadvantage that OCV cannot be dynamically obtained online and retains the advantages of the OCV method, which is convenient, intuitive, and less computational. However, the direct estimation based on the model is greatly affected by the accuracy of the model and the current measurement. The model-based adaptive filter method is a closed-loop method, and the frequently reported algorithms are mainly Kalman filtering algorithms and their derivatives, including extended Kalman filtering (EKF), H∞ observer, synovial observer, etc. [81–83]. Plett et al. estimated SOC using the EKF as early as 2004 [84]. To overcome the error caused by the linearization of the EKF model, the unscented Kalman filter (UKF) was adopted [85–87]. This method can overcome the influence of initial SOC and system noise on SOC estimation results with strong robustness. However, it depends on model accuracy.

(6) SOC estimation based on an electrochemical model. J. Li et al. and J. Li et al. [70,88] estimated the battery SOC based on the electrochemical mechanism model and the lithium content of the positive and negative electrodes. The electrochemical model has high model accuracy, which is very beneficial to improving SOC accuracy. However, the electrochemical model involves many parameters and coupled partial differential equations [89], which is unsuitable for online applications.

(7) SOC estimation based on the black box model. SOC estimation algorithms based on the black box model mainly include artificial neural networks [90], fuzzy control, and support vector machines (SVM) [91]. In this method, the relationship between some macro physical parameters and battery SOC is trained. This method does not consider the inherent reaction characteristics of the battery and has a strong self-learning ability, which is suitable for some highly nonlinear systems [92]. However, this method relies on the quantity of data heavily.

In summary, the method of SOC estimation by the ECM has good comprehensive advantages and is very suitable for SOC estimation at the vehicle end. With the development of big data and cloud computing, electrochemical model-based or black box model methods can be applied individually or jointly to improve SOC estimation accuracy based on the powerful computing power and abundant data in the cloud.

3.2. SOH Estimation Methods

3.2.1. Status of Battery Aging Models

There are three main types of the existing LIBs aging models: mechanism model, empirical and semi-empirical model [93,94] (Table 1). The empirical model is the black box model, and the mechanism model based on the electrochemical mechanism model is the white box model [95]. The computational burden of the mechanism model is huge [96]. Although many simplified mechanism models exist, their application in BMS is still limited. The empirical model is the battery aging model obtained by fitting the battery aging experiment. It generally considers the effects of temperature, charge, discharge rate, and cycle times. The frequently reported mechanism model is the Arrhenius model [97,98], and its expression is shown in Equations (3) and (4).

$$k = \frac{dQ_{loss}}{dt} = A \cdot \exp(-\frac{E_a}{RT}) \tag{3}$$

$$Q_{loss} = A \cdot \exp(-\frac{E_a}{RT}) \cdot t^z \tag{4}$$

where Q_{loss} is the capacity attenuation, A is a constant greater than zero, E_a is the active energy, T is the temperature, R is the ideal gas constant, t is time, and z is the time index. It is noted that A, Ea/R, and z can be fitted according to the battery durability test.

It can be seen that the empirical model relies on a large number of durability aging data to calibrate the model parameters. If multiple influencing factors need to be investigated at the same time, the experimental workload will be significantly increased. In addition, due to the complicacy of the real vehicle working condition and the influence of many external uncertain factors, the application of the empirical model has the following problems: (1) how to use the empirical model to predict the battery life with high accuracy under complex and extreme working conditions; (2) how to solve the model parameter mismatch of the empirical model. The complicacy of the semi-empirical model is between the empirical model and the mechanism model. It can partly reflect the battery aging mechanism [99], but it still needs a lot of experimental data to calibrate the battery models.

Table 1. Typical aging model of LIBs.

	Empirical Model	Semi-Empirical Model	Mechanism Model
Modeling method	Fitting by experimental data	An empirical model considering the partial aging mechanism	The side reaction equations are established based on the electrochemical mechanism.
Advantages	Simple; Low computational burden	It can reflect some internal characteristics with less computational burden.	The depth reflects the internal state of the battery.
Disadvantages	Parameter mismatch	many experiments are needed to calibrate parameters.	The model is complex, and the calculation is large.
Typical model	Arrhenius model [97]	Extended equivalent circuit battery model [100,101]	P2D model [102]

3.2.2. Online SOH Estimation Methods

During the long aging cycle of LIBs, the loss of lithium-ion inventory (LLI), loss of active material (LAM), and loss of electrolyte (LE) are caused by the joint action of many factors such as electrochemical, thermal, and external mechanical stress [103,104]. In the external form, aging causes the capacity decline and internal resistance increase in the battery. Therefore, the SOH can be measured by the ratio between the real battery capacity and the nominal battery capacity or the ratio between the actual battery impedance and its nominal impedance [105]. Battery SOH is closely related to battery safety, remaining useful life (RUL), SOE, etc. Therefore, SOH estimation has become a hotspot of battery state estimation [55,106].

The common SOH estimation methods include model-driven, data-driven, and fusion methods [107,108]. From the accuracy and robustness of capacity estimation, the model-driven method is unsuitable for practical application under complex conditions. Data-driven methods include the following types: (1) The characteristic-driven method is where the correlation between the battery characteristics and the battery capacity is established. Common characteristics include battery differential voltage [109], charge–discharge curve [110], and incremental capacity curve [111,112]. In our previous study [113], according to the partial charging curve, we proposed a practical capacity estimation method, which has the advantages of simple calculation and is suitable for online estimation. (2) The SOC-electric quantity method [114] calculates the battery capacity based on the variation ratio of the electric quantity to the corresponding SOC, and the expression is as follows:

$$C_{norm} = \frac{\Delta Q}{\Delta SOC} \tag{5}$$

where C_{norm} is the battery capacity, and ΔQ and ΔSOC are the change in electric quantity and SOC, respectively.

As can be seen from the above Equation (5), the capacity estimation accuracy is closely related to the SOC accuracy. Therefore, the joint estimation of SOC and SOH is widely used. Although data-driven methods may have ideal real-time estimation accuracy, the factors affecting capacity loss have not been well considered. In recent years, data and model fusion methods have been developed to enhance capacity estimation accuracy, stability, and robustness. Figure 2 shows a novel capacity estimation frame that combines data-driven and model-driven methods [115]. The basic principle and process of this method are as follows: First, the battery capacity is estimated by model-driven and data-driven methods, respectively. In the process of battery aging, the capacity estimated by the model-driven method is stable, but the accuracy is poor due to parameter mismatch. The capacity obtained by the data-driven method has good accuracy but lacks stability. Second, the model parameters are closed-loop controlled by using the difference between the capacities obtained by the above two methods as the feedback signal, the model parameters are updated in real-time, and the new capacity is obtained by using the model-driven method. Finally, the new capacity driven by the model and the capacity driven by the data is fused to obtain the estimated capacity. The proposed framework has the advantages of both capacity-driven and data-driven methods, and the estimated battery has high accuracy and high stability [97].

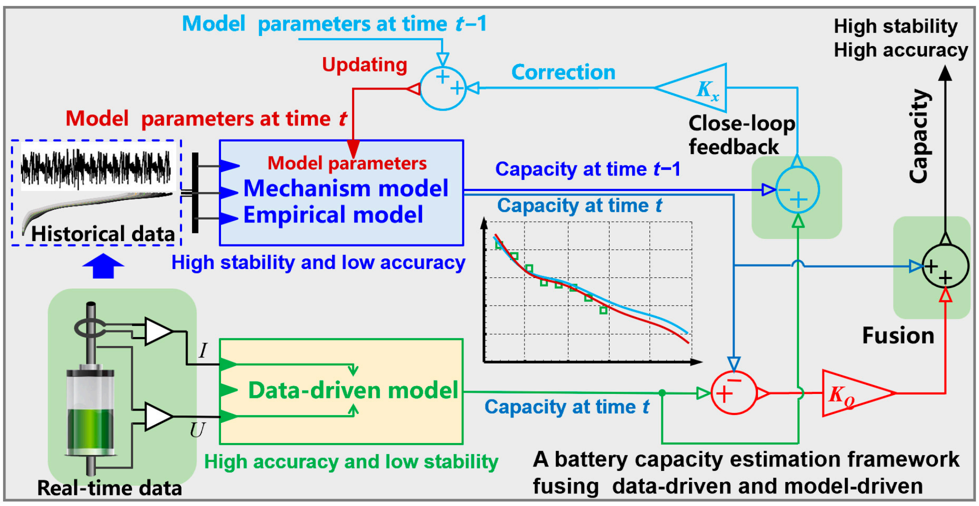

Figure 2. A novel battery capacity estimation frame that fuses the data-driven and model-driven methods [115].

3.3. SOE Estimation Methods

3.3.1. Definition of SOE

SOE is reflected as residual energy of the battery [116], which is related to the amount of charge that the battery can discharge and the voltage during the battery discharge. Compared with SOC, SOE is more suitable for estimating the driving range of EVs [117,118]. SOE is divided into two types. The first defines SOE as the theoretical residual energy (TRE) of the battery, and the second defines SOE as the residual discharge energy (RDE) of the battery [119]. TRE is the energy that can be released when the battery is discharged to SOC = 0 with a very small discharge current. RDE is the energy that can be released by the battery when it is discharged to the cutoff voltage under a certain load condition and at a certain ambient temperature. The difference between the two is shown in Figure 3. It can be seen that the TRE of the battery is a state value inside the battery, indicating the energy currently stored in the battery, independent of the temperature, load condition, etc. The RDE of the battery can be expressed by the shaded area of the solid red line in Figure 3, which is related to the discharge rate, load condition, ambient temperature, and other factors [120]. In conclusion, the estimation of battery SOE, whether for TRE or RDE, is the important significance for optimizing the energy management strategy of BMS and improving the accuracy of estimation of EV driving range.

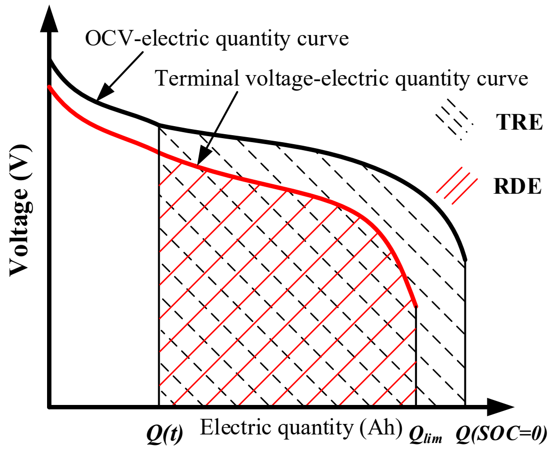

Figure 3. Schematic diagram of TRE and RDE.

3.3.2. Status of Theoretical Remaining Energy

The methods for estimating the battery TRE mainly include the direct calculation method, power integration method, OCV method, model-based filtering algorithm, machine learning method, and joint estimation method. They are briefly described as follows:

(1) Direct calculation method. The voltage is averaged in a certain way and set at a constant value, and the SOE is obtained from the current SOC, the total battery energy, the capacity, and the average voltage. The common calculation expression is shown in Equation (6). The direct calculation method is simple and practical. However, because the average value of the battery voltage is approximated, a large error will be caused, and the SOE estimation is affected by the SOC accuracy. If there are large errors in SOC, the errors will be transmitted to SOE.

$$SOE = SOC \times \frac{OCV_{avg} \times C_{Bat}}{E_{Bat}} \tag{6}$$

where OCV_{avg} is the average value of OCV, C_{Bat} is the standard capacity, and E_{Bat} is the maximum energy.

(2) Power integration method. This method is similar to the AH for estimating SOC in principle, as shown in Equation (7). This method is simple and does not need to estimate

SOC. However, the initial error cannot be eliminated, and the accumulated error will be caused due to the insufficient accuracy of the sensor.

$$SOE(t) = SOE(t_0) - \frac{\int_{t_0}^{t} (p_e + q_h)dt}{E_{bat}} \quad (7)$$

where p_e is the electric power of the battery and q_h is the thermal power of the battery.

(3) OCV method. The method utilizes the correlation between OCV and battery SOE. However, the OCV of the battery can only be obtained after a long time of standing. It is difficult to obtain stable OCV when the battery is in a dynamic working environment. Therefore, the OCV method is limited to SOE estimation.

(4) Model-based filtering method. This method uses the power integration method to estimate the SOE and then uses some filtering algorithm to correct the SOE based on the battery model, which has self-convergence. Common filtering algorithms include the KF algorithm [84,121], particle filter (PF) algorithm [122], and H-infinity algorithm [123,124]. KF algorithm is a closed-loop correction of SOE using Kalman gain and is widely used to estimate SOE [20,118,125–130]. Wang et al. [131] used the recursive least square (RLS) method to identify the model parameters offline and then the EKF algorithm to estimate the SOE. Dong et al. [132] used the EKF algorithm to determine the battery model parameters online and used the PF algorithm to estimate the SOE, realizing online SOE estimation. The model-based filtering algorithm has high accuracy and can avoid the cumulative error of SOE. This method corrects SOE based on the OCV and SOE. However, this relationship is only determined when SOE is defined as the TRE. In addition, the estimation accuracy of the method is influenced by the battery model accuracy [133].

(5) Machine learning method. In the late years, the machine learning method has been generally used to estimate SOE [134–137]. Liu et al. [134] used current and temperature as training inputs to build an inverse neural network to estimate the battery SOE. Heraldo et al. [137] used long-term and short-term ways to predict the future voltage and then estimated the battery SOE e through Monte Carlo sampling. The SOE estimation accuracy based on machine learning depends heavily on training data.

(6) Joint estimation method. Zheng et al. [138] first estimated the battery SOC, then estimated the SOE through the relationship between SOE and SOC, and estimated the battery total energy using the moving sliding window method. The joint estimation method usually has higher accuracy than the single SOE estimation method. The key to estimating SOE by joint estimation is finding a clear relationship between SOE and other states.

3.3.3. Status of Remaining Discharge Energy

The battery RDE is closely related to future operating conditions, ambient temperature, battery health, and other factors [138,139]. Therefore, the coupling effects of these factors need to be considered when estimating the RDE. Prediction-based methods are usually used [140–143]. Liu et al. [140] predicted the current sequence, SOC sequence, model parameter sequence, and voltage sequence of the battery in the future time series. Then, the RDE was calculated by the current and voltage sequences in the prediction domain. Mona et al. [143] performed Gaussian mixture clustering on the historical conditions of the battery and obtained the hidden Markov model to predict the future conditions of the battery through supervised learning. Then, the battery RDE was estimated. Ren et al. [119] used the moving average method to collect the historical power of the battery to predict the future SOC, model parameters, and voltage sequences and then estimated the RDE. The technical difficulty of RDE is the accurate prediction of future working conditions.

The characteristics and application scope of common SOE estimation methods are listed in Table 2. The SOE estimation method considering complex working conditions and multiple factors needs to be further studied. In our previous study [144], an RDE estimation framework for future load forecasting and considering battery temperature and aging effects was proposed, which is illustrated in Figure 4. Its basic principle and process are as follows: First, a hidden Markov model (HMM) is implemented to predict the future load of batteries. The capacity test is then performed at different temperatures to determine the limiting SOC. Third, a forgetting factor RLS algorithm identifies and updates battery model parameters online to solve the problem the parameter mismatch issue. According to the predicted current, SOC, and voltage sequences, the RDE is estimated under different operation conditions.

Table 2. Characteristics and application scope of SOE estimation methods.

	Estimation Method	Characteristics	Definition of SOE TRE	RDE
1	Direct calculation method	Simple with large error	✓	
2	Power integration method	Simple with a cumulative error	✓	
3	OCV method	Simple with limited use conditions	✓	
4	Model-based filtering method	Accurate; it can avoid cumulative error; complex	✓	
5	Machine learning method	Need a lot of data for training	✓	
6	Joint estimation method	High precision; need to find the relationship between different states	✓	
7	Prediction-based method	High accuracy but accurate future working condition is the key		✓

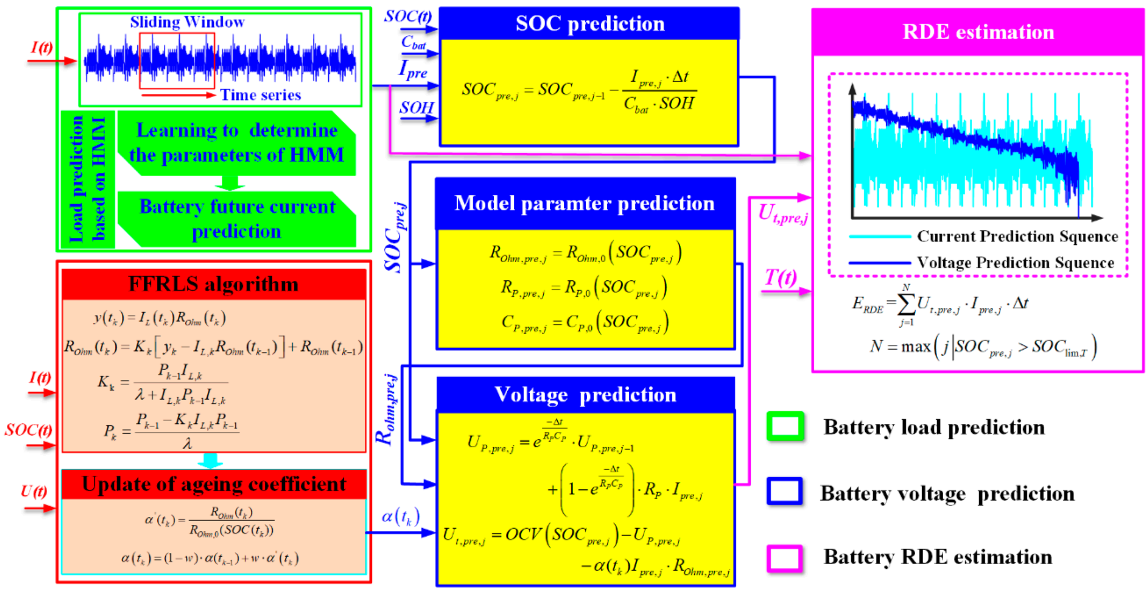

Figure 4. A novel RDE estimation framework considering future load prediction [144].

3.4. SOP Estimation Methods

SOP is generally characterized by peak power. The specific meaning is maximum battery power that can absorb or release within time under the limit of voltage, current, SOC, etc. During the driving process of EVs, the SOP is updated by the BMS in real-time to evaluate whether the battery can meet the power demand when the vehicle is accelerating or uphill [145]. Common SOP estimation methods are summarized as follows:

(1) Experimental method. The experimental method is to obtain SOP by conducting experiments according to the battery standard power test procedures, such as the USABC test in the United States [146], the JEVS test in Japan [147], and the standard battery test in China [4]. The experimental method is accurate and easy to realize, but the operation process is long and cannot be applied online.

(2) Characteristic mapping method. The static correlation between the battery power and some parameters can be obtained by a standard battery test, which is called the characteristic map. Then, the SOP can be obtained through table lookup or interpolation according to the current battery parameters. The hybrid pulse power characterization (HPPC) test is the most commonly used map extraction method. Xiong et al. [148] proposed a method to calculate the battery peak power using the HPPC test. The main drawback of the method is that it is not suitable for dynamic working conditions, and the characteristic map needs to be calibrated continuously with the battery aging.

(3) Limiting conditions method. In this method, battery peak current is calculated by considering the current, voltage, SOC, and other limitations. The peak power equals the product of the peak current and the OCV. The basic principle and flow of this method are shown in Figure 5, in which $I_{\max}^{dch}$ is the peak charging current; $I_{\min}^{cha}$ is peak discharging current; $I_{\min}^{cha,vol}$ is minimum chargeable current; $I_{\max}^{dch,vol}$ is maximum dischargeable current limited by the terminal voltage; $I_{\max}^{dch}$ and $I_{\min}^{cha}$ are the peak charging current and peak discharging current, respectively; and $U_t(t)$ is the terminal voltage. This method has three core technologies: (1) Establishing which battery model is used to estimate the battery voltage and SOC. (2) How the parameters of the battery model are obtained to improve the SOC estimation accuracy. (3) How the peak power under the boundary limit zone is determined.

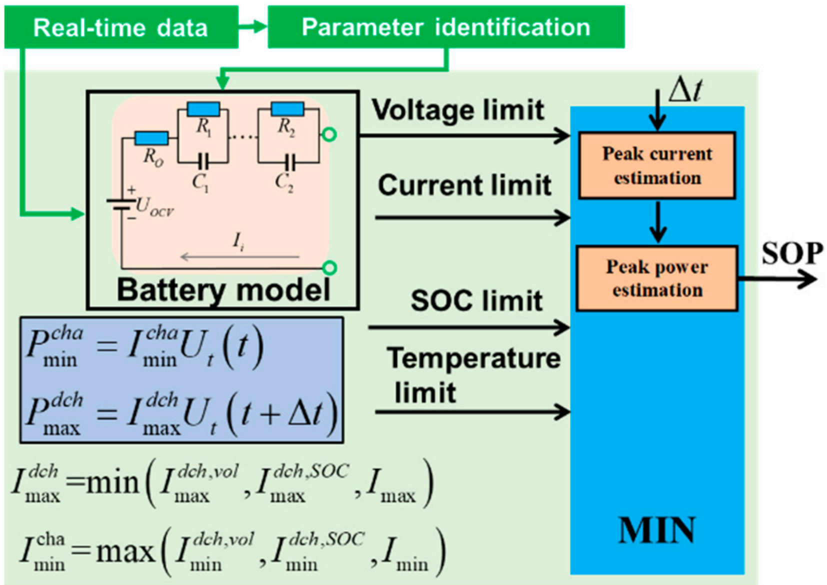

Figure 5. An SOP estimation framework under multiple limitations.

In previous studies, the IOECM is the most used in SOP estimation [149–153], followed by the FOECM [46]. There are two methods of model parameter identification: offline and online. The adaptability of offline identification is poor, so the online identification method is the future trend. The common online identification method is RLS and forgetting factor RLS (FFRLS) [144]. In previous studies, voltage, current, and SOC limitations are commonly used limiting conditions for the SOP estimation [154–157]. In addition, temperature limitations are additionally considered to ensure the SOP estimation accuracy at extreme temperatures [158,159].

3.5. Joint Estimation Methods

From the above analysis, the battery state estimation methods are very rich. There is no major technical difficulty in realizing a single battery state estimation, and many algorithms can achieve high theoretical estimation accuracy. However, considering that the measurement signal is very limited under the actual complex vehicle conditions, this is a problem that is badly in need to improve the actual estimation accuracy of the battery state. In addition, the relationship between battery states is mutually coupled and affected, which can be described as follows. The capacity and internal resistance used to characterize the battery SOH are essential parameters for battery SOC estimation, directly affecting SOC estimation accuracy. SOC and model parameters are the critical parameters for SOP estimation. The SOC, capacity, and internal resistance directly affect the SOE estimation. These relationships can be illustrated in Figure 6.

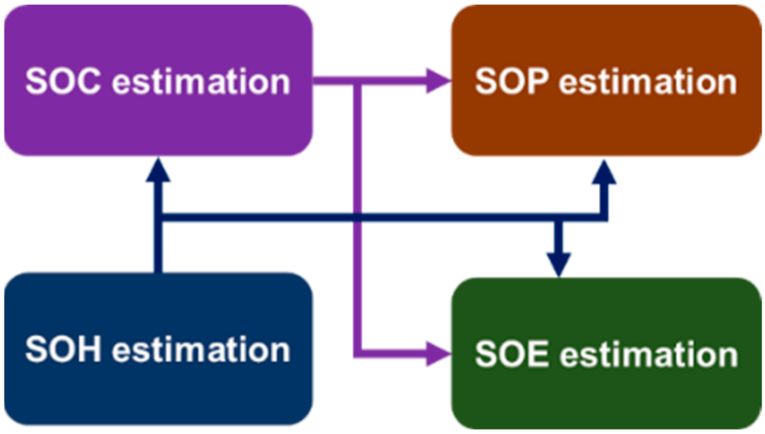

Figure 6. Interrelation between various state estimates.

Therefore, joint estimation methods are being developed and widely used to improve the accuracy of battery estimation. They can generally include the following types: (1) Joint estimation of model parameters and a single state [160–162]; Q. Yu et al. [163] proposed a joint estimation method of model parameters and SOC, in which the H-infinity filter is used to estimate battery model parameters online, and the unscented KF is used to estimate SOC. (2) Joint estimation of two battery states; the joint estimation of SOC and SOH is the most studied [164–168], and the joint estimation of SOC and SOP [16,169–171], SOC, and SOE [131,172–174] are widely reported. (3) Combined estimation of three or more battery states; P. Shrivastava et al. [175] proposed a joint estimation framework of SOC, SOE, SOP, and SOH. P. Shen et al. [114] proposed a combined estimation scheme of battery model parameters, SOC, SOH, and SOP. The process of the framework is as follows: First, SOC is estimated to be resolved by EKF. Then, the FFRLS algorithm can realize online identification of battery model parameters. Finally, SOH and SOP estimations are conducted based on the updated parameters.

Based on our previous studies [25,144], a joint frame of SOC, SOH, SOE, and SOP is proposed, as shown in Figure 7. The main principle of the proposed frame is as follows: First, the model parameters and OCV curve are updated in real-time using the FFRLS algorithm. Then, the SOC is updated using the EKF or UKF algorithm by the updated model parameters and the battery capacity. Third, the SOC-electric quantity method is used to estimate the SOH in real-time based on the updated SOC, and the SOE-SOC curve and the total energy are updated in real-time using the ordinary least squares (OLS) algorithm [25]. Fourth, SOC and SOE-SOC curve is used to estimate SOE using the UKF algorithm. Finally, the limit condition method is used to estimate the SOP in real time. The above algorithm framework cooperatively estimates multiple battery states with high accuracy and robustness, which can adapt to battery aging and environmental temperature changes better.

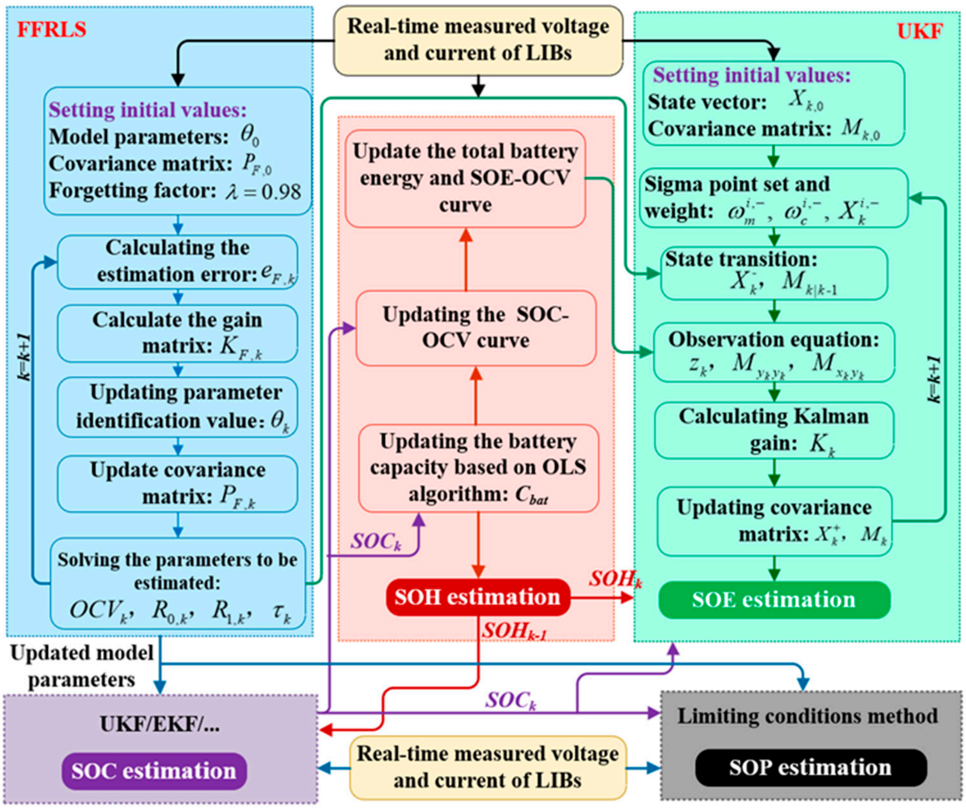

Figure 7. A joint estimation frame of SOC, SOH, SOE, and SOP.

4. Future Directions

With the development of big data, intelligent algorithms, and cloud platforms, a trend of smart and networked BMS is becoming increasingly obvious, which will effectively improve the battery state estimation accuracy and thus improve the life and safety of batteries. As shown in Figure 8, the critical future development trends of the battery state estimation can be summarized as follows:

(1) Intelligent sensing. Intelligent sensors are implanted in the battery to collect the internal signals in the battery to enrich the key signal input of BMS. Y. Yu et al. [176] monitored the internal structure deformation and temperature of LIBs in real time through embedded distributed optical fiber. J. Schmitt et al. [177] integrated a small pressure sensor into a battery to measure the internal gas pressure. However, these built-in sensors have a single function and may affect the energy density and durability of LIBs. It is a significant future development direction to develop a small intelligent sensor that integrates multiple sensors and is safely built into the battery. It will effectively detect the complex signals inside the battery and thus improve the battery state estimation accuracy and battery safety. In addition, thermal management is crucial to battery safety, and the new thermal intelligent sensors will also play an active role in the future. In this context, battery state estimation will become more abundant, and the existing state estimation methods will be completely improved.

(2) Model and signal enhancement. LIBs have a long-life cycle, in which the model parameters change with the battery aging, resulting in insufficient accuracy of battery state estimation in the whole life cycle due to a mismatch of model parameters and adequate signals. Migration learning brings feasible solutions for battery models and signal enhancement [178–181]. X. Thang et al. [182] restored large-scale battery aging data sets by combining industrial data with accelerated aging tests through migration-based machine learning, reducing the cost of aging tests. Y. Li et al. [183] migrated the convolutional neural network model pre-trained on the extensive battery data set to the small data set of the target battery through transfer learning technology to improve the capacity estimation

accuracy. Generally, the following resources can be used for the transfer learning in battery state estimation: (a) simulation model; (b) battery public data set; (c) battery experimental data set.

(3) Cloud-to-edge-based state estimation. With the development of cloud technology and the internet of things, battery state estimation is developing towards the cloud to edge [184]. The edge side collects the voltage and current data in real time. The cloud has strong computing power and can run the electrochemical model and intelligent algorithms, and the application of big data in the cloud is more flexible [185]. The cloud side cooperates to improve the exactitude of battery state estimation. The cooperation between cloud and edges can enhance the accuracy and stability in battery state estimation.

(4) Battery state estimation under vehicle network interaction. In recent years, smart energy systems have been booming. The fast charging, V2V, V2G, V2H/B, and other advanced technologies of EVs have established the information exchange between batteries and other physical systems, bringing new challenges and opportunities to battery state estimation. For example, V2G may accelerate battery aging, but the information exchange between the vehicle and the charging pile during charging provides rich information for battery state estimation.

(5) Life cycle intelligent management. The intelligent algorithm can deeply mine the internal and intrinsic characteristics of the battery and improve the state estimation exactitude and robustness. Therefore, battery state estimation integrated with advanced intelligent algorithms will be an eternal theme. Artificial intelligence and cloud network are reshaping and upgrading traditional battery state estimation methods. Advanced intelligent algorithms (deep learning and migration learning) are widely used in battery state estimation. Sun, Q. et al. [186] proposed a battery state estimation method based on metabolic even GM (1,1). The proposed method can achieve the goal that the overall error of power battery SOC estimation under different temperatures is less than 1%. Falai, A. et al. [187], based on an artificial intelligence algorithm, proposed to realize accurate onboard SOH estimation by identifying the best SOC window during battery charging, with an error of 0.4%. Ma, L. et al. [188] proposed a novel data-driven method estimation of SOC and SOE simultaneously based on long and short-term memory (LSTM) deep neural network, which can achieve the mean absolute error (MAE) of SOC and SOE estimates of 0.91% and 1.09%, respectively. In addition, the state estimation of the battery will run through the whole life cycle of LIBs, such as defect prediction during battery production [189] and residual value estimation during battery echelon utilization [190,191].

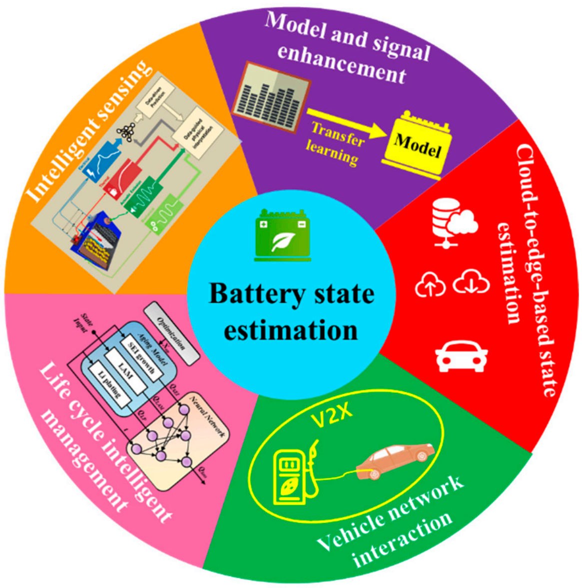

Figure 8. Future directions of the battery state estimation.

5. Conclusions

State estimation is one of the most basic functions of BMS. Accurate state estimation can prolong the battery life and improve battery safety. This paper comprehensively reviews the research status, technical challenges, and development direction of typical battery state estimation (SOC, SOH, SOE, and SOP). Specifically, limited measurable signals, mismatch of model parameters, severe nonlinearity, and time variability of battery state are the main challenges of battery state estimation. Accordingly, intelligent sensing, cloud computing, big data, and intelligent algorithms are feasible solutions. The accuracy and stability of battery state estimation are steadily improving through intelligent sensing to obtain more abundant signals, advanced intelligent algorithms to strengthen the model and signal characteristics, cloud computing, and big data to mine characteristic signals deeply. The accurate co-estimation of battery states under complex and extreme working conditions is challenging research, and intelligent batteries and advanced technologies are reshaping the battery state estimation methods. By adopting multi-dimensional, multi-level, and multi-scale signal information mining and state estimation representation, combined with the characteristics of discontinuous and continuous information, the combined optimal joint estimation method can solve the problem of battery state estimation accuracy under complex and extreme working.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
LIBs	Lithium-ion batteries
EVs	Electric vehicles
BMS	Battery management system
RLS	Recursive least square
FFRLS	Forgetting factor recursive least square
ECM	Equivalent circuit model
RDE	Residual discharge energy
TRE	Theoretical residual energy
SVM	Support vector machine
SOC	State of charge
OCV	Open-circuit voltage
SOH	State-of-health
SOP	State-of-power
SOE	State-of-energy
SOS	State-of-safety
V2G	Vehicle-to-grid
V2H/B	Vehicle-to-home/buildings
V2V	Vehicle-to-vehicle
IOECM	Integer-order equivalent circuit mode
FOECM	Fractional-order equivalent circuit model
EIS	Electrochemical impedance spectroscopy

IC	Incremental capacity
AH	Ampere-hour
EKF	Extended Kalman filtering
UKF	Unscented Kalman filter
LLI	Loss of lithium-ion inventory
LAM	Loss of active material
LE	Loss of electrolyte
RUL	Remaining useful life
LSTM	Long and short-term memory
MAE	Mean absolute error

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