WANG, S., JIA, X., TAKYI-ANINAKWA, P., STROE, D.-I. and FERNANDEZ, C. 2023. Review: optimized particle filtering strategies for high-accuracy state of charge estimation of LIBs. *Journal of The Electrochemical Society* [online], 170(5), article 050514. Available from: https://doi.org/10.1149/1945-7111/acd148

Review: optimized particle filtering strategies for high-accuracy state of charge estimation of LIBs.

WANG, S., JIA, X., TAKYI-ANINAKWA, P., STROE, D.-I. and FERNANDEZ, C.

2023

Review—Optimized Particle Filtering Strategies for High-Accuracy State of Charge Estimation of LIBs

Journal:	*Journal of The Electrochemical Society*
Manuscript ID	JES-109757.R1
Manuscript Type:	Review Paper
Date Submitted by the Author:	14-Apr-2023
Complete List of Authors:	Wang, Shunli; Southwest University of Science and Technology, Jia, Xianyi; Southwest University of Science and Technology Takyi-Aninakwa, Paul; Southwest University of Science and Technology Stroe, Daniel-Ioan; Aalborg University, The Department of Energy Technology Fernandez, Carlos; Robert Gordon University
Keywords:	lithium-ion battery, state of charge, SOC estimation methods, modeling methods, improved PF algorithms

Review—Optimized Particle Filtering Strategies for High-Accuracy State of Charge Estimation of LIBs

Shunli Wang,[1,2,z] Xianyi Jia,[2] Paul Takyi-Aninakwa,[2] Daniel-Ioan Stroe,[3] and Carlos Fernandez[4]

[1] College of Electrical Engineering, Sichuan University, Chengdu, China

[2] School of Information Engineering, Southwest University of Science and Technology, Mianyang 621010, China

[3] Department of Energy Technology, Aalborg University, 9220 Aalborg East, Denmark

[4] School of Pharmacy and Life Sciences, Robert Gordon University, Aberdeen AB10-7GJ, UK

Abstract: Lithium-ion batteries (LIBs) are used as energy storage systems due to their high efficiency. State of charge (SOC) estimation is one of the key functions of the battery management system (BMS). Accurate SOC estimation helps to determine the driving range and effective energy management of electric vehicles (EVs). However, due to complex electrochemical reactions and nonlinear battery characteristics, accurate SOC estimation is challenging. Therefore, this review examines the existing methods for estimating the SOC of LIBs and analyzes their respective advantages and disadvantages. Subsequently, a systematic and comprehensive analysis of the methods for constructing LIB models is conducted from various aspects such as applicability and accuracy. Finally, the advantages of particle filtering (PF) over the Kalman filter (KF) series algorithm for estimating SOC are summarized, and various improved PF algorithms for estimating the SOC of LIBs are compared and discussed. Additionally, this review provides corresponding suggestions for researchers in the battery field.

[z]E-mail: wangshunli1985@qq.com

1. Introduction

With the development of society, energy demand is growing, the scenarios of energy consumption are becoming richer, and the demand for energy storage is also increasing [1]. LIBs (LIBs) have become the main component of energy storage systems (ESS) due to their advantages of long cycle life, low self-discharge, high energy, and power densities, no memory effect, lightweight, etc. [2]. However, due to the variety of application scenarios for energy storage devices, such as large-scale energy storage devices and widely used electric vehicles (EVs), their different operation modes and conditions can have peculiar effects on them. Because the nonlinear electrochemical characteristics of LIBs are easily affected by different factors, such as operating temperature, charge-discharge current, discharge depth, aging status, etc. [3]. To master the current operating state of charge (SOC) value of the LIBs [4], accurately evaluating the current state of health (SOH) [5] and remaining useful life (RUL) [6] status by quantitatively and qualitatively analyzing and calculating the above characteristics is crucial.

Research on the SOC estimation method for LIBs has gradually become an essential topic in battery management studies [7]. Accurately estimating the state of LIBs ensures the economical, convenient, safe, and stable operation of equipment under several working conditions [8], which has become the focus of the majority of researchers. Current battery state estimation methods are mainly applied to EVs [9], consumer electronics, and power storage systems [10]. However, they are rarely used in communication base stations to provide an uninterrupted power supply for data centers, aviation, and military fields [11]. Several kinds of estimation methods that are currently in use have their corresponding advantages and disadvantages, which need to be optimized [12]. Therefore, it is urgent to improve the state estimation methods of LIBs and verify them under different working conditions.

SOC is a direct representation of the remaining battery capacity or energy [13]. It is provided by the battery management system (BMS), which can reflect the instantaneous peak power state and the SOH state [14] and timely ensure that the battery operates safely. Therefore, accurate SOC estimation plays a key role in the BMS of EVs and has become the focus of many researchers [15]. To obtain SOC, researchers have carried out a lot of relevant studies [16], including the establishment of advanced battery models, SOC estimation models, and the application of different mathematical methods in the evaluation process [17]. To obtain the aging status of used batteries, an evaluation model of battery health status is constructed [18], and advanced mathematical methods are proposed for the health evaluation [19]. The principle and model are analyzed for the SOC prediction of LIBs, as well as the data-driven method that can be used for this evaluation purpose [20, 21]. In the above research, the application and improvement of new methods in SOC evaluation are proposed that are based on the current research hotspots of big data and artificial intelligence.

The remaining parts of this review are organized as follows: Section 2 describes the definition of LIBs, as well as an introduction and analysis of all major estimation methods. Section 3 provides a detailed and comprehensive overview of modeling methods for LIBs, with a comparison of the advantages and disadvantages of each model. Section 4 introduces commonly used parameter identification methods. Section 5 discusses the advantages of particle filtering, compares and summarizes the estimation results of various improved particle filtering algorithms, and discusses future directions from the perspective of the current situation. The conclusion is presented in Section 6.

2. Research status of SOC estimation methods

2.1 Definition of SOC of LIBs

State of charge (SOC) refers to the remaining battery capacity. The value of SOC refers to the ratio of the remaining battery capacity to the rated capacity under certain discharge conditions [22]. The SOC value is a relative quantity expressed as a percentage, and the range of SOC values is 0-100% [23].

The SOC of a LIB reflects the remaining capacity at the current moment during its operation. The SOC value of batteries cannot be directly measured, and can only be indirectly measured through other external parameters of the battery [24], which plays an important role in the assessment of battery health status [25]. The SOC value is defined as the ratio of the current remaining capacity of a LIB to its fully charged capacity at a certain moment when fully quiescent [26], the expression is shown in Equation (1).

$$SOC_t = \frac{Q_t}{Q_0} \times 100\% \tag{1}$$

In Equation (1), Q_t is the remaining capacity of the battery at time t, and Q_0 is the rated capacity. The SOC value is between 0 and 1. When SOC is 1, it indicates that the battery is fully charged, and when SOC is equal to 0, it indicates that the battery is completely discharged [27]. Among them, discharge capacity can be expressed as the integral of current over time [28]. Considering that the amount of electricity that a battery can release in actual work is often lower than its nominal value due to internal resistance [29], the Coulombic efficiency (also known as discharge efficiency, refers to the ratio of battery discharge capacity to the amount of charging capacity in the same cycle [30], that is, the percentage of discharge capacity to charging capacity) can be corrected as shown in Equation (2).

$$SOC_t = SOC_{t_0} - \frac{\int_{t_0}^{t} I(t)\eta dt}{Q_0} \tag{2}$$

Among them, SOC_{t_0} is the remaining capacity of the t_0 LIB. From t_0 to t, the battery discharges with current $I(t)$, with the discharge direction as the positive direction, and $I(t)$ is the working current of the battery.

2.2 Analysis of various SOC estimation methods of LIBs

As a parameter to measure the current remaining capacity of the battery, the SOC estimation is the key to ensuring battery safety and optimizing the battery life level [31]. On the other hand, it also provides the user with the current state of the device in real time, which can improve the users' experience [32]. As in a typical secondary battery, the essence of the charging and discharging processes is the de-embedding motion of lithium ions between the positive and negative plates [33]. In addition, there are a series of side reactions between the positive and negative plates and the electrolyte, so there are a variety of electrochemical reactions coupled inside the battery [34]. In the LIB application process, the battery material, aging degree, ambient temperature, overcharge and over-discharge, and other factors affect the internal reaction process of LIBs [35], thereby greatly increasing the difficulty in SOC estimation [36]. The commonly used SOC estimation methods include the following types.

(1) Direct measurement method

The OCV-SOC method: in the entire life cycle of LIBs, the mapping relationship between the SOC and OCV is approximately constant [37]. This method estimates the SOC value by measuring the OCV situation of the battery [38], and its principle is simple with a low calculation amount. Whereas the problem is that due to the difference in electrochemical and concentration polarization effects, the OCV value cannot be measured until the internal state is completely balanced [39], so this method is not suitable for conditions where there are real-time estimation needs. In addition, along with the aging process of LIBs [40], the battery capacity, internal resistance, and other parameters will change [41]. The mapping relationship between OCV and SOC will also change, so the polynomial coefficient needs to be adjusted from time to time [42].

Another commonly used direct measurement method is the AC impedance method, which analyzes the chemical reaction process and state inside the LIB by measuring the AC impedance spectrum of the battery at different frequencies [43], thereby calculating the SOC of the battery. Specifically, the AC impedance method applies a small sinusoidal current to a LIB and then measures the voltage response of the battery [44]. At different frequencies, the AC impedance spectra of LIBs exhibit different morphologies [45], which reflect the electrochemical reactions inside the battery and their changes with SOC. By analyzing the AC impedance spectrum, the internal resistance, charge transfer resistance, diffusion resistance, and other parameters of the battery can be obtained, thereby calculating the SOC of the battery.

(2) Ampere-hour integration method

The ampere-hour (Ah) integration method: this method obtains the power change value by integrating the current [46]. This method is simple and real-time, but it needs to determine the initial SOC value at the t_0 moment. The accuracy of the initial value will directly affect the estimation accuracy [47]. Also, the integral calculation in this method will cause a cumulative effect of the estimation error [48]. If the sensor accuracy is insufficient, it will eventually lead to an increasing deviation between the estimated result and the true value [49].

(3) Data-driven method

The data-driven method: this approach treats the LIB as a black box [50], which uses a large amount of experimental data to establish a mapping relationship between the amount of pending state and the input excitation as well as the output response [51]. Wang, Kai, et al [52]. elaborated on the application of neural network models in predicting the health status of LIBs. Sun, HL, et al [53]. used neural network algorithms to accurately capture the health status of LIBs. When using the data-driven method for SOC estimation, the calculation procedure generally includes the following three steps: (1) The collected data is pre-processed, the datasets are divided into training, testing, and validation sets, and it can be modified to focus on the significance of data normalization [54]; (2) The model structure and hyperparameters are determined using the training dataset to train the model and the testing and validation datasets for verification of the model's performance [55]; (3) Model testing with the test dataset is conducted to determine whether the accuracy meets the requirements [56]. Data-driven approaches require the collection of large amounts of experimental data [57], which is time-consuming and not highly accurate [58]. The neural network model is shown in Figure 1.

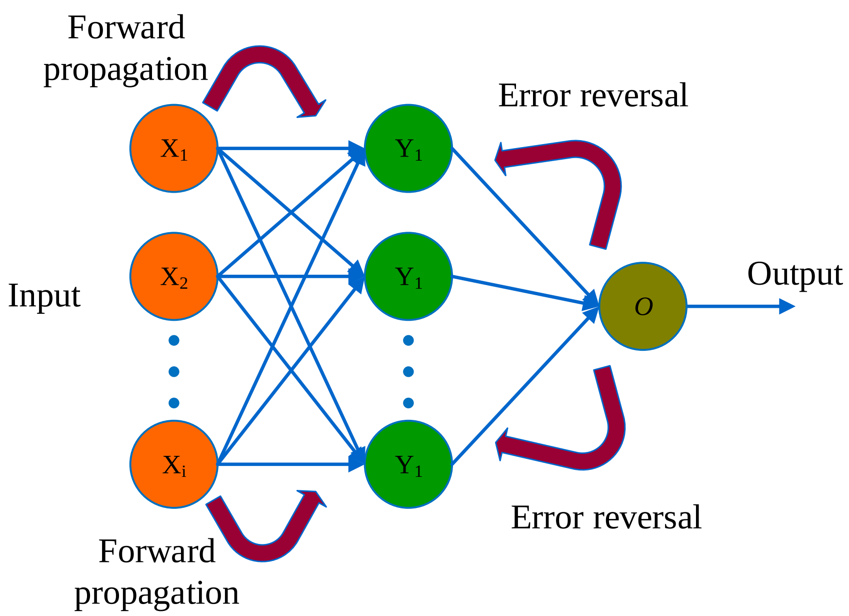


Figure 1. Neural network model

(4) Physical model-based method

The model-based estimation method constructs a SOC estimation framework by establishing a battery model based on a state-space equation and applying filter or observer algorithms for estimating the SOC value [59]. Commonly used filter and observer algorithms include Kalman filters (KFs) based on Gaussian distributions and their improved algorithms, Bayesian filters, PFs, H∞ observers, etc [60]. It is worth noting that some filters need to assume that the noise is white noise, which does not correspond to reality, so this assumption will cause some estimation errors [61].

(5) Hybrid method

The hybrid method refers to a method that combines multiple SOC estimation methods, comprehensively considering the advantages and disadvantages of multiple methods [62], to improve the accuracy and reliability of estimation. Each of the above methods has its advantages and disadvantages, and there may be errors and uncertainties when used alone [63]. The hybrid method combines multiple estimation methods and uses appropriate weights for comprehensive calculation based on actual data and conditions in different situations, to obtain more accurate and reliable SOC estimation results [64]. The hybrid method can adaptively adjust according to the needs of different application scenarios, thereby further improving the accuracy and reliability of SOC estimation [65]. However, the implementation of this method is relatively cumbersome. Although it can improve estimation accuracy for certain data, it is difficult to adapt to multiple data conditions [66].

2.3 Comparison and Analysis of SOC estimation methods

In summary, many studies have been carried out on the SOC estimation of LIBs. Although the SOC estimation accuracy has been significantly improved, there are still many problems that have not been overcome. Comparing, summarizing, and analyzing the above methods for estimating the SOC of LIBs, as shown in Figure 2, it can be seen that each estimation method has its advantages and disadvantages.

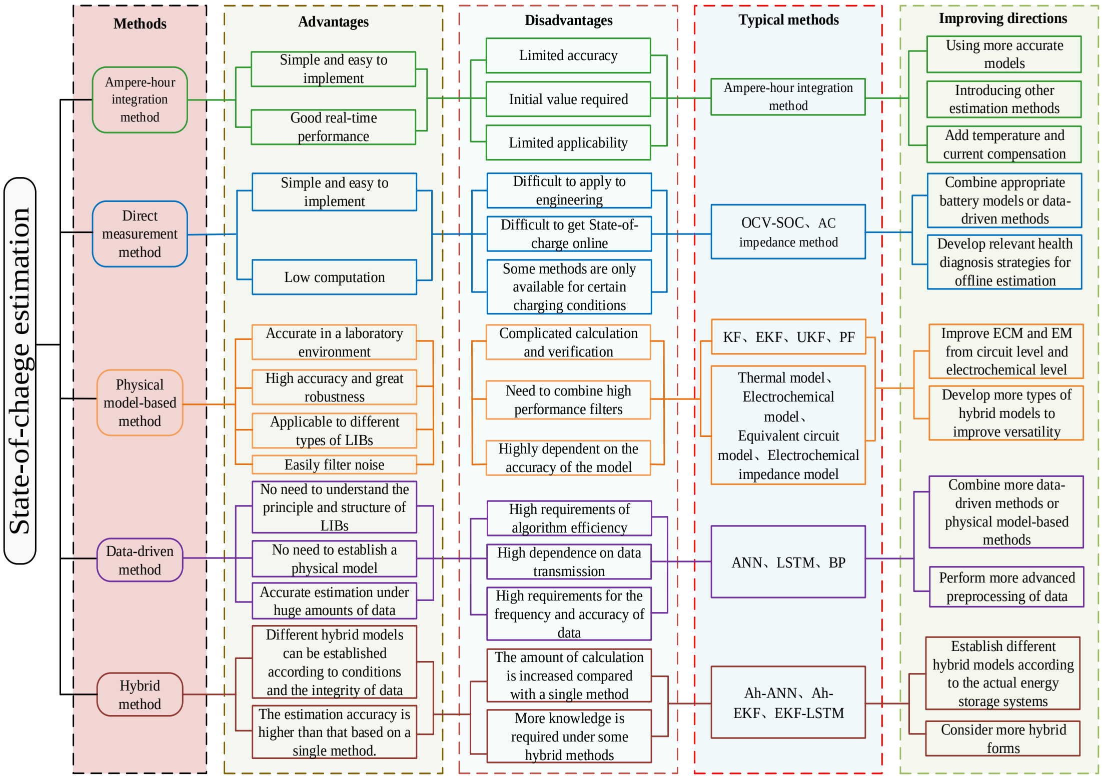


Figure 2. Comparison of four SOC estimation methods

However, in practice, using physical model-based methods and a mixture of physical models to estimate the SOC of LIBs is the most widely used method. Compared with other methods, it can adapt to various data under various operating conditions and has high accuracy and good real-time performance. At the same time, it can also characterize the internal mechanisms of LIBs.

3. *Analysis of various modeling methods of LIBs*

3.1. Electrochemical modeling method

The electrochemical model (EM) of LIBs is based on the porous electrode theory and the concentrated solution theory [67]. The internal reaction, electrochemical reaction, thermodynamic, and kinetic processes are described by partial differential equations [68], according to which the internal characteristics of the LIBs are studied from the basic mechanisms [28]. Currently, the main EM types of LIBs include the single-particle model, the quasi-two-dimensional mathematical model, and the simplified quasi-two-dimensional model [69]. As for modeling at the mechanism level [70], it can reflect in detail the charge capacity change, aging degree, and heat generation of LIBs in the application process [71].

The single-particle model simplifies the positive and negative electrodes of the battery into two spherical particles, which is the most simple EM [72]. It has the advantages of a simple structure and fewer computational complexities, but its main disadvantage is the large deviation under complex working conditions [73]. Consequently, the quasi-two-dimensional mathematical model is a P2D model [74]. The positive and negative electrodes of the battery are equivalent to countless spherical particles, which is highly accurate but complex in the calculation process [75]. It is suitable for theoretical support research in the laboratory. The complexity of the simplified quasi-2D model is between that of the single particle model and the quasi-2D model [76]. However, because the EM itself uses partial differential equations to describe the internal reaction of LIBs [77], it is difficult to apply in engineering due to the many variables in the equations. It is generally used in the battery development of manufacturers. The quasi-2D model is shown in Figure 3.

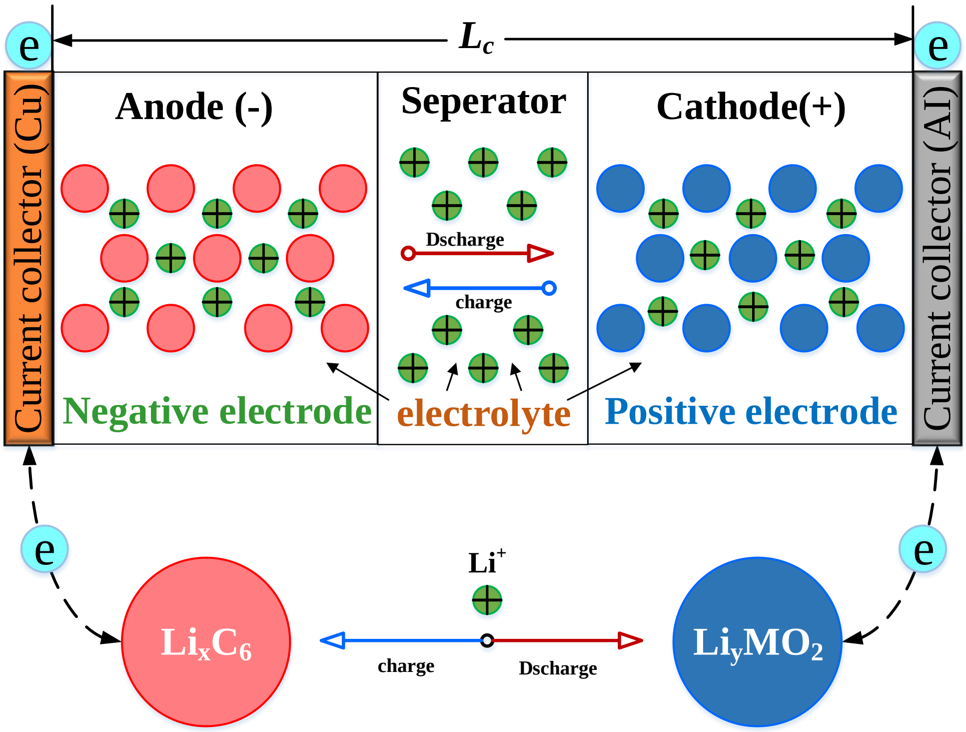


Figure 3. Quasi-2D model

The electrochemical model is used to estimate the SOC of a LIB by considering the chemical reactions that occur inside the battery. This model can be used to monitor the real-time status and performance of the battery [35]. However, the electrochemical model is complex and requires high computational power and accuracy as it involves many parameters such as electrode materials, electrolytes, etc [78]. Moreover, it requires the acquisition and processing of large amounts of data in real-time, which may increase energy consumption and reduce the battery life of the system. Additionally, the accuracy of the model depends on too many factors. Therefore, using the electrochemical model to estimate the SOC of a LIB is not a time-saving or efficient approach.

3.2. Thermal modeling method

The thermal model of LIBs is a mathematical model used to describe the internal temperature changes of LIBs [79]. It consists of two main parts: heat transfer and heat generation. Heat transfer considers the transfer and distribution of heat within the battery, while heat generation considers the heat generated by chemical reactions within the battery [80]. The thermal model can accurately estimate and predict the temperature distribution and thermal characteristics of LIBs, which is helpful to improve the performance and safety of batteries [81]. It can also help optimize the design and control strategies of battery systems and improve battery life and performance [82]. Thermal model is shown in Figure 4.

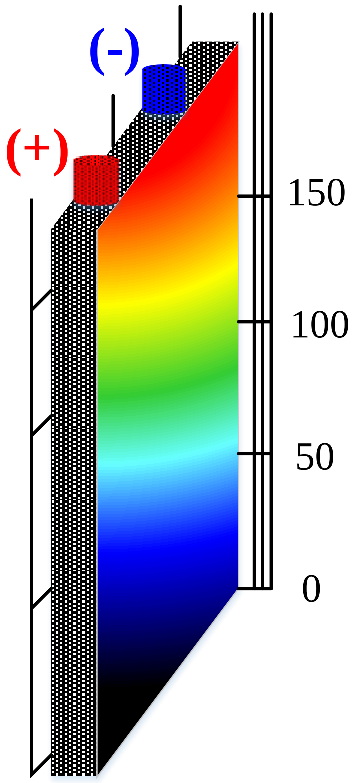


Figure 4. Thermal model model

However, the establishment of a thermal model for LIBs requires a significant amount of time and resources, involving modeling and experimental verification of various aspects such as the battery's materials, structure, and usage [83]. The modeling complexity is high, and the accuracy of the thermal model is influenced by multiple factors, such as the battery's initial state, environmental temperature, and usage mode, which require real-time calibration and adjustment, adding to the complexity of software development and system integration. The thermal model is not suitable for estimating the SOC of LIBs due to its high complexity, difficulty in parameter identification, and limited model accuracy [84]. The parameters in the thermal model of LIBs need to be measured through experiments, but due to the complexity of the internal structure of the battery and the diversity of working conditions, parameter identification is relatively difficult, requiring a large amount of experimental data and repeated model validation [85]. Even thermal models that have been repeatedly validated have limited accuracy in estimating SOC.

3.3. Electrochemical impedance modeling method

The electrochemical impedance model of LIBs is a mathematical model used to describe the complex electrochemical reactions, transmission, and energy storage processes inside LIBs [86]. This model is usually represented by electrochemical impedance spectroscopy. Electrochemical impedance spectroscopy is an experimental technique for measuring the internal reaction kinetics of LIBs [87]. It obtains the electrochemical impedance spectrum of LIBs by measuring their electrochemical response under an AC electric field [88]. This spectrum consists of multiple circular arcs, each representing a circuit component with specific electrochemical significance within the LIB [89]. The electrochemical impedance model is shown in Figure 5.

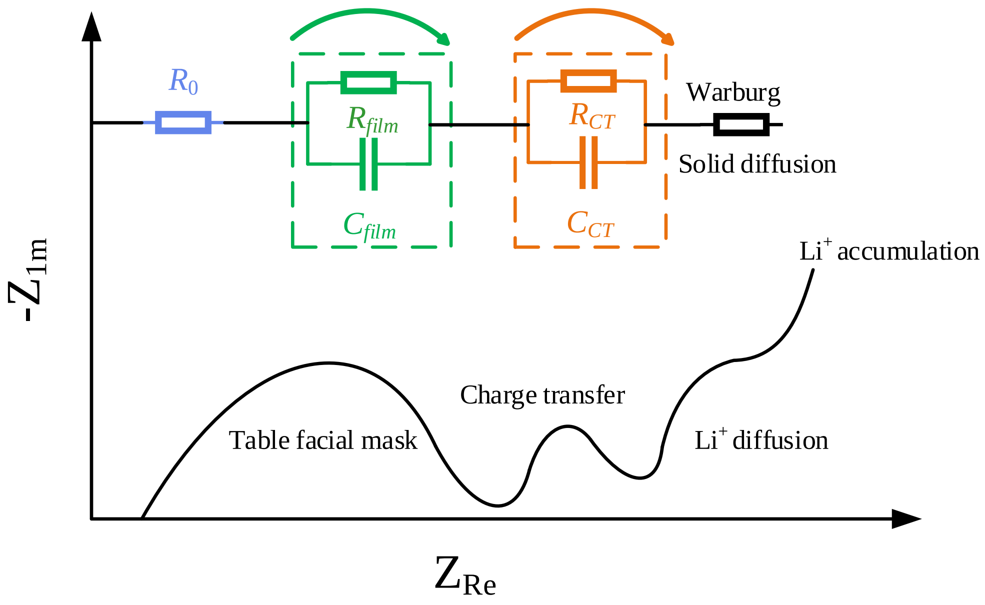


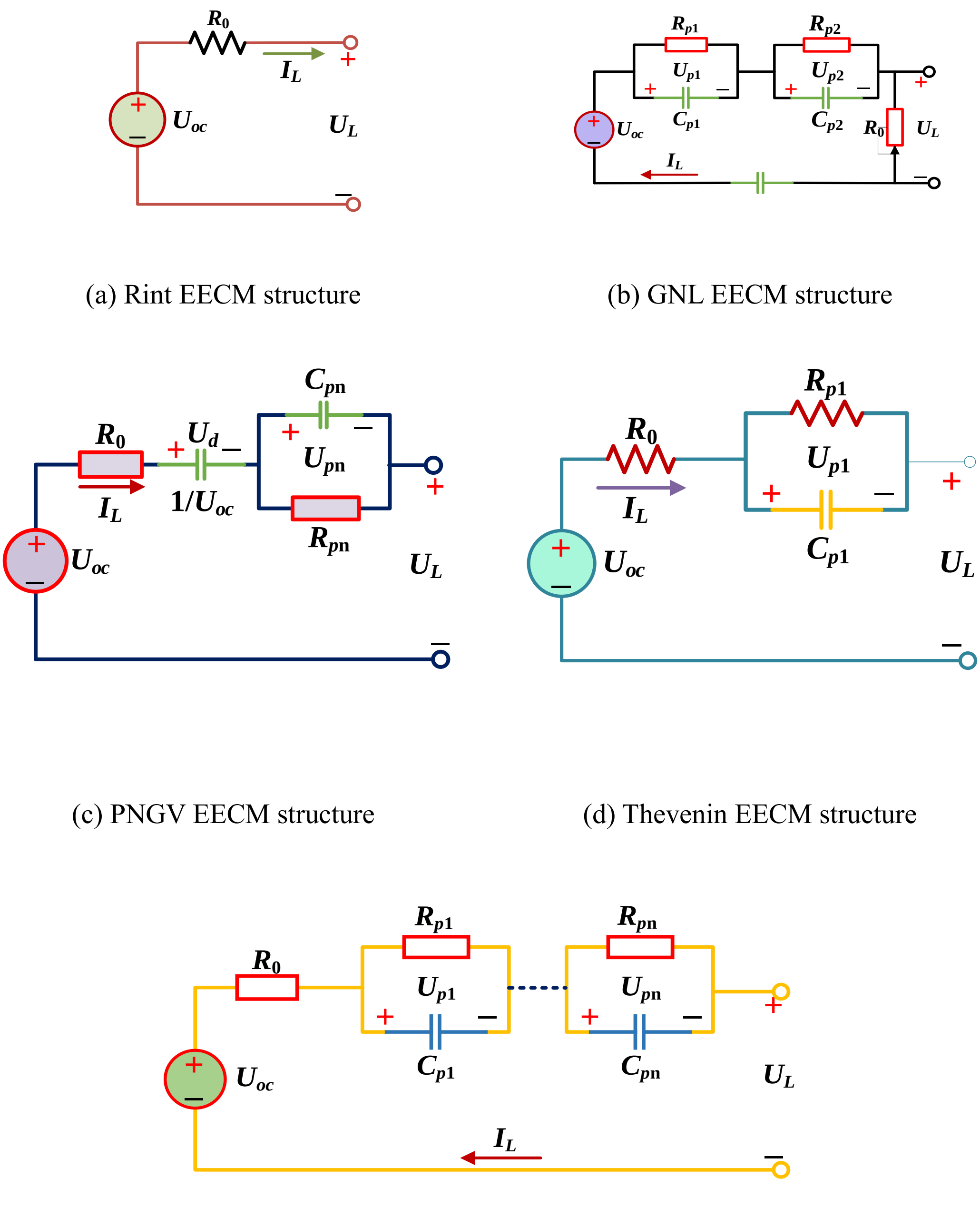
Figure 5. Electrochemical impedance model

The LIB electrochemical impedance model can provide highly accurate SOC estimates, as electrochemical impedance reflects the comprehensive reflection of internal chemical reactions and charge transport within the battery, and can reflect the true internal state of the battery [89]. Additionally, the LIB electrochemical impedance model can estimate SOC online without offline processing and data transmission, which is very useful for applications that require quick response and accurate estimation of battery SOC [88]. However, the accuracy of the LIB electrochemical impedance model is influenced by the battery operating conditions, and therefore, it is necessary to model and calibrate the impedance of the battery under different conditions [90]. Secondly, the LIB electrochemical impedance model has a large number of parameters [91], and the determination of model parameters requires experimental testing and model fitting, which requires a lot of time and effort. Additionally, with the continuous increase of battery life and changes in internal chemical reactions, the LIB electrochemical impedance model needs to be constantly updated and maintained, otherwise it will affect the accuracy of SOC estimation [92]. The latest impedance spectroscopy measurement technology and electrochemical impedance spectroscopy based on lithium-ion battery health state estimation technology are summarized by Zhang, M, et al [93].

As the battery's lifespan continues to increase and the internal chemical reactions of the battery charge, the LIB electrochemical impedance model needs to be constantly updated and maintained, otherwise it will affect the accuracy of SOC estimation [94]. This is because the battery's impedance parameters may change over time, leading to inaccurate estimation of the battery's SOC. Therefore, regular updating and maintenance of the electrochemical impedance model are necessary to ensure accurate SOC estimation and optimal battery performance.

3.4. Compound EECMs modeling method

By far, Equivalent circuit model (ECM) is the most widely used battery model at present, which has the characteristics of simple calculation and accurate description of battery characteristics [95]. ECMs are electrical components that characterize the dynamic characteristics of LIBs [96]. It is widely used because it clearly shows the mathematical relationship between each element of the LIB, its current-voltage characteristics, and its SOC value [97]. The EECM uses electrical components such as resistors, capacitors, voltage sources, etc., to describe the charging and discharging characteristics of a LIB through different combinations, which is a semi-empirical model [98]. Generally, an ECM consists of three components, which include the open-circuit voltage (OCV) source, the ohmic resistor [99], and the resistor-capacitor (RC) circuit networks. Conventional ECMs, such as the Rint, general nonlinear (GNL), partnership for new generation vehicles (PNGV), Thevenin, resistor-capacitor (RC), etc., models [100]. The different EECM structures established for battery state parameter estimation methods are presented in Figure 6.



(a) Rint EECM structure (b) GNL EECM structure

(c) PNGV EECM structure (d) Thevenin EECM structure

(e) Multiple order RC EECM structure

Figure 6. Different types of conventional EECM structures

Figure 6 shows commonly used EECMs, which are used for LIBs status monitoring by controlling and monitoring the dynamic characteristics of LIBs under different operating conditions. Generally, I_L is the load current flowing through the circuit, R_0 is the internal ohmic resistance, U_{oc} is the open-circuit voltage, and U_L is the terminal voltage of the battery. R_{p1} and C_{p1} are the electrochemical polarization resistance and capacitance. In Figure 6 (c), U_d and U_{pn} are the voltage across $1/U_{oc}$ and C_{pn}. Also, R_{pn}, C_{pn}, and U_{pn} are the nth-order polarization resistance and capacitance, and the voltage drop across the multiple-order circuit networks, respectively. Thevenin and RC modeling types usually consist of three main components. They take both the ohmic resistance and electrochemical polarization of the LIBs into account [101]. The model structure is relatively simple, with less calculation, and has good practical value [102]. They can accurately simulate the charging and discharging behavior of LIBs under constant current and temperature conditions without significant changes in the health status of LIBs. It conducts the diagnosis of the SOC, health status, or power status of LIBs [103].

Choosing an appropriate ECM under different conditions is crucial, it accurately monitors the status of the LIB and improves the performance of the BMS system [104]. It has been demonstrated to function in lead-acid, nickel-metal hydride, LIB, sodium-ion, and zinc-ion batteries [105]. The simplest model only takes the internal ohmic resistance into account, such as the Rint, which is not adequate to represent the battery dynamics during operation [106]. The Rint model consists of an ideal voltage source and an internal ohmic resistor. The structure is simple, and the parameters are easy to identify, but the dynamic process cannot be described. When the battery flows through a large current, its simulation error increases and the simulation accuracy greatly decreases, so it is generally used to describe the ideal battery [107]. The GNL model makes a detailed distinction between the internal characteristics of LIBs, especially with the introduction of self-discharge factors [61]. The model has better accuracy and practicability, but the establishment of the model and the identification of parameters are more complex [108].

The PNGV model uses a series capacitor to describe the change of open circuit voltage of the LIB with the time integral of current, which reflects both the battery capacity and DC response characteristics of the battery [109]. Therefore, it is possible to simultaneously estimate the SOC, SOP, and battery usable capacity of the LIB and realize the estimation of the battery health state [110]. The model can describe the battery ground output characteristics, but the series capacitor will increase the cumulative error [111]. The EECM simulates the electrical characteristics of LIB through voltage, current, resistance, capacitance, and other circuit components. The ideal EECM should be able to simulate the actual battery voltage under any current excitation [112]. Although adding more RC loops can more accurately characterize the state characteristics of the battery, excessive RC loops will greatly increase the computational complexity [113]. When modeling the EECM, the higher the order, the more accurately the model can theoretically characterize the internal working characteristics of the battery [111]. However, the increase in the order of the model will also lead to higher complexity. The more parameters that need to be identified, the more difficult the engineering application will be [114].

The battery ECM contains a variety of model structure frameworks [115]. The advantage of a simple combination structure is that it allows for a fast and low-cost model, but the simulation accuracy will also be low [116]. While the model with a more comprehensive combination structure will improve accuracy, it will also bring greater complexity, making the identification parameters and calculation process more difficult [117]. Therefore, in practice, the advantages and disadvantages of existing EECMs should be weighed, and a suitable circuit model should be selected through comprehensive analysis [116]. For most LIBs, these models are computationally efficient and have reasonable accuracy [118].

The equivalent circuit model can simulate the characteristics of LIBs quite accurately, including internal resistance, electrochemical reactions, etc [119]. Therefore, it can estimate the SOC of the battery more accurately. Additionally, it can quickly estimate the SOC in real-time scenarios where time sensitivity is crucial, which is essential in applications such as electric vehicles that require real-time monitoring of the battery's status.

3.5. Comparison and analysis of estimation modeling methods of LIBs

In this section, the advantages and disadvantages of the aforementioned lithium-ion models used for estimating battery SOC are summarized. By considering multiple perspectives, we have identified the battery model that is relatively most suitable for estimating the SOC of LIBs.

Table 1. Comparison of estimation modeling methods of LIBs

Models	**Advantages**	**Disadvantages**
Electrochemical model	1. High reliability. 2. Wide applicability.	1. Complex model construction. 2. High energy consumption. 3. Strong dependency.
Thermal model	1. Internal temperature changes are considered. 2. The impact of battery aging and lifespan on battery performance is considered.	1. High modeling complexity. 2. The model needs real-time calibration and adjustment. 3. The accuracy of battery SOC can only be improved within a certain range.

Electrochemical impedance model	1. High estimation accuracy. 2. No measurement is required inside the battery. 3. Can be used for online estimation.	1. Model accuracy depends on battery operating conditions. 2. Difficulty in determining model parameters. 3. It is difficult to update and maintain the model
Compound EECMs	1. High accuracy 2. Good real-time performance	1. Real-time measurement of voltage and current is required

As can be seen in **Error! Reference source not found.**, from the perspective of practical engineering applications, the compound EECM method is the optimal choice, which can ensure accuracy with a small amount of computation.

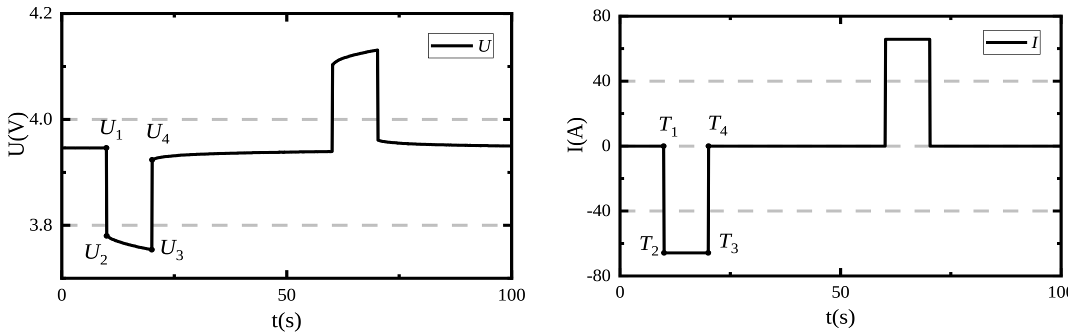
4. Parameter identification methods

The composite equivalent circuit model of a LIB is composed of basic elements such as resistors, capacitors, and current sources. It is an important tool used to describe the internal chemical reactions and charging and discharging characteristics of the battery. After constructing a compliant equivalent circuit model, battery parameter identification is necessary for better control and management of the LIB. Parameter identification methods can be broadly divided into offline parameter identification and online parameter identification.

(1) Offline parameter identification

Offline parameter identification is the process of testing LIBs under specific test conditions and using the test data to determine the model parameters [120]. These test conditions typically include variables such as charging and discharging currents, voltage, and temperature. By measuring and recording these variables and using known mathematical algorithms to fit the model, the model parameters can be calculated [121]. Offline parameter identification usually requires a large amount of experimental data and computing resources, so careful planning and execution of experiments and efficient algorithms for data processing and model fitting are needed [122]. This identification method relies on testing experiments. Taking the simplest first-order equivalent circuit as an example, model parameters are obtained through HPPC testing experiments [123]. Based on the HPPC experiment shown in the figure below, a 10-second discharge is conducted at time T1, and the voltage drop from T1 to T2 and the voltage rise from T3 to T4 are caused by the internal resistance effect of the dynamic LIB. Therefore, the battery's ohmic internal resistance R_0 can be obtained based on the voltage change and the discharge current I at the discharge time, as shown in Equation (3).

$$R_0 = \frac{|U_1 - U_2| + |U_4 - U_3|}{2I} \tag{3}$$



(a) One HPPC test voltage curve (b) Current curve of one HPPC test

Figure 7. One HPPC testing experiment

In the HPPC test, the voltage change from stage U2 to U3 is mainly caused by the polarization effect. The parameters characterizing the polarization effect can be identified based on the voltage change from U2 to U3 and the corresponding current change at that time. Before the pulse discharge, the dynamic LIB is stored for a long time, and the internal polarization voltage of the battery is 0, which can obtain the zero-state response of the equivalent circuit model. The zero-state response equation of the dynamic LIB is shown as Equation (4).

$$U_L = U_{OC} + U_0 + U_P(1 - e^{-\frac{t}{\tau}}) \tag{4}$$

In Equation (4), U_{OC} represents the open circuit voltage of a LIB, while U_0 represents the voltage portion attributed to the ohmic resistance (R_0) in the equivalent circuit model (ECM), with $U_0 = I \cdot R_0$. U_0 represents the polarization voltage of the RC loop in ECM, with $U_P = I \cdot R_P$. Simplifying Equation (4) yields Equation (6), which is used to fit the voltage of the battery's zero state response.

$$f = a + b(1 - e^{\frac{-t}{c}}) \tag{5}$$

In Equation (6), $a = U_{OC} + U_0$, where the open-circuit voltage UOC can be obtained by leaving the cell at rest for a long time during HPPC testing. b represents the model polarization voltage U_P, c is the time constant of the RC circuit in the Thevenin model, t is the sampling time during voltage and current measurement, and f is the measured terminal voltage of the dynamic LIB, which is equal to U_L. Based on the zero-state response of the terminal voltage, the values of the parameters a, b, and c in Equation (6) can be obtained by fitting the terminal voltage curve using the least squares method. This achieves parameter identification of the equivalent circuit model, and the model parameters are shown in Equation (7).

$$\begin{cases} R_0 = \dfrac{(a - U_{OC})}{I} \\ R_P = b/I \\ C_P = c/R_P \end{cases} \tag{6}$$

Then, according to the calculation Equation mentioned above and combined with experimental data, the fitting polynomial of each parameter concerning SOC is calculated using the fitting tool at ten points of SOC from 1 to 0.1. The offline parameter identification method mainly identifies the model parameters through specific test experiments, which can obtain better identification results under specific conditions of use [124]. However, the equivalent circuit model parameters of a power LIB differ under different usage conditions and environmental temperatures [125]. Therefore, the generalization ability of the model parameters obtained by offline parameter identification is poor and not universal. Usually, the offline parameter identification method needs to identify parameters under different usage conditions and temperatures, construct an interpolation table of the obtained model parameters, and finally obtain higher universality by looking up the table during use.

(2) Online parameter identification

The online parameter identification method is an important approach for identifying model parameters by using real-time measured data to estimate the model parameters [126]. Compared with the offline parameter identification method, the online method directly uses the voltage, current, and other parameters collected by sensors at the current moment to estimate the equivalent circuit model parameters in real time [127]. Using the online parameter identification method can ignore the influence of some parameters of the equivalent circuit model of dynamic LIBs, such as environmental temperature and operating conditions [128]. Therefore, the online parameter identification method is more versatile [129]. The online parameter identification method for LIBs can be divided into two types: the neural network identification method and the identification method based on the least square (LS) algorithm [127]. However, the neural network algorithm is rarely used in parameter identification because it also requires offline parameter identification to identify parameters under different conditions to obtain training samples. Additionally, the neural network algorithm can be directly used for estimating battery state parameters. The Recursive Least Square (RLS) algorithm is widely used in online parameter identification. RLS algorithm is an online parameter identification method based on the LS algorithm [130]. The LS algorithm is a classic system identification method that seeks the best function match by minimizing the sum of the squared errors, thereby obtaining the solution of a system parameter. Based on the relationship between voltage and current in the ECM of a dynamic LIB, the ECM can be transformed into a discrete system as shown in Equation (7).

$$\boldsymbol{A}(z^{-1}) \cdot Y(k) = \boldsymbol{B}(z^{-1}) \cdot U(k) + v(k) \tag{7}$$

In Equation (7), $Y(k)$ represents the output of a dynamic LIB, namely the battery terminal voltage UL; $U(k)$ represents the input of the dynamic LIB, it is the discharge current I;. Based on Equation (7), the discrete equation of the battery model for $Y(k)$ can be obtained, as shown in Equation (8).

$$\begin{aligned} Y(k) = -a_0 Y(k-1) - a_1 Y(k-2) - \cdots - a_n Y(k-n) + b_0 U(k-1) \\ + b_1 U(k-2) + \cdots + b_{n-1} U(k-n) + v(k) \end{aligned} \tag{8}$$

In Equation (8), a_0 to a_{n-1} and b_0 to b_{n-1} are the coefficients of the discrete system. By representing the discrete system of the dynamic LIB shown in Equation (8) in the form of least squares, Equation (9) can be obtained.

$$\begin{cases} Y(k) = \boldsymbol{h}(k)^T\boldsymbol{\theta}(k) + v(k) \\ \boldsymbol{h}(k) = [-Y(k-1) \quad \dots \quad -Y(k-n) \quad U(k-1) \quad \dots \quad U(k-n)]^T \\ \boldsymbol{\theta}(k) = [a_0 \quad \dots \quad a_{n-1} \quad b_0 \quad \dots \quad b_{n-1}]^T \end{cases} \tag{9}$$

In Equation (9), $Y(k)$ represents the output matrix of the system to be identified, while $h(k)$ represents the variables of the system to be identified. The RLS online parameter identification algorithm is shown in Equation (10), where I represents the identity matrix.

$$\begin{cases} \boldsymbol{\theta}_{N+1} = \boldsymbol{\theta}_N + \gamma \cdot \boldsymbol{P}_N\boldsymbol{h}(N+1)[Y(N+1) - \boldsymbol{h}^T(N+1)\boldsymbol{\theta}_N] \\ \gamma = [\boldsymbol{h}^T(N+1)\boldsymbol{P}_N\boldsymbol{h}(N+1) + 1]^{-1} \\ \boldsymbol{P}_{N+1} = [\boldsymbol{I} - \gamma \cdot \boldsymbol{P}_N\boldsymbol{h}(N+1)\boldsymbol{h}^T(N+1)]\boldsymbol{P}_N \end{cases} \tag{10}$$

In practical applications, the RLS online parameter identification method may cause data saturation. Therefore, a forgetting factor can be used to reduce the weight of historical data in the parameter identification process, increase the influence of current data on the parameter identification results, and improve the accuracy of the parameter identification results. The forgetting factor recursive least square (FFRLS) algorithm is shown in Equation (11).

$$\begin{cases} \boldsymbol{\theta}_{N+1} = \boldsymbol{\theta}_N + \gamma \cdot \boldsymbol{P}_N\boldsymbol{h}(N+1)[Y(N+1) - \boldsymbol{h}^T(N+1)\boldsymbol{\theta}_N] \\ \gamma = [\boldsymbol{h}^T(N+1)\boldsymbol{P}_N\boldsymbol{h}(N+1) + \lambda]^{-1} \\ P_{N+1} = \dfrac{[\boldsymbol{I} - \gamma \cdot \boldsymbol{P}_N\boldsymbol{h}(N+1)\boldsymbol{h}^T(N+1)]\boldsymbol{P}_N}{\lambda} \end{cases} \tag{11}$$

In Equation (11), λ is the forgetting factor. Using the recursive algorithm mentioned above, the equivalent circuit model parameters can be effectively identified online. However, both the RLS and FFRLS algorithm assume that the system noise is Gaussian white noise [131], while in practical applications, the noise is colored. Based on the recursive extended least squares algorithm with a forgetting factor, the colored noise in the parameter measurement is considered in the parameter identification process. Therefore, the FFRLS algorithm has higher precision in parameter identification [132]. To accurately estimate the parameters of the equivalent circuit model, the FFRLS algorithm is used for online identification of the parameters in the equivalent circuit model of a dynamic LIB, which can effectively perform real-time parameter identification. Optimized particle filtering strategies for SOC estimation

5. Optimized PF strategies for SOC estimation

5.1 *The advantages of estimating the SOC of LIBs by PF.*

Particle filtering (PF) is a filtering technique based on Monte Carlo methods, which approximates the posterior distribution of the state space by weighting and sampling a set of particles [133]. Unlike the Kalman filter, PF does not require linearization of the state space model and can handle non-linear and non-Gaussian distributions. In the estimation of SOC in LIBs, PF can provide more accurate SOC estimation, especially in special operating conditions such as high-power discharge, high-temperature, and low-temperature, due to the non-linear and non-Gaussian characteristics of LIBs [134]. Kalman filtering (KF) is a filtering technique based on Bayesian filtering, which estimates the posterior distribution of the state space by linearizing the state space model and assuming noise in both the state space and measurement models [135]. The accuracy of KF decreases when dealing with non-linear and non-Gaussian distributions. The advantages of PF over KF are as follows: (1) PF can handle situations with nonlinearity and non-Gaussian distributions, while KF requires methods such as extended or unscented KF to handle them [136]. (2) PF does not require linearization of the state-space model, thus it can estimate the state-space more accurately [137]. (3) PF can improve estimation accuracy by increasing the number of particles, but the accuracy of KF is limited by assumptions about the state space model and measurement model.

5.2 *Iterative working principle of PF method*

PF uses N-weighted samples (i.e. particles) to approximate the posterior probability density $P(X_t|y_{1:t})$. This method uses the distribution of samples to approximate the true distribution of the state variable X and is widely used in systems where modeling is difficult [138], avoiding the linear Gaussian assumption of KF. $P(X_t|y_{1:t})$ describes the distribution of state X_t, including its possible values and the probability of each value. Similarly, samples also can describe probability distributions. By treating X_t as a random variable and collecting enough sample values, the distribution of X_t can be described through the values and corresponding probabilities of the samples. The idea of PF is shown in Equation (12).

$$\hat{X} = E(X_{\text{set}}) = \frac{1}{N}\sum_{i=1}^{N} w_i x_i \tag{12}$$

In Equation (12), $\hat{X}$ represents the estimated value of the state, x_i represents the value of the i-th sample particle, and w_i represents the weight of the i-th particle, which indicates the probability of the particle's value. The idea of PF is to use samples to simulate the probability distribution of the state X_t. Under the same conditions, the more particles there are, the more accurate the simulation results will be, but the corresponding computational cost will also increase. The iterative steps of PF are shown below.

Table 2. The calculation steps of SOC estimation based on the PF algorithm

Step 1	Particle set initialization, setting the number of particles, and determining the initial state values based on prior probabilities.
Step 2	Importance sampling. $\{x_{k-1}^{(i)}\}_{i=1}^{N}$
Step 3	Normalizing importance weights.

	$w_k^i = \frac{w_k}{\sum_{i=1}^{N} w_k^i}$
Step 4	Since particles with positions far from the true mean value will have their weights continuously reduced to near-zero during the iteration process, the number of particles will be greatly reduced, leading to biased estimation results. Therefore, it is necessary to perform resampling on the particle set and normalize the weights again.
Step 5	Calculation output. $\hat{x}_k = E(x_k \vert y_k) \approx \sum_{i=1}^{N} x_k^i \cdot \overline{w}_k^i$

In PF, importance sampling is crucial to the final filtering result [139]. The principle behind importance sampling is to make the sampled particles match the region of the maximum likelihood function distribution as closely as possible. PF-based SOC estimation flowchart of LIBs as shown in Figure 8.

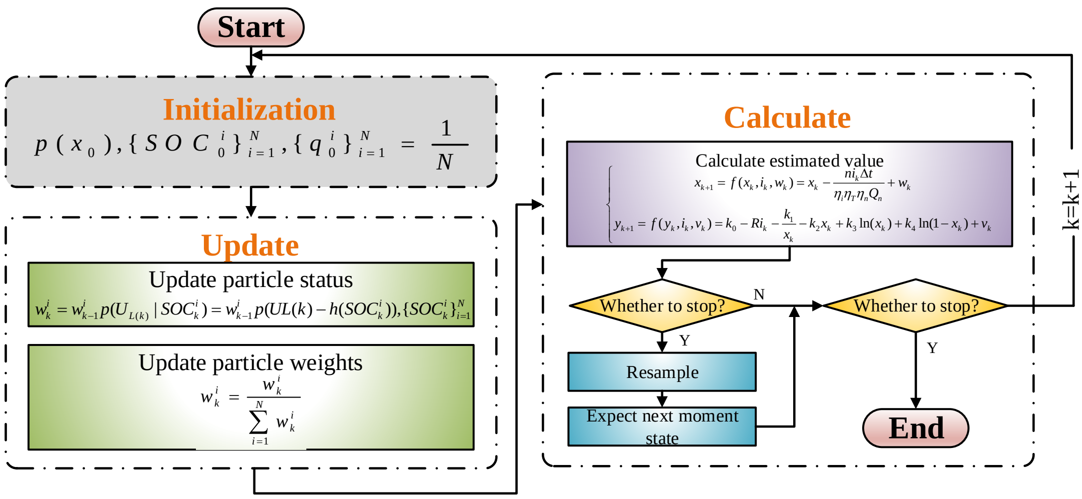


Figure 8. PF-based SOC estimation flowchart of LIBs

5.3 *Comparison and analysis of state estimation effects of different improved PF methods*

In recent years, many researchers have improved particle filter algorithms in different ways and combined them with different equivalent circuit models to improve the SOC estimation accuracy of LIBs, and tested and verified them under various operating conditions and temperature conditions to improve the universality of the improved algorithm.

Hui Pang et al. [140] proposed a composite SOC estimation approach for LIBs using a back-propagation neural network (BPNN) and extended Kalman particle filter (EKPF). The experimental results show that the proposed method has higher accuracy and robustness compared to the other two SOC estimation methods. Shuxian Li et al [141] proposed the fractional-order model and adaptive dual Kalman filtering algorithm, then, to improve the accuracy of SOC estimation considering capacity loss, the particle filter algorithm is applied to update capacity online in real-time. The simulation results show that the accuracy of battery capacity prediction based on particle filter is high under the condition of capacity loss.

Wu, Tiezhou et al. [134] aiming at the particle degradation problem of the traditional sequential importance sampling in the standard particle filter algorithm, the improved firefly algorithm is used to replace the re-sampling of the traditional particle filter to suppress the particle depletion during the execution of the standard particle filter algorithm. Zhang, Ming, et al. [142] present a particle filter-based hybrid filtering method, particularly for SOC estimation of Li-ion cells in EVs. A sampling importance resampling particle filter is used in combination with a standard Kalman filter and an unscented Kalman filter as a proposal distribution for the particle filter to be made much faster and more accurate. Xu, Wei, et al. [143] proposed a multi-timescale adaptive dual particle filter to identify the battery parameters and estimate the battery SOC with online measured data for satisfying the fast-varying behavior of SOC and slow-varying behavior of battery parameters.

Duan et al. [144] made data statistics on the same LIB, then applied the extended Kalman filter (EKF) for comparative analysis. It is observed that the key to PF accuracy lies in the resampling stage. Finally, the life estimation is carried out with the help of MATLAB simulation software. The experiment shows that the PF algorithm is better, and the error in life estimation is less than 5%. In addition, Bartlett et al. [145] also successfully applied the PF method to the ESP model and predicted and verified the surface and average SOC values of composite electrodes. It is worth mentioning that the observability of the nonlinear battery system is deduced and proved in detail, which provides a theoretical reference for the application of the filtering algorithm in EM. However, due to the increase in computing burden and the absence of new observation information in the algorithm, the practical application of the PF method in EM will still be further improved and perfected in the next few years.

In contrast to the EKF series algorithms, PF chooses sample points using a Bayesian model. Its benefit is that by increasing the number of particles, it can arbitrarily and precisely approximate the posterior density. Currently, the PF method has made pleasing advancements in the application of state estimation and life estimation of EVs with power batteries ECM, which serves as a good benchmark for research on the use of PF and EM in combination to estimate battery SOC value.

The key criteria are introduced to compare different models in the literature to find the best method for battery SOC estimation. The predicted effects were obtained and compared using RMSE, and MaxE as evaluation criteria, as shown in Table 3.

Table 3. States estimation effects of different improved PF methods

Years	Methods	Modeling methods	Operating conditions	Parameter identification methods	temperature	RMSE	MaxE
2022	BPNN-EKPF [146]	Second-order EECM	CCD/UDDS	FFRLS	25℃	<0.28%	-
2019	ADKF-PF [141]	Fractional-order ECM	FUDS	Offline	5℃	-	<2%
2020	UPF [147]	Thevenin EECM	Dst	Offline	-10-45℃	-	<4.13%
2020	ADPF [143]	Second-order EECM	FUDS/DST	RLS	0-50℃	<2.7%	<3.2%
2022	IFA-PF [134]	Second-order EECM	DST	FFRLS	Unspecified	-	<2%
2022	IWDF-PF [148]	Second-order EECM	HPPC/BBDST	FFRLS	25℃	<0.6%	<1.39%
2020	SIR-PF [142]	Second-order EECM	UDDS	Offline	Unspecified	<0.8%	-
2021	GPSO-PF [149]	Second-order EECM	DVCT	Offline	25℃	-	<0.89%
2021	IGEK-PF [59]	Second-order EECM	HPPC/UDDS	Offline	25℃	<1.31%	<2.23%
2020	LSSVM-UPF [150]	-	DST	-	Unspecified	<2%	-

From the table above, it can be seen that different improved PF algorithms are very effective in estimating the remaining capacity of LIBs. For different operating conditions of batteries, the appropriate circuit model can be selected from the composite equivalent circuit, among which the second-order equivalent circuit model is widely applicable and can be used in various types of operating conditions.

6. Conclusion and Policy Implications

Accurate estimation of battery status is the key to the difficulty of monitoring the status of

LIBs, and various improved PF algorithms improve the estimation accuracy and robustness. This article reviews different methods for estimating the state of charge (SOC) of LIBs, summarizes the advantages and disadvantages of each method, and rigorously analyzes, compares, and reviews the improvement directions of different estimation methods based on various factors. The analysis results show that model-based methods and hybrid methods that include model-based methods have smaller computational requirements and greater universality. Subsequently, this article analyzes different types of models for LIBs, systematically summarizes the advantages and disadvantages of various models when used to estimate the SOC of LIBs, and through comprehensive comparative analysis, the composite equivalent model is used to estimate the SOC of LIBs without requiring high data requirements, and can quickly characterize battery characteristics while ensuring accuracy.

At the same time, this article also reviews commonly used parameter identification methods and compares the advantages and disadvantages of online and offline parameter identification. Finally, this article summarizes the advantages of PF over Kalman filtering and briefly introduces its iterative principle. Then, it compares the accuracy and universality of various improved PF algorithms for estimating the state of charge (SOC) of LIBs under different operating conditions. The results show that the improved PF algorithm based on a composite equivalent circuit model can ensure the accuracy of SOC estimation, and this estimation method can be applied to various operating conditions. Therefore, future research can focus on using improved methods of PF and hybrid methods containing PF for estimating the SOC of LIBs. In summary, this review has made a significant contribution to the accurate estimation of SOC and helps expand the use of LIBs. The widespread use of LIBs can promote energy conservation, reduce carbon dioxide emissions, and protect the environment, helping to achieve peak emission and carbon neutrality goals.

This review can also provide valuable overviews and suggestions for researchers in the battery field. Future work will examine state estimation methods for LIBs packs as well as other status estimation or prediction methods for real-time effective BMS applications.

Acknowledgment

The work was supported by the National Natural Science Foundation of China (No. 62173281, 61801407), the Sichuan Science and Technology Program (No. 2019YFG0427), the China Scholarship Council (No. 201908515099), and the Fund of Robot Technology used for the Special Environment Key Laboratory of Sichuan Province (No. 18kftk03).

Reference

1. Royston, S., J. Selby, and E. Shove, *Invisible energy policies: A new agenda for energy demand reduction.* Energy Policy, 2018. **123**: p. 127-135.

2. Zhang, K., J. Yin, and Y. He, *Acoustic Emission Detection and Analysis Method for Health Status of Lithium Ion Batteries.* Sensors, 2021. **21**(3) : p. 31-45.

3. Wang, Z., et al., *A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles.* Energy Reports, 2021. **7**: p. 5141-5161.

4. Fan, B. and J. Pu, *State of Charge Prediction for Lithium-ion Batteries.* Electric Power Components and Systems, 2014. **42**(5): p. 464-470.

5. Hu, X., Y. Guo, and R. Zhang, *Review of State-of-health Estimation Methods for Lithium-ion Battery.* Journal of Power Supply, 2022. **20**(1): p. 126-133.

6. Deng, L., et al., *A rest-time-based prognostic model for remaining useful life prediction of lithium-ion battery.* Neural Computing & Applications, 2021. **33**(6): p. 2035-2046.

7. Zhang, H., et al., *Nonlinear-Drifted Fractional Brownian Motion With Multiple Hidden State Variables for Remaining Useful Life Prediction of Lithium-Ion Batteries.* Ieee Transactions on Reliability, 2020. **69**(2): p. 768-780.

8. Hu, W. and S. Zhao, *Remaining useful life prediction of lithium-ion batteries based on wavelet denoising and transformer neural network.* Frontiers in Energy Research, 2022. **10**: p. 84-98.

9. Farmann, A. and D.U. Sauer, *Comparative study of reduced order equivalent circuit models for on-board state-of-available-power prediction of lithium-ion batteries in electric vehicles.* Applied Energy, 2018. **225**: p. 1102-1122.

10. Bose, B.K., *Power Electronics, Smart Grid, and Renewable Energy Systems.* Proceedings of the Ieee, 2017. **105**(11): p. 2011-2018.

11. An, Z., *Research on residual life prediction method of lithium ion battery for pure electric vehicle.* International Journal of Materials & Product Technology, 2021. **63**(1-2): p. 86-95.

12. Qu, J., et al., *A Neural-Network-Based Method for RUL Prediction and SOH Monitoring of Lithium-Ion Battery.* Ieee Access, 2019. **7**: p. 87178-87191.

13. Laadjal, K. and A.J.M. Cardoso, *Estimation of Lithium-Ion Batteries State-Condition in Electric Vehicle Applications: Issues and State of the Art.* Electronics, 2021. **10**(13) : p. 127-135.

14. Lipu, M.S.H., et al., *Data-driven state of charge estimation of lithium-ion batteries: Algorithms, implementation factors, limitations and future trends.* Journal of Cleaner Production, 2020. **277**: p. 18-36.

15. Zhang, Z., et al., *Review of SoC Estimation Methods for Electric Vehicle Li-ion Batteries.* Journal of Electronics & Information Technology, 2021. **43**(7): p. 1803-1815.

16. Qiu, X., W. Wu, and S. Wang, *Remaining useful life prediction of lithium-ion battery based on improved cuckoo search particle filter and a novel state of charge estimation method.* Journal of Power Sources, 2020. **450**: p. 32-44.

17. Potrykus, S., et al., *Advanced Lithium-Ion Battery Model for Power System Performance Analysis.* Energies, 2020. **13**(10) : p. 1127-1135.

18. Jin, X., *Aging-Aware optimal charging strategy for lithium-ion batteries: Considering aging status and electro-thermal-aging dynamics.* Electrochimica Acta, 2022. **407**: p. 36-52.

19. Zhang, Z.Q., et al., *State-of-health estimation for the lithium-ion battery based on gradient boosting decision tree with autonomous selection of excellent features.* International Journal of Energy Research, 2022. **46**(2): p. 1756-1765.

20. Wang, J. and C. Wen, *Real-Time Updating High-Order Extended Kalman Filtering Method Based on Fixed-Step Life Prediction for Vehicle Lithium-Ion Batteries.* Sensors (Basel, Switzerland), 2022. **22**(7) : p. 89-100.

21. Xie, Y. and X. Cheng, *Review of State Estimation of Lithium-ion Battery with Machine Learning.* Automotive Engineering, 2021. **43**(11): p. 1720-1729.

22. Cui, Z., et al., *A comprehensive review on the state of charge estimation for lithium-ion battery based on neural network.* International Journal of Energy Research, 2022. **46**(5): p. 5423-5440.

23. Chen, D., et al., *A novel hybrid equivalent circuit model for lithium-ion battery considering nonlinear capacity effects.* Energy Reports, 2021. **7**: p. 320-329.

24. Li, S., et al. *Research Progress of Equivalent Circuit Models for SOC Estimation of Batteries in Electric Vehicles*. in *IEEE Transportation Electrification Conference and Expo (ITEC Asia-Pacific)*. 2014. Beijing, PEOPLES R CHINA: p. 136-152.

25. Mu, H., et al., *A novel fractional order model based state-of-charge estimation method for lithium-ion battery.* Applied Energy, 2017. **207**: p. 384-393.

26. Tang, X.P., et al., *Joint estimation of state-of-charge and state-of-health for all cells in the battery pack using "leader-follower"strategy.* Etransportation, 2023. **15**: p. 127-135.

27. Rodriguez-Iturriaga, P., et al., *A novel Dual Fractional-Order Extended Kalman Filter for the improved estimation of battery state of charge.* Journal of Energy Storage, 2022. **56**: p. 16-35.

28. Wu, L.X., et al., *Online SOC Estimation Based on Simplified Electrochemical Model for Lithium-Ion Batteries Considering Current Bias.* Energies, 2021. **14**(17) : p. 18-35.

29. Liu, Y.F., et al., *State of Charge Estimation of Lithium-Ion Batteries Based on Temporal Convolutional Network and Transfer Learning.* Ieee Access, 2021. **9**: p. 34177-34187.

30. Li, L.L., Z.F. Liu, and C.H. Wang, *The Open-Circuit Voltage Characteristic and State of Charge Estimation for Lithium-Ion Batteries Based on an Improved Estimation Algorithm.* Journal of Testing and Evaluation, 2020. **48**(2): p. 1712-1730.

31. Hannan, M.A., et al., *A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations.* Renewable & Sustainable Energy Reviews, 2017. **78**: p. 834-854.

32. Arevalo, P., et al., *Energy control and size optimization of a hybrid system (photovoltaichidrokinetic) using various storage technologies.* Sustainable Cities and Society, 2020. **52**: p. 1287-1295.

33. Meng, J., et al., *Overview of Lithium-Ion Battery Modeling Methods for State-of-Charge Estimation in Electrical Vehicles.* Applied Sciences-Basel, 2018. **8**(5) : p. 189-

200.

34. Liu, L., J. Zhu, and L. Zheng, *An Effective Method for Estimating State of Charge of Lithium-Ion Batteries Based on an Electrochemical Model and Nernst Equation.* Ieee Access, 2020. **8**: p. 211738-211749.

35. Gao, Y.Z., et al., *Co-Estimation of State-of-Charge and State-of- Health for Lithium-Ion Batteries Using an Enhanced Electrochemical Model.* Ieee Transactions on Industrial Electronics, 2022. **69**(3): p. 2684-2696.

36. Zheng, Y., et al., *Investigating the error sources of the online state of charge estimation methods for lithium-ion batteries in electric vehicles.* Journal of Power Sources, 2018. **377**: p. 161-188.

37. Pillai, P., et al., *Open-Circuit Voltage Models for Battery Management Systems: A Review.* Energies, 2022. **15**(18) : p. 89-101.

38. Zhang, Q., et al., *Fractional calculus based modeling of open circuit voltage of lithium-ion batteries for electric vehicles.* Journal of Energy Storage, 2020. **27**: p. 157-169.

39. Zhou, W., et al., *Review on the Battery Model and SOC Estimation Method.* Processes, 2021. **9**(9) : p. 195-206.

40. Fan, K.S., et al., *Time-efficient identification of lithium-ion battery temperature-dependent OCV-SOC curve using multi-output Gaussian process.* Energy, 2023. **268**: p. 136-151.

41. Aktas, A., Y. Kircicek, and M. Ozkaymak, *Modelling and Validation Analysis According to Temperature Effect of Different Type Batteries.* Thermal Science, 2020. **24**(2): p. 1031-1043.

42. Yu, P., et al., *Study of hysteresis voltage state dependence in lithium-ion battery and a novel asymmetric hysteresis modeling.* Journal of Energy Storage, 2022. **51**: p. 127-135.

43. Ning, J., et al., *A rapid detection method for the battery state of health.* Measurement, 2022. **189**: p. 564-580.

44. Luo, Y.F., *A Multi-Frequency Electrical Impedance Spectroscopy Technique of Artificial Neural Network-Based for the Static State of Charge.* Energies, 2021. **14**(9) : p. 187-200.

45. Wang, L.M., et al., *Instantaneous estimation of internal temperature in lithium-ion battery by impedance measurement.* International Journal of Energy Research, 2020. **44**(4): p. 3082-3097.

46. Chen, Z.L., et al., *Lithium-ion battery state of charge estimation strategy for industrial applications.* Proceedings of the Institution of Civil Engineers-Energy: p. 198-211.

47. Ji, Y.J., S.L. Qiu, and G. Li, *Simulation of second-order RC equivalent circuit model of lithium battery based on variable resistance and capacitance.* Journal of Central South University, 2020. **27**(9): p. 2606-2613.

48. Ren, L.C., et al., *Comparison of robustness of different state of charge estimation algorithms.* Journal of Power Sources, 2020. **478**: p. 127-135.

49. Lai, X., et al., *A Fuzzy State-of-Charge Estimation Algorithm Combining Ampere-Hour and an Extended Kalman Filter for Li-Ion Batteries Based on Multi-Model Global Identification.* Applied Sciences-Basel, 2018. **8**(11) : p. 145-160.

50. Finegan, D.P., et al., *The Application of Data-Driven Methods and Physics-Based Learning for Improving Battery Safety.* Joule, 2021. **5**(2): p. 316-329.

51. Wu, L., X. Fu, and Y. Guan, *Review of the Remaining Useful Life Prognostics of Vehicle Lithium-Ion Batteries Using Data-Driven Methodologies.* Applied Sciences-Basel, 2016. **6**(6) : p. 1287-1305.

52. Guo, Y., et al., *Online estimation of SOH for lithium-ion battery based on SSA-Elman neural network.* Protection and Control of Modern Power Systems, 2022. **7**(1) : p. 3-19.

53. Sun, H.L., et al., *A method for estimating the aging state of lithium-ion batteries based on a multi-linear integrated model.* International Journal of Energy Research, 2022. **46**(15): p. 24091-24104.

54. Lyu, Z. and R. Gao, *A model-based and data-driven joint method for state-of-health estimation of lithium-ion battery in electric vehicles.* International Journal of Energy Research, 2019. **43**(14): p. 7956-7969.

55. Hametner, C., S. Jakubek, and W. Prochazka, *Data-Driven Design of a Cascaded Observer for Battery State of Health Estimation.* Ieee Transactions on Industry Applications, 2018. **54**(6): p. 6258-6266.

56. Jiang, H., et al., *Multiple health indicators assisting data-driven prediction of the later service life for lithium-ion batteries.* Journal of Power Sources, 2022. **542**: p. 127-135.

57. How, D.N.T., et al., *State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review.* Ieee Access, 2019. **7**: p. 136116-136136.

58. Jiang, B., et al., *An adaptive capacity estimation approach for lithium-ion battery using 10-min relaxation voltage within high state of charge range.* Energy, 2023. **263**: p. 5-21.

59. Zhengxin, J., et al., *An Immune Genetic Extended Kalman Particle Filter approach on state of charge estimation for lithium-ion battery.* Energy, 2021. **230**: p. 35-52.

60. Ji, S.Y., et al., *A Multi-Scale Time Method for the State of Charge and Parameter*

Estimation of Lithium-Ion Batteries Using MIUKF-EKF. Frontiers in Energy Research, 2022. **10**: p. 1111-1126.

61. Shrivastava, P., et al., *Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries.* Renewable & Sustainable Energy Reviews, 2019. **113**: p. 1105-1123.

62. Cui, Z., et al., *A combined state-of-charge estimation method for lithium-ion battery using an improved BGRU network and UKF.* Energy, 2022. **259**: p. 127-135.

63. Cui, Z., et al., *Hybrid Methods Using Neural Network and Kalman Filter for the State of Charge Estimation of Lithium-Ion Battery.* Mathematical Problems in Engineering, 2022. **2022**: p. 7-25.

64. Peng, J.C., et al., *A Review of Lithium-Ion Battery Capacity Estimation Methods for Onboard Battery Management Systems: Recent Progress and Perspectives.* Batteries-Basel, 2022. **8**(11) : p. 189-205.

65. Lipu, M.S.H., et al., *Deep learning enabled state of charge, state of health and remaining useful life estimation for smart battery management system: Methods, implementations, issues and prospects.* Journal of Energy Storage, 2022. **55**: p. 87-103.

66. Lipu, M.S.H., et al., *Intelligent SOX Estimation for Automotive Battery Management Systems: State-of-the-Art Deep Learning Approaches, Open Issues, and Future Research Opportunities.* Energies, 2023. **16**(1) : p. 18-35.

67. Santos, C. and F. La Mantia, *Recent advances in reactor design and control for lithium recovery by means of electrochemical ion pumping.* Current Opinion in Electrochemistry, 2022. **35**: p. 1271-1295.

68. Parke, C.D., et al., *An Efficient Electrochemical Tanks-in-Series Model for Lithium Sulfur Batteries.* Journal of the Electrochemical Society, 2020. **167**(16) : p. 11-25.

69. Li, X., et al., *A simplified multi-particle model for lithium ion batteries via a predictor-corrector strategy and quasi-linearization.* Energy, 2016. **116**: p. 154-169.

70. Lee, Y.K., J. Park, and W. Lu, *A Comprehensive Experimental and Modeling Study on Dissolution in Li-Ion Batteries.* Journal of the Electrochemical Society, 2019. **166**(8): p. A1340-A1354.

71. Ren, L., et al., *An algorithm for state of charge estimation based on a single-particle model.* Journal of Energy Storage, 2021. **39**: p. 19-41.

72. Pugalenthi, K., H. Park, and N. Raghavan, *Piecewise Model-Based Online Prognosis of Lithium-Ion Batteries Using Particle Filters.* Ieee Access, 2020. **8**: p. 153508-153516.

73. Heubner, C., et al., *Electrochemical single-particle measurements of electrode*

materials for Li-ion batteries: Possibilities, insights and implications for future development. Electrochimica Acta, 2020. **330**: p. 127-135.

74. Jokar, A., et al., *Review of simplified Pseudo-two-Dimensional models of lithium-ion batteries.* Journal of Power Sources, 2016. **327**: p. 44-55.

75. Liu, B., X. Tang, and F. Gao, *Joint estimation of battery state-of-charge and state-of-health based on a simplified pseudo-two-dimensional model.* Electrochimica Acta, 2020. **344**: p. 19-35.

76. Oca, L., et al., *Physico-chemical parameter measurement and model response evaluation for a pseudo-two-dimensional model of a commercial lithium-ion battery.* Electrochimica Acta, 2021. **382**: p. 1277-1296.

77. Vermeer, W., G.R. Chandra Mouli, and P. Bauer, *A Comprehensive Review on the Characteristics and Modeling of Lithium-Ion Battery Aging.* Ieee Transactions on Transportation Electrification, 2022. **8**(2): p. 2205-2232.

78. Ren, L.C., et al., *An algorithm for state of charge estimation based on a single-particle model.* Journal of Energy Storage, 2021. **39**: p. 1854-1870.

79. Zheng, X. and Z. Zhang, *State of charge estimation at different temperatures based on dynamic thermal model for lithium-ion batteries.* Journal of Energy Storage, 2022. **48**: p. 7-34.

80. Ma, Y., et al., *SOC Oriented Electrochemical-Thermal Coupled Modeling for Lithium-Ion Battery.* Ieee Access, 2019. **7**: p. 156136-156149.

81. Zhu, J.G., et al., *An improved electro-thermal battery model complemented by current dependent parameters for vehicular low temperature application.* Applied Energy, 2019. **248**: p. 149-161.

82. Li, J.F., et al., *Parameter updating method of a simplified first principles-thermal coupling model for lithium-ion batteries.* Applied Energy, 2019. **256**: p. 1120-1135.

83. Lyu, C., et al., *State of charge estimation based on a thermal coupling simplified first-principles model for lithium-ion batteries.* Journal of Energy Storage, 2019. **25**: p. 47-63.

84. Chen, L.G., et al., *Core temperature estimation based on electro-thermal model of lithium-ion batteries.* International Journal of Energy Research, 2020. **44**(7): p. 5320-5333.

85. Chen, Z.J., et al., *Numerical study on the heat generation and thermal control of lithium-ion battery.* Applied Thermal Engineering, 2023. **221**: p. 1-15.

86. Chen, N., et al., *Estimating the State-of-Charge of Lithium-Ion Battery Using an H-Infinity Observer Based on Electrochemical Impedance Model.* Ieee Access, 2020. **8**:

p. 26872-26884.

87. Ouyang, K.L., et al., *Data-Driven-Based Internal Temperature Estimation for Lithium-Ion Battery Under Variant State-of-Charge via Electrochemical Impedance Spectroscopy.* Energy Technology, 2022. **10**(3) : p. 19-35.

88. Huang, C., et al., *Interacting Multiple Model for Lithium-Ion Battery State of Charge Estimation Based on the Electrochemical Impedance Spectroscopy.* Electronics, 2023. **12**(4) : p. 127-135.

89. Zhang, J., et al., *Variable-Order Equivalent Circuit Modeling and State of Charge Estimation of Lithium-Ion Battery Based on Electrochemical Impedance Spectroscopy.* Energies, 2021. **14**(3) : p. 321-345.

90. Wang, Q.K., et al., *State of Charge-Dependent Polynomial Equivalent Circuit Modeling for Electrochemical Impedance Spectroscopy of Lithium-Ion Batteries.* Ieee Transactions on Power Electronics, 2018. **33**(10): p. 8449-8460.

91. Adaikkappan, M. and N. Sathiyamoorthy, *Modeling, state of charge estimation, and charging of lithium-ion battery in electric vehicle: A review.* International Journal of Energy Research, 2022. **46**(3): p. 2141-2165.

92. Feng, F., et al., *Electrochemical impedance characteristics at various conditions for commercial solid-liquid electrolyte lithium-ion batteries: Part 1. experiment investigation and regression analysis.* Energy, 2022. **242**: p. 784-801.

93. Zhang, M., et al., *Electrochemical Impedance Spectroscopy: A New Chapter in the Fast and Accurate Estimation of the State of Health for Lithium-Ion Batteries.* Energies, 2023. **16**(4) : p. 18-45.

94. Feng, F., et al., *Electrochemical impedance characteristics at various conditions for commercial solid-liquid electrolyte lithium-ion batteries: Part. 2. Modeling and prediction.* Energy, 2022. **243**: p. 131-158.

95. Liu, Z., et al., *A Simplified Fractional Order Modeling and Parameter Identification for Lithium-Ion Batteries.* Journal of Electrochemical Energy Conversion and Storage, 2022. **19**(2) : p. 45-67.

96. Choi, W., et al., *Modeling and Applications of Electrochemical Impedance Spectroscopy (EIS) for Lithium-ion Batteries.* Journal of Electrochemical Science and Technology, 2020. **11**(1) : p. 127-135.

97. Chen, P., et al., *Evaluation of Various Offline and Online ECM Parameter Identification Methods of Lithium-Ion Batteries in Underwater Vehicles.* Acs Omega, 2022. **7**(34): p. 30504-30518.

98. Du, X., et al., *An Information Appraisal Procedure: Endows Reliable Online*

Parameter Identification to Lithium-Ion Battery Model. Ieee Transactions on Industrial Electronics, 2022. **69**(6): p. 5889-5899.

99. Nikohan, A., et al., *Complete cell-level lithium-ion electrical ECM model for different chemistries (NMC, LFP, LTO) and temperatures (-5 degrees C to 45 degrees C) - Optimized modelling techniques.* International Journal of Electrical Power & Energy Systems, 2018. **98**: p. 133-146.

100. Li, J., et al., *A review of current research on lithium-ion battery modeling.* Thermal Power Generation, 2021. **50**(7): p. 1-7.

101. Khaki, B. and P. Das, *An equivalent circuit model for Vanadium Redox Batteries via hybrid extended Kalman filter and Particle filter methods.* Journal of Energy Storage, 2021. **39**: p. 3-26.

102. Lin, C., et al., *A novel multi-model probability battery state of charge estimation approach for electric vehicles using H-infinity algorithm.* Applied Energy, 2016. **166**: p. 76-83.

103. Hentunen, A., T. Lehmuspelto, and J. Suomela, *Time-Domain Parameter Extraction Method for Thevenin-Equivalent Circuit Battery Models.* Ieee Transactions on Energy Conversion, 2014. **29**(3): p. 558-566.

104. Farmann, A., W. Waag, and D.U. Sauer, *Adaptive approach for on-board impedance parameters and voltage estimation of lithium-ion batteries in electric vehicles.* Journal of Power Sources, 2015. **299**: p. 176-188.

105. Lencwe, M.J., et al., *Integrated Fuzzy-Logic and Triple-Loop PI-Based Management Strategy for a Lead-Acid/Lithium-Ion Hybrid Battery Energy Storage System.* Applied Sciences-Basel, 2022. **12**(14) : p. 88-101.

106. Geng, Z., et al., *Bridging physics-based and equivalent circuit models for lithium-ion batteries.* Electrochimica Acta, 2021. **372**: p. 61-83.

107. Liu, F., et al., *Online joint estimator of key states for battery based on a new equivalent circuit model.* Journal of Energy Storage, 2022. **52**: p. 127-135.

108. Rahmoun, A. and H. Biechl, *Modelling of Li-ion batteries using equivalent circuit diagrams.* Przeglad Elektrotechniczny, 2012. **88**(7B): p. 152-156.

109. Jiang, Z., et al., *Fractional modeling and parameter identification of lithium-ion battery.* Ionics, 2022. **28**(9): p. 4135-4148.

110. You, H.W., et al., *Analysis of equivalent circuit models in lithium-ion batteries.* Aip Advances, 2018. **8**(12) : p. 1844-1860.

111. Nikolian, A., et al., *Lithium Ion BatteriesDevelopment of Advanced Electrical Equivalent Circuit Models for Nickel Manganese Cobalt Lithium-Ion.* Energies, 2016.

9(5) : p. 33-52.

112. Su, J., et al., *An equivalent circuit model analysis for the lithium-ion battery pack in pure electric vehicles.* Measurement & Control, 2019. **52**(3-4): p. 193-201.

113. Guo, X., et al., *Research on equivalent circuit model for power battery.* Transducer and Microsystem Technology, 2022. **41**(1): p. 62-64,68.

114. Gao, P., C. Zhang, and G. Wen, *Equivalent circuit model analysis on electrochemical impedance spectroscopy of lithium metal batteries.* Journal of Power Sources, 2015. **294**: p. 67-74.

115. Liu, X., et al., *Online Identification of Power Battery Parameters for Electric Vehicles Using a Decoupling Multiple Forgetting Factors Recursive Least Squares Method.* Csee Journal of Power and Energy Systems, 2020. **6**(3): p. 735-742.

116. Zheng, Y., et al., *An accurate parameters extraction method for a novel on-board battery model considering electrochemical properties.* Journal of Energy Storage, 2019. **24**: p. 35-53.

117. Seaman, A., T.-S. Dao, and J. McPhee, *A survey of mathematics-based equivalent-circuit and electrochemical battery models for hybrid and electric vehicle simulation.* Journal of Power Sources, 2014. **256**: p. 410-423.

118. Xiao, R., et al., *A novel estimation of state of charge for the lithium-ion battery in electric vehicle without open circuit voltage experiment.* Energy, 2022. **243**: p. 78-91.

119. Geng, Y.F., H. Pang, and X.F. Liu, *State-of-charge estimation for lithium-ion battery based on PNGV model and particle filter algorithm.* Journal of Power Electronics, 2022. **22**(7): p. 1154-1164.

120. Wang, Q.Q., et al., *An online method to simultaneously identify the parameters and estimate states for lithium ion batteries.* Electrochimica Acta, 2018. **289**: p. 376-388.

121. Yang, K., Y.G. Tang, and Z. Zhang, *Parameter Identification and State-of-Charge Estimation for Lithium-Ion Batteries Using Separated Time Scales and Extended Kalman Filter.* Energies, 2021. **14**(4) : p. 127-135.

122. Chen, P.Y., et al., *Evaluation of Various Offline and Online ECM Parameter Identification Methods of Lithium-Ion Batteries in Underwater Vehicles.* Acs Omega, 2022. **7**(34): p. 30504-30518.

123. Sun, C.C., et al., *Improved parameter identification and state-of-charge estimation for lithium-ion battery with fixed memory recursive least squares and sigma-point Kalman filter.* Electrochimica Acta, 2021. **387**: p. 11-35.

124. Zhu, Q., et al., *Iterative learning based model identification and state of charge estimation of lithium-ion battery.* Iet Power Electronics, 2019. **12**(4): p. 852-860.

125. Chen, H., et al., *ARWLS-AFEKE: SOC Estimation and Capacity Correction of Lithium Batteries Based on a Fusion Algorithm.* Processes, 2023. **11**(3) : p. 564-580.

126. Yang, S.C., et al., *A parameter adaptive method for state of charge estimation of lithium-ion batteries with an improved extended Kalman filter.* Scientific Reports, 2021. **11**(1) : p. 484-501.

127. Ouyang, Q., J. Chen, and J. Zheng, *State-of-Charge Observer Design for Batteries With Online Model Parameter Identification: A Robust Approach.* Ieee Transactions on Power Electronics, 2020. **35**(6): p. 5820-5831.

128. Wang, H., Y.P. Zheng, and Y. Yu, *Joint Estimation of SOC of Lithium Battery Based on Dual Kalman Filter.* Processes, 2021. **9**(8) : p. 564-590.

129. Long, H.Y., et al., *Model Parameters Online Identification and SOC Joint Estimation for Lithium-Ion Battery Based on a Composite Algorithm.* Journal of Electrical Engineering & Technology, 2019. **14**(4): p. 1485-1493.

130. Peng, N., et al., *Online parameters identification and state of charge estimation for lithium-ion batteries using improved adaptive dual unscented Kalman filter.* International Journal of Energy Research, 2021. **45**(1): p. 975-990.

131. Lao, Z.Z., et al., *A Novel Method for Lithium-Ion Battery Online Parameter Identification Based on Variable Forgetting Factor Recursive Least Squares.* Energies, 2018. **11**(6) : p. 127-135.

132. Xia, B.Z., et al., *Online Parameter Identification and State of Charge Estimation of Lithium-Ion Batteries Based on Forgetting Factor Recursive Least Squares and Nonlinear Kalman Filter.* Energies, 2018. **11**(1) : p. 15-27.

133. Ye, M., H. Guo, and B.B. Cao, *A model-based adaptive state of charge estimator for a lithium-ion battery using an improved adaptive particle filter.* Applied Energy, 2017. **190**: p. 740-748.

134. Wu, T.Z., et al., *SOC and SOH Joint Estimation of Lithium-Ion Battery Based on Improved Particle Filter Algorithm.* Journal of Electrical Engineering & Technology, 2022. **17**(1): p. 307-317.

135. Xia, B.Z., et al., *A Comparative Study of Three Improved Algorithms Based on Particle Filter Algorithms in SOC Estimation of Lithium Ion Batteries.* Energies, 2017. **10**(8) : p. 1-16.

136. Xu, W., J.L. Xu, and X.F. Yan, *Lithium-ion battery state of charge and parameters joint estimation using cubature Kalman filter and particle filter.* Journal of Power Electronics, 2020. **20**(1): p. 292-307.

137. Liu, Q.H., et al., *Evaluation of LFP Battery SOC Estimation Using Auxiliary Particle*

Filter. Energies, 2019. **12**(11) : p. 98-121.

138. Hao, X.Y., et al., *An improved forgetting factor recursive least square and unscented particle filtering algorithm for accurate lithium-ion battery state of charge estimation.* Journal of Energy Storage, 2023. **59**: p. 3-15.

139. Wang, J.R., et al., *Lithium-Ion Battery State-of-Charge Estimation Using Electrochemical Model with Sensitive Parameters Adjustment.* Batteries-Basel, 2023. **9**(3) : p. 46-60.

140. Pang, H., et al., *A Composite State of Charge Estimation for Electric Vehicle Lithium-Ion Batteries Using Back-Propagation Neural Network and Extended Kalman Particle Filter.* Journal of the Electrochemical Society, 2022. **169**(11) : p. 364-390.

141. Li, S.X., et al., *Fractional-order modeling and SOC estimation of lithium-ion battery considering capacity loss.* International Journal of Energy Research, 2019. **43**(1): p. 417-429.

142. Zhang, M., K. Wang, and Y.T. Zhou, *Online State of Charge Estimation of Lithium-Ion Cells Using Particle Filter-Based Hybrid Filtering Approach.* Complexity, 2020. **2020**: p. 127-135.

143. Xu, W., et al., *A multi-timescale adaptive dual particle filter for state of charge estimation of lithium-ion batteries considering temperature effect.* Energy Science & Engineering, 2020. **8**(8): p. 2784-2798.

144. Duan, B., et al., *Remaining useful life prediction of lithium-ion battery based on extended Kalman particle filter.* International Journal of Energy Research, 2020. **44**(3): p. 1724-1734.

145. Bartlett, A., et al., *Electrochemical Model-Based State of Charge and Capacity Estimation for a Composite Electrode Lithium-Ion Battery.* Ieee Transactions on Control Systems Technology, 2016. **24**(2): p. 384-399.

146. Pang, H., et al., *A Composite State of Charge Estimation for Electric Vehicle Lithium-Ion Batteries Using Back-Propagation Neural Network and Extended Kalman Particle Filter.* Journal of the Electrochemical Society, 2022. **169**(11) : p. 154-169.

147. Liu, X.T., et al., *A Dynamic State-of-Charge Estimation Method for Electric Vehicle Lithium-Ion Batteries.* Energies, 2020. **13**(1) : p. 1277-1301.

148. Qiao, J.L., et al., *A novel intelligent weight decreasing firefly-particle filtering method for accurate state-of-charge estimation of lithium-ion batteries.* International Journal of Energy Research, 2022. **46**(5): p. 6613-6622.

149. Wang, X.Y., et al., *A Novel Gaussian Particle Swarms optimized Particle Filter Algorithm for the State of Charge Estimation of Lithium-ion Batteries.* International

Journal of Electrochemical Science, 2020. **15**(10): p. 10632-10648.

150. Song, Y.C., et al., *A hybrid statistical data-driven method for on-line joint state estimation of lithium-ion batteries.* Applied Energy, 2020. **261**: p. 1-21.