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Review

Advances in the Study of Techniques to Determine the Lithium-Ion Battery's State of Charge

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Abstract: This study explores the challenges and advances in the estimation of the state of charge (SOC) of lithium-ion batteries (LIBs), which are crucial to optimizing their performance and lifespan. This review focuses on four main techniques of SOC estimation: experimental measurement, modeling approach, data-driven approach, and joint estimation approach, highlighting the limitations and potential inaccuracies of each method. This study suggests a combined approach, incorporating correction parameters and closed-loop feedback, to improve measurement accuracy. It introduces a multi-physics model that considers temperature, charging rate, and aging effects and proposes the integration of models and algorithms for optimal estimation of SOC. This research emphasizes the importance of considering temperature and aging factors in data-driven approaches. It suggests that the fusion of different methods could lead to more accurate SOC predictions, an important area for future research.

Keywords: lithium-ion batteries; SOC; influencing factors; estimation

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1. Introduction

Lithium-ion batteries (LIBs), as effective means of storage for electrical technologies, are frequently employed in many applications, such as automobiles, consumer electronics equipment, and large-scale energy storage equipment, as shown in Figure 1. However, improvements in energy utilization efficiency and the development and management of high-integration and high (energy)-density battery pack systems are necessary to address issues related to energy output and storage safety, range anxiety, and other LIB problems in complex working conditions [1,2]. The state of charge (SOC) is the ratio between the current remaining capacity of the battery and its nominal capacity [3]. This can visually display the remaining battery capacity and operating status, indirectly reflect the remaining battery life, provide data support and correction solutions for battery energy management, and maximize the efficiency of the battery pack. Temperature, aging, charge and discharge rates, and equalization significantly impact the SOC of LIBs [4]. Accurately monitoring and estimating LIBs' SOC is essential for their applications. This is a scientific challenge that requires immediate attention to existing or emerging batteries and battery management systems. The essence of LIB operation is the de/intercalation movement of lithium ions. As the number of electrochemical reactions occurring at the electrode/electrolyte interface and active materials gradually accumulates, the LIB gradually ages [5]. This process is also associated with a rise in internal resistance and a gradual or sharp decline in capacity. The increased internal resistance will further increase the self-heating release of the LIB [6], which affects the change in the battery's SOC. It also affects the consistency of the battery pack. Simultaneously, as Figure 1 shows, the environmental temperature during the charge and discharge of LIBs has an essential impact on battery performance. High temperatures might cause thermal runaway and battery explosion. Lithium dendrites develop rapidly at freezing temperatures, causing a rapid decrease in battery performance and capacity [7]. In addition, improper use of the charging rate of LIBs can also accelerate the consumption of battery life and reduce the battery charge capacity [8]. It is apparent that a comprehensive consideration of the factors influencing the SOC of lithium batteries through methodologies including battery measurement and modeling estimation facilitates a more accurate estimation of the actual SOC throughout the operation of lithium batteries.

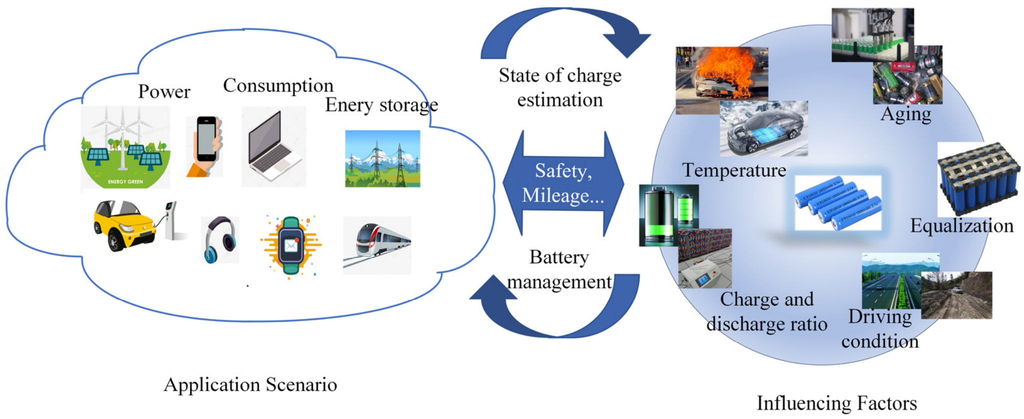


Figure 1. Factors affecting LIBs' performance and lifespan under complex operating conditions.

As shown in Figure 2, the common SOC estimating approaches are experimental measurement, modeling estimation, data-driven prediction, and combined/hybrid approaches. Experimental measuring methods consist of the ampere-hour integration approach, open circuit voltage strategy, the Coulomb method, internal resistance measurement, and the terminal voltage technique. These methods involve the estimation of the SOC by measuring the battery's regular parameter values throughout experiments. The estimation and its application are straightforward. However, these depend on the initial SOC. In addition, the open circuit voltage approach necessitates a long term remaining to reduce the impact of polarization reactions. The modeling methods can be divided into two categories: electrochemical models and equivalent circuit models. They simulate the characteristics of batteries by establishing a lithium battery model and combining it with state estimation algorithms for SOC estimation [9,10]. Electrochemical models include the pseudo-two-dimensional (P2D) model and later simplified single-particle models based on the P2D model, as well as the currently widely studied multi-physics model. The electrochemical model adopts the porous electrode and concentrated solution theories using partial differential equations, which properly reflect LIBs' internal reaction process. However, its numerous parameters and the calculation can be complex, so model reduction techniques are often needed. The equivalent circuit model simulates the working status of batteries using electrical components, making it more appropriate for real-time engineering applications and allowing for studies in both the time and frequency domains. Because of their simplicity and dependability, the Thevenin and dual polarization (DP) models are more widely utilized. The data-driven strategy focuses on the input–output relationship of LIBs and estimates their SOC using the correlation gained from training data. This approach does not involve the investigation of its intrinsic electrochemical reaction or degradation mechanism, but it necessitates a large and high-quality dataset. Improved joint estimating methods are constantly emerging in response to the benefits and drawbacks of the various strategies discussed above. For example, the joint estimation of electrochemical models and equivalent circuit models may not only truly reflect the physical meaning of internal parameters of LIBs but also have the characteristics of being simple models and putting in a real-time solid performance. The joint estimation of the electrochemical model and data-driven method is used to obtain the neural network's training parameters through accurate battery modeling in the initial phase, to ensure that the parameters determined are closely matched to the battery, and the rules obtained through a large amount of data training can provide feedback to the electrochemical model. The performance of batteries under various operating situations and variables will require further in-depth research in the future, and efforts to integrate several methodologies for more accurate SOC estimation of lithium batteries will continue.

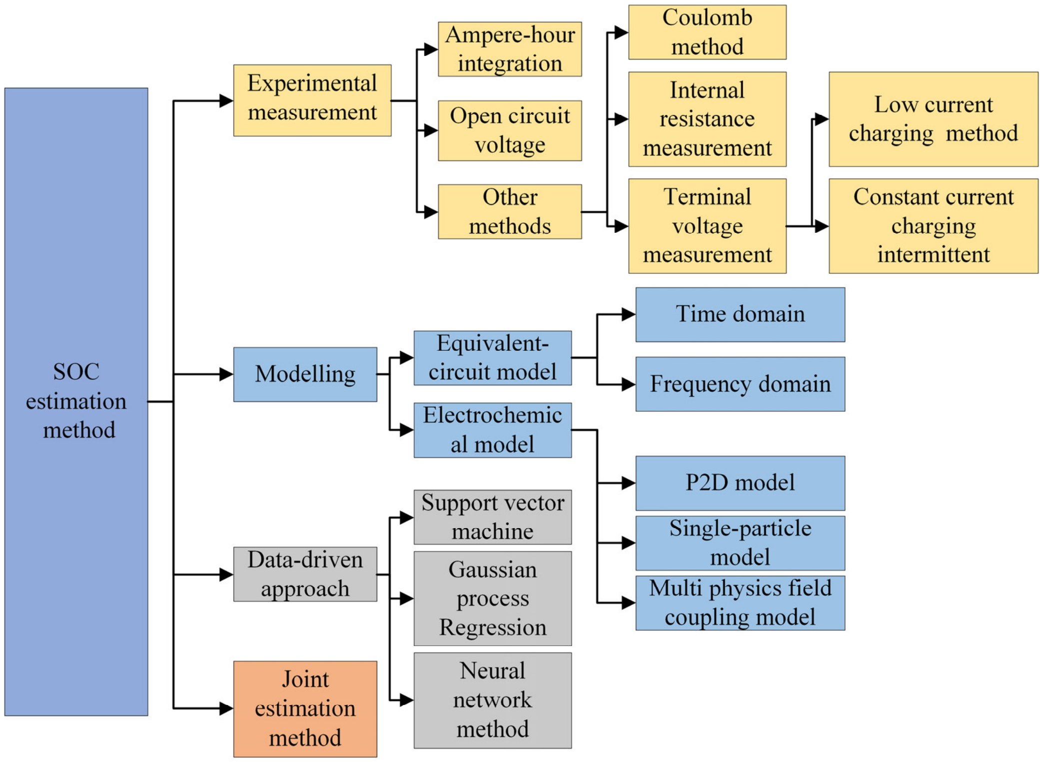


Figure 2. Classification of SOC estimation methods.

In summary, this review will use the principles, methods, and applications of SOC estimation as classification methods to summarize the concepts and advantages and disadvantages of experimental measurement, model, data-driven, and joint estimation methods. It focuses on analyzing the theoretical and experimental descriptions of the interference of temperature, charging rate, and aging factors on lithium batteries under complex working situations. This review summarizes the research status of various estimation methods within different influencing factors. Further research directions on SOC estimation techniques for LIBs under complicated operating conditions are discussed.

2. Experimental Measurement Method

2.1. Ampere-Hour Integration Method

The ampere-hour integration approach (also known as the current integration method) estimates the SOC of LIBs during battery charging and discharging by integrating the current in the time domain [11]. The calculation formula is as follows:

$$SOC(k) = SOC(k_0) - \int_{k_0}^{k} \frac{I(k)\eta}{Q_n} dk \quad (1)$$

where k is the sampling time; k_0 is the initial time; $SOC(k_0)$ is the initial SOC value; $I(k)$ is the current value with respect to the sampling time; η is the Coulomb charging and discharging efficiency of the battery; and Q_n is the rated capacity value of the battery. The ampere-hour integration approach is simple to use and has minimal computing expenses. But it only records the amount of electricity entering and exiting the battery, disregarding changes in its internal condition. This method relies on the initial value of SOC, and the precision of current sampling and the battery operating temperature can affect the accuracy of current testing. The ampere-hour integration method estimation system is a non-closed-loop feedback system. If the present measurement value is not accurate enough, this will lead to the accumulation of SOC estimation errors. Zhang et al. [12] pointed out that the error in SOC estimation using the standard ampere-hour integration approach varies by 10% depending on temperature, charge rate, and other factors. Correction parameters can be utilized to address the issue of parameter value influence [13]. Zhang et al. [14] employed the open circuit voltage approach to determine the initial SOC. During the final stage of constant current discharge, they used the load voltage method to detect and provide feedback on the cumulative error of the ampere-hour integration method SOC. They improved the traditional ampere-hour integration method by considering factors such as temperature, charging efficiency, and number of cycles.

2.2. Open Circuit Voltage Method

Voltage characteristics related to LIBs include electromotive force, open circuit voltage, terminal voltage, and so on. The open circuit voltage approach establishes the OCV-SOC function connection at a specific temperature [15]. Using the existing OCV-SOC function relation, the corresponding SOC is obtained by monitoring the OCV of the LIB [16]. However, a lengthy period of idling before testing is needed to reduce the polarization voltage of the battery, to achieve stable measurement results. This determines that it is unsuitable for practical applications such as frequent power changes during electric vehicle startup. Moreover, the OCV-SOC function relationship of LIBs is not constant. It may change with battery aging, environmental temperature changes, and internal chemical reactions, which result in errors when measuring the SOC of LIBs [17]. The open circuit voltage is frequently employed in conjunction with the ampere-hour integration approach to measure the initial SOC value.

2.3. Other Methods

In addition to the ampere-hour integration approach and the open circuit voltage approach, there are other methods to obtain the SOC of batteries through experiments, such as the internal resistance measurement method, the Coulomb approach, and the terminal voltage approach. The terminal voltage method includes the small current charge and discharge method and the constant electrical current charging and discharging intermittent methods. Both methods use the principle of reducing the impact of battery polarization reactions. It charges and discharges lithium batteries with tiny multiples or small current fluctuations to achieve stability and assess their SOC. However, this method has a long discharge time and is mostly applicable to laboratory research. The Coulomb method estimates how much capacity remains in a battery by measuring the value of the net charge pouring through or out of it. This approach allows you to retrieve the battery's original capacity through preset or repeated charging cycles, which is more convenient. However, this method requires exceptionally high accuracy in measuring currents and related devices, making it experimentally expensive [18]. The internal resistance measuring technique primarily calculates the SOC of the battery by using the functional connection between SOC and internal resistance, which may immediately represent the battery's internal features. However, the battery resistance will vary with temperature, leading to an inaccurate estimate of the SOC. Chen et al. [19] used the least squares interpolation algorithm to model the internal resistance of batteries at different charging rates, states of charge, and temperatures, and they estimated the charging internal resistance under different states using the established multi-factor dynamic internal resistance model, effectively reducing errors.

3. Modeling Method

The current model-based methodology for estimating the SOCs of lithium batteries consists of electrochemical models and equivalent circuit models. The electrochemical model accurately and realistically reflects the internal characteristic reactions of lithium batteries from microscopic perspectives such as the ion concentration and polarization reactions. The equivalent circuit model uses electrical elements to simulate the charging and discharge behavior of the battery with high precision. Figure 3 shows the basic process of the modeling method.

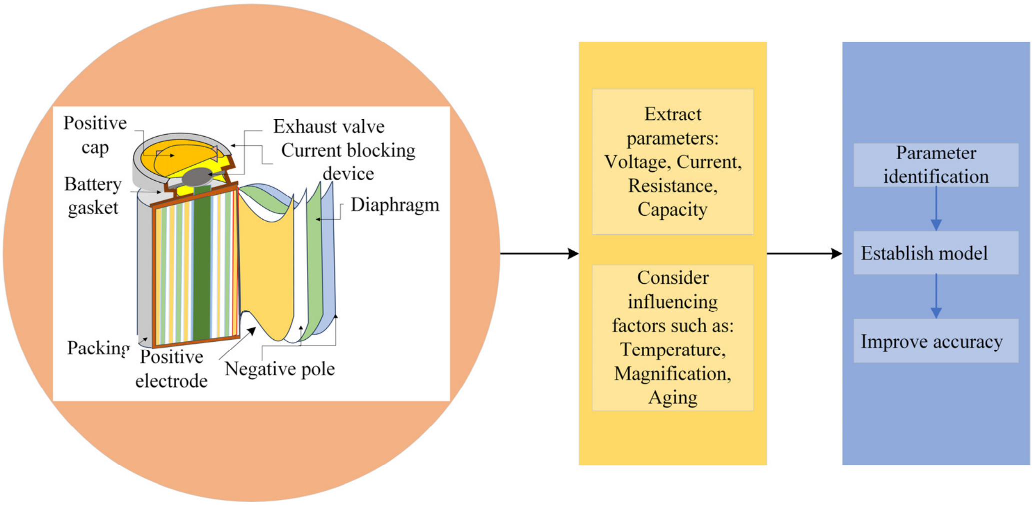


Figure 3. Modeling process diagram of lithium-ion batteries.

3.1. Electrochemical Modeling Method

The electrochemical model is based on the electrochemical mechanisms of reaction such as lithium-ion diffusion and migration inside the battery [20], mainly including the pseudo two-dimensional (P2D) electrochemical model, single particle model (SPM), single particle model with electrolyte dynamics, and multi-physics model [21].

Doyle and others proposed a P2D model for LIBs in 1993 based on the porous electrode theory, highly concentrated solution principle, and kinetic equations. The model simulates the constant current discharging and charging process of LIBs [22]. The P2D model precisely estimates the electrochemical reactions inside lithium batteries, but it is computationally intensive and complex. T. F. Fuller et al. [23] applied concentrated solution theory to investigate the distribution of lithium-ion concentrations and cell potential. The SPM model [24] and other model parameter adaptation techniques [25] can also estimate battery SOC and model parameters simultaneously. While the SPM can provide insights into basic mechanisms and behaviors of LIBs, it is often necessary to employ more complex models or combine the SPM with other approaches to achieve accurate predictions for practical applications. Chen et al. [26] proposed an extended SPM to improve the charge–discharge rate. Yang et al. [27] enriched the research by exploring the spatial evolution of the temperature dependence of lithium-ion diffusion in LIBs. Lin et al. [28] found that, after several cycle life tests, the formation of the solid electrolyte interphase (SEI) layer at different stages of cycle life resulted in a reduction in the battery capacity. Furthermore, the thermal–electrochemical model revealed that temperature significantly impacts battery capacity [29]. Guan et al. [30] predicted the SEI growth rate using a phase field model to predict SEI films' morphological evolution and structure. Porosity grading can minimize the degradation of battery capacity. The self-release heat of the battery increases as ambient temperature decreases due to a polarization reaction and internal ohmic resistance loss. The optimized design of the electrode thickness, porosity, particle size, conductivity, and driving cycle power strategy will reduce the loss of the battery capacity, allowing the battery's SOC to be controlled in an ideal state [28–35].

In addition, LIBs are highly interdisciplinary, involving, for instance, mechanical degradation, chemical diffusion, electrochemical reactions, electron conduction, and others [36]. Therefore, the study of multiple scales and multi-physical LIBs has always been a key direction for researchers [37,38]. The multi-physical field coupling model can model the functioning of lithium batteries more realistically from different perspectives, such as force, electricity, heat, and electrochemistry. Pals et al. introduced the energy conservation equation into the P2D model and established an electrical–thermal (ET) coupled model to elucidate the relationship between electrochemistry and temperature [39,40]. Cernak et al. studied the impact of various particle shapes with blended electrodes on mechanical stress reduction and subsequent improvement of cycle stability [41]. Li et al. investigated the interaction between electrochemistry and ion transfer mechanics at the macro electrode and microparticle scales [42].

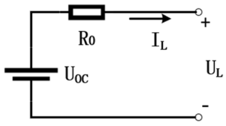
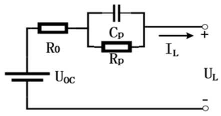
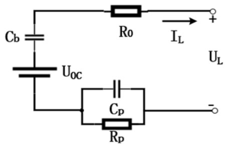
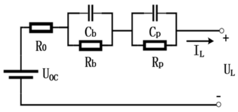
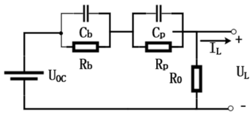
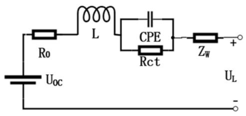
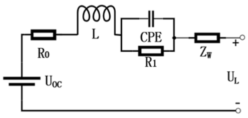
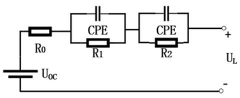
In summary, electrochemical models have the characteristics of interpretability of reaction mechanisms, complexity and difficulty in calculation, and coupling of multiple physics. Therefore, using appropriate methods, while decoupling and reducing the order of complex multi-physical fields, to accurately describe the working mechanism and process is the focus of future study in LIBs.

3.2. Equivalent Circuit Modeling Method

The equivalent circuit model mainly uses circuit components such as capacitors, resistors, and inductors to reflect the exterior functioning properties of lithium batteries and reflect the battery's current condition. The commonly used equivalent circuits to estimate the SOC of lithium batteries include Rint, Thevenin, partnership for a new generation of vehicles (PNGV), dual polarization (DP), general nesting logit (GNL), Randles models, and other improved models. Table 1 introduces common equivalent circuit models from the aspects of model structure, parameters, and benefits and drawbacks of the models.

In the Rint model [43,44], U_{oc} represents an ideal voltage source; R_0 is the battery's equivalent resistance; U_L is the battery terminal voltage; and U_{OCV} is the open circuit voltage when no external load is present. The open circuit voltage U_{OCV} and the battery internal resistance R_0 are both functions of LIBs' SOC and are temperature dependent. This model has a fundamental framework and is straightforward to compute; however, it ignores the interior chemical processes of LIBs and is only appropriate for replicating the ideal functioning state of batteries. In response to the shortcomings of the Rint model, Hidalgo and Milishchuk proposed a Thevenin model that considers the internal chemical reactions of batteries [45,46]. This circuit model uses a first-order RC circuit to reflect the polarization reactions within the battery, which may accurately describe the battery's dynamic response [47]. The structure is relatively simple, with Ohmic resistance R_0 responsible for a sudden voltage drop relative to the current pulse applied, and polarizing capacitance C_p and resistance R_p expressing the battery's rebound characteristics. However, LIBs work in complex situations in practical applications, and a single RC circuit is not enough to fully reflect the dynamic performance of the battery. The PNGV structure [48] improves the first-order Thevenin model, which incorporates *a* capacitor element, C_b, that characterizes the battery capacity and the open circuit voltage as the battery capacity increases. In accordance with Kirchhoff's law, the model's state formula and output function are as follows: the model possesses a more straightforward structure and higher accuracy and dynamic performance compared to the first-order Thevenin model, but voltage hysteresis has not been considered and immediate accuracy is not ideal. The order of RC equivalent circuit models includes zero order, first-order, second-order (also known as DP) [49], and multi-order models. The second-order RC model is one order higher than the Thevenin model and has a higher model accuracy. It is worth noting that the greater the order of the RC equivalent circuit model, the better. Although more advanced orders can more accurately estimate the internal response and outward operating condition of LIBs, the model becomes more complex and difficult to calculate. The GNL model considers the self-discharge factor on the basis of the DP model [50], which has a higher simulation accuracy for aging batteries and can give the state estimation values have more minor errors and fast-tracking [51]. However, at the same time, the model is also more complex and difficult to calculate.

Table 1. Comparison of common equivalent circuit models for LIBs.

	Model	Circuit	Advantage	Disadvantage
Time domain	Rint		Simple structure and calculation; easy to determine parameters	Only simulates ideal SOC, ignoring the internal battery reactions
	Thevenin		Higher accuracy; simpler calculation; describes polarization reaction	Insufficient RC order; parameters are affected by aging and temperature
	PNGV		Real-time estimation of open circuit voltage, capacity changes, and SOC	Difficulty in identifying cumulative errors in parameters
	DP		Higher simulation degree; strong real-time performance	More complex structure, without considering factors such as temperature;
	GNL		High simulation accuracy; considers the effects of self-discharge and overcharging	complex model and calculations; difficult noise and parameter identification
Frequency domain	Randles model		High model accuracy, reflecting the internal chemical reactions from the frequency domain	Not necessarily consistent with time-domain characteristics
	Improved Thevenin model		Low calculation cost; the internal chemical reactions are analyzed from the frequency domain	Not necessarily consistent with time-domain characteristics
	Improved DP model		High model accuracy, reflecting the internal chemical reactions from the frequency domain	Not necessarily consistent with time-domain characteristics

The above-mentioned ECM model is a simulation of the working characteristics of batteries from a time-domain perspective. A similar battery model is an integer order equivalent circuit model that can represent the functioning condition of batteries more realistically as the model order increases. However, a higher order also means that the model is complex and difficult to calculate. The energy transfer between the battery and the load/excitation during charging and discharging frequently causes the battery to enter a high-frequency signal stress state, and a sequence of parallel RC networks cannot accurately depict the battery's internal response. As a result, in recent years, an increasing number of researchers have deployed fractional order equivalent (FOM) models to investigate batteries, which may more appropriately represent the electrochemical processes of lithium-ion batteries, such as the transfer of charge, material transfer, and the double layer effect.

As shown in Figure 4, a typical LIB electrochemical impedance spectroscopy (EIS) data curve is broken down into three sections: low-frequency linear segment, intermediate frequency semi-elliptical segment, and high-frequency inductive segment. The equivalent circuit model is the Randles model [52]. We applied various frequency sinusoidal AC signals and amplitudes to battery electrochemical systems to obtain more accurate electrochemical impedance spectrum test results, thereby gaining an accurate understanding of the dynamic characteristics of batteries at different frequencies: (1) using Z_W to represent the low-frequency Warburg impedance related to lithium-ion diffusion dynamics with positive and negative electrodes; (2) the constant phase element (CPE) and polarization resistance's parallel connection represents the mid-frequency semi-elliptical segment related to transfer of charge reaction and double-layer capacitance; and (3) inductance L explains the battery's inductance properties and the inductive composition brought by the testing cable and connecting device. Among them, R_0 is the Ohmic internal resistance, R_{ct} is the charge transfer impedance, and the CPE's impedance expression in the complex frequency domain is $Z_{CPE}(s) = 1/C_P s^{\alpha}$; C_P is a parameter similar to capacitance; and α is the order, $\alpha \in (0, 1)$. When α = 0, the CPE is equivalent to resistance; when α = 1, the CPE is equivalent to capacitance. Pablu et al. [53] improved the high-frequency part based on the Randles model and found that complex models suitable for EIS fitting may not be optimal in time-domain fitting. Therefore, it is important to focus on this difference when modeling the high-frequency part, and different high-frequency models can be selected according to the other application fields. In addition, some researchers have also made fractional order improvements to the Thevenin and DP models to ensure high simulation and computational efficiency [54]. Simone et al. [55] analyzed the variation in internal resistance with SOC and temperature in various aging scenarios based on electrochemical impedance spectroscopy. They established a mathematical model to forecast how battery internal resistance would change in response to aging, SOC, and temperature.

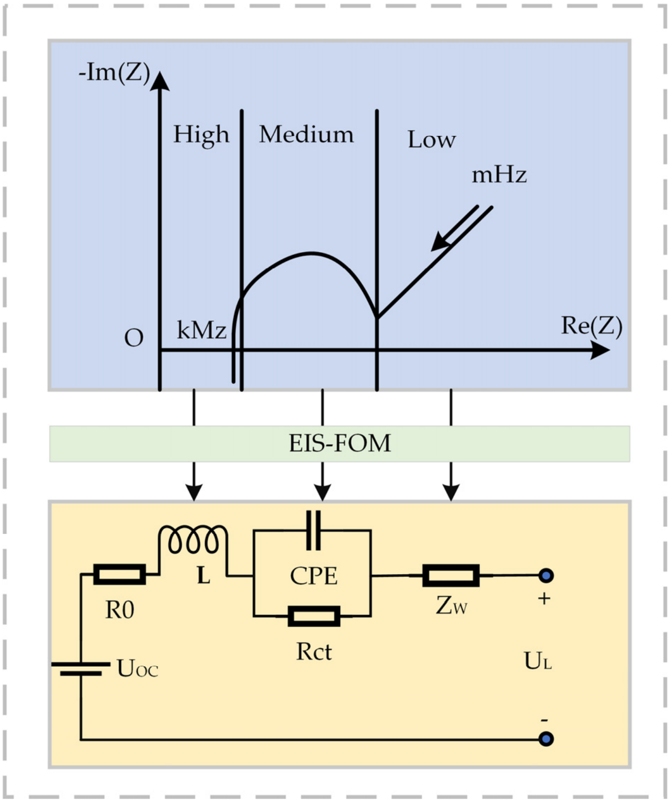


Figure 4. Typical LIB's EIS and its equivalent circuit model.

4. Data-Driven Approach

Data-driven methods do not consider the electrochemical reaction mechanism within the battery but instead use machine learning techniques to create a nonlinear mapping connection between the charging characteristics of LIB and its charging state [56]. Data mining techniques are used to analyze and extract lithium battery characteristics, train and establish models utilizing the patterns exhibited by large amounts of test data, and then use online monitoring data parameters to input the models in order to predict the SOC of the lithium battery efficiently.

The three primary data-driven techniques are neural networks (NNs), support vector machine (SVM), and Gaussian process regression (GPR). The support vector machine method is robust but is inappropriate for processing large amounts of data [57]. Zhang et al. established a sparse least squares support vector machine model to achieve online estimation of battery SOC by selecting a tiny percentage of data samples to capture their changing features [58]. Gaussian regression is also more suitable for lightweight data processing. Ali et al. improved the adaptive Gaussian-regression-based SOC estimate technique, which directly maps battery parameters, for instance, temperature, capacity, and voltage, to the corresponding model, achieving SOC estimation on embedded platforms [59]. A Gaussian process regression (GPR)-based data-driven approach is proposed to address the issue of inconsistency in battery packs, which results in an SOC estimation performance lower than that of the conventional models with estimation errors of 3.9% under various dynamic cycles, temperatures, aging circumstances, and even extreme situations [60]. The neural network only needs to use physical data measurable by lithium batteries to establish a model, and then the model is trained by extracting these data features, with strong nonlinear mapping ability. Researchers often integrate neural network estimation with other estimation methods to make neural network estimation more accurate. For example, integrating feedforward neural networks with Kalman filtering can reduce errors and accurately produce an estimate under temperature conditions and initial capacity changes [61]. Ali et al. presented a novel long short-term memory (LSTM) network that achieves accurate SOC estimation by using a time step internal attention mechanism and position encoding, thereby obtaining the optimal root mean square error with an average absolute error of 0.68% and 0.91%, respectively [62]. Liu et al. propose a unique data-driven prediction method (DDP) for properly modeling battery aging and capacity across several scales and physical fields, capturing dynamic deviations based on in situ data measurement, and monitoring battery SOC and health [63–65].

5. Joint Estimation Method

The experimental measurement method requires obtaining experimental data through extensive LIB charging and draining experiments under different working circumstances, which can be time consuming. Model-based SOC estimation methods require high model accuracy and a significant amount of time to establish battery models. The data-driven rule requires a large and accurate dataset to train neural networks and high completeness and accuracy of the dataset samples. Whether it is an experimental method, electrochemical model approach, equivalent circuit model approach, or data-driven approach, every method has its own shortcomings, so the joint estimation method has gradually come to be widely used by many.

5.1. SOC Estimate Approach Based on the Combination of a Model and Algorithm

The model-based SOC estimation method includes model establishment and a state estimation algorithm, as shown in Figure 5. This method requires first analyzing the model parameters through a parameter identification algorithm and determining specific values to obtain complete model parameters and create the model. Finally, based on the model, the state equation is established to observe and estimate the SOC.

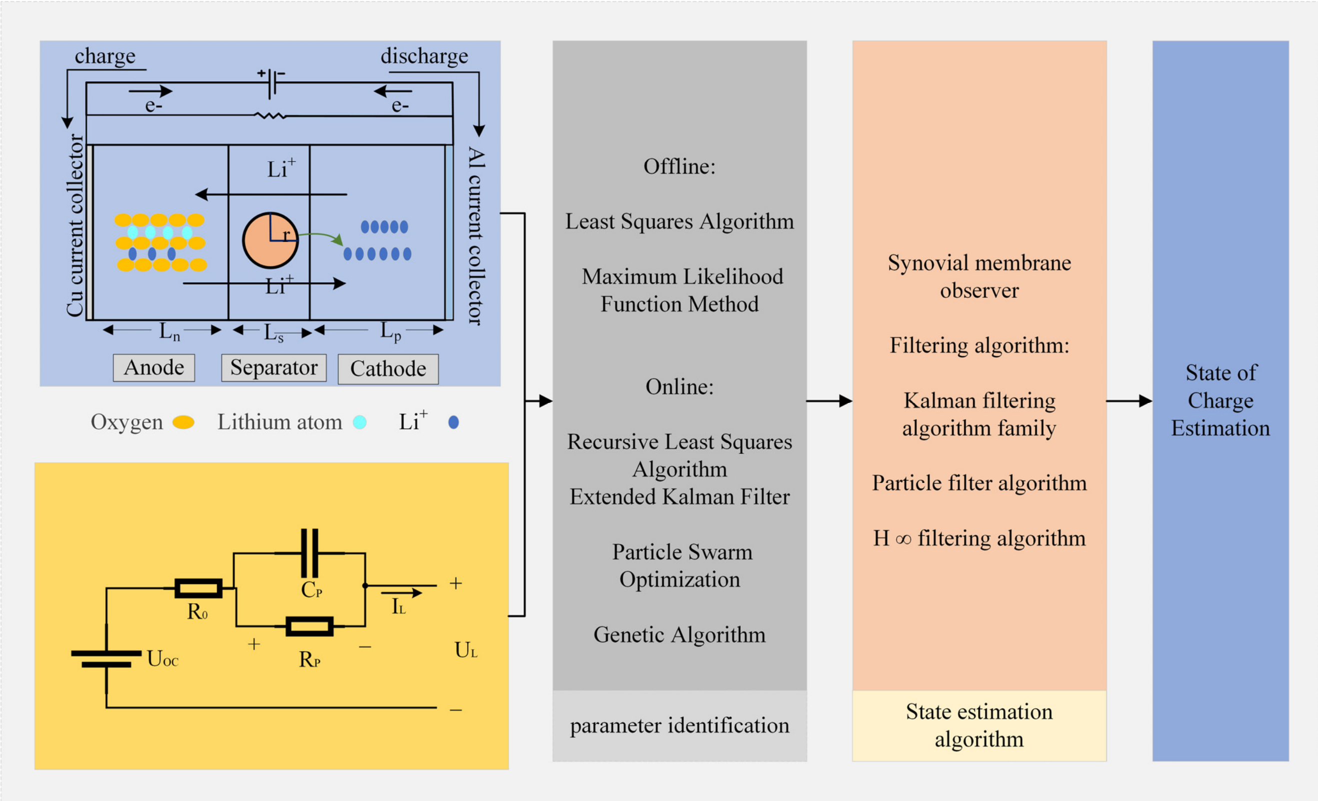


Figure 5. Model-based SOC estimation for LIBs.

5.1.1. Model Parameters' Identification

There are two ways to establish models: offline and online. Offline modeling simulates the static working state of lithium batteries, and the corresponding parameter identification is also obtained offline. In the subsequent estimation of te SOC, parameter identification is not necessary, so the model is straightforward to compute. The corresponding methods include the least squares algorithm [66] and the maximum likelihood function method [67]. However, LIBs cannot always be in the ideal state during parameter identification. Complex operating conditions and factors such as battery degradation and aging can lead to inconsistencies between the battery's actual condition and the collected data, making it impossible to guarantee the precision of the model. Online modeling is a continuous estimation of model parameters based on the particular state in which lithium batteries operate, to capture completely the dynamic functioning of lithium batteries. The model has high accuracy, but the corresponding computational workload is also higher. The corresponding methods currently include a recursive least squares algorithm [68], an extended Kalman filtering algorithm [69], a particle swarm optimization algorithm [70], a genetic algorithm [71], etc.

5.1.2. State Estimation Algorithm

State estimation methods are mainly separated into two categories: filter-based and sliding film observer-based methods. The filtering algorithms include the H-infinity filter (AHIF) algorithm, particle filtering algorithm, and Kalman filtering method family. The Kalman family algorithms mainly consist of the unscented Kalman filter (UKF), cubature Kalman filter (CKF), and extended Kalman filter (EKF).

The Kalman filtering algorithm was first developed by R E. Kalman [72], who proposed a technique that uses the current state variable based on the estimated values from the previous moment and the observed values from the current moment, with the minimal mean square error serving as the estimation criterion. However, this algorithm can only be limited to linear systems; when used in nonlinear systems, it is necessary to linearize the nonlinear system's observation equations and state equations. The extended Kalman filtering algorithm [73] utilizes first-order Taylor expansion to locally linearize nonlinear system equations, allowing for the use of Kalman-filtering-algorithm-related theories in nonlinear systems. However, there are issues with computational complexity and mistakes brought on by omitting higher-order terms. To address the issue of errors brought on by omitting higher-order terms, Cheng et al. used finite difference methods to linearize the original Taylor expansion term, resulting in higher accuracy [74]. The unscented Kalman filtering algorithm is similar to the extended Kalman algorithm in that both linearize nonlinear systems to enable their application to Kalman filtering algorithms. Sigma sampling is performed near the estimation points using an unscented transformation, and the Gaussian density function represented by these sampling points is utilized to approximate the state probability density operation, resulting in the prediction model's mean and variance. This method simplifies the computational complexity and has higher accuracy, but there is a problem of filtering divergence due to the adverse determination of the error covariance matrix [75]. The volumetric Kalman filtering algorithm samples are in accordance with the spherical radial criteria and variance of a nonlinear system using an equally weighted point set. Compared to EKF and UKF, it has higher accuracy and a faster calculation speed [76]. The sliding film observer method designs the sliding film surface based on the state equation of lithium batteries, and it uses sliding film variable structure control to replace traditional state observers, to ensure that the operational status of lithium batteries can be monitored and forecasted at any given moment. This algorithm has a strong anti-interference ability [77].

5.2. Combining Different Methods

The joint estimation method supplements the experimental measurement method, model method, state estimation algorithm, and data-driven method mentioned above, making the estimation method of SOC simpler, faster, more accurate, and reliable.

Buchicchio et al. [78] proposed an approach for SOC estimate based on EIS and equivalent circuit models, to explain battery impedance's frequency and temporal domain characteristics, and validated this method through effective model training on datasets including EIS measurements from four lithium-ion cylinder batteries at various SOC values. Sun et al. [79] focused on the practicality of electrochemical models and their applicability under complex environmental temperatures. They used the finite difference method and Galerkin method to reduce the sequence of solid–liquid phase equations of the P2D model and combined the P2D framework with the equivalent circuit model via transfer functions. Not only does this consider the influence of temperature on lithium batteries, but it also successfully reduces and simplifies the electrochemical model. Yu et al. [80] proposed a method to integrate the internal mechanistic knowledge of batteries into a deep learning framework. Firstly, use a simplifying electrochemical model to generate physical variables associated with the mechanism to broaden the DL model's input. Additionally, identifying highly linked variables by integrating Bayesian optimization with long short-term memory (LSTM) networks. By incorporating all of the chosen, highly associated variables into the together trained input, the best SOC estimation performance can be achieved. The findings show that the suggested approach enhances SOC estimate performance at a negligible computational cost increase. Liu et al. [81] proposed a method for constructing a digital-twin-based thermocouple model for battery cells with lithium ion, which inputs the surface battery temperature in various charging and discharging circumstances into a dual polarization (DP) equivalent circuit model to more accurately forecast the temperature, capacitance, and internal resistance of lithium-ion batteries over time.

6. Conclusions and Outlook

6.1. Conclusions

Accurate monitoring and estimation of LIBs' SOC is vital to ensure the full performance of batteries and battery systems. The following are the primary conclusions:

(1) The modeling methods can be divided into equivalent circuit model types and electrochemical models. The P2D model was first proposed to simulate the internal response mechanism of lithium-based batteries in detail. Due to its complex model and complicated calculation, simplified single-particle models and single-particle models considering electrolytes have emerged. LIBs are often subjected to complex working conditions involving multiple physical fields such as mechanics, electrochemistry, and thermodynamics. Therefore, the multi-physical model can simulate more accurately the working state of lithium batteries. Model reduction methods can be used for complex model problems. The equivalent circuit model compares and analyzes the model methods from two perspectives: time and frequency domains. The time-domain model simulates the working state of lithium batteries by changing the order of RC parallel circuits to control different levels of accuracy and model complexity. The frequency-domain model establishes a fractional order equivalent model by separating different frequency bands through electrochemical impedance spectroscopy, which can reveal the dynamic features of lithium batteries at various frequencies. The optimal performance of lithium batteries in the frequency domain does not correspond one-to-one with the time domain, so it is necessary to choose an approach to gauge the lithium batteries' SOC according to the specific needs of the scenario.

(2) The data-driven method for estimating the LIBs' SOC does not consider the internal reaction mechanism and the external working state of the batteries. Its accuracy depends on the breadth of the dataset and the robustness of the training network algorithm. The adaptive Gaussian regression technique translates elements such as temperatures, age, and charge speed to the response model to improve the accuracy of the SOC estimation. However, updating the training data in real-time is essential. In addition, integrating neural network methods with other algorithms, such as Kalman filtering, can also help reduce model errors.

(3) The SOC prediction processes for LIBs are influenced by various factors, and there is also a coupling association among the battery's multiple factors. Different estimation methods cannot simultaneously meet the requirements of real-time online, high-precision, and high-speed SOC estimation. Therefore, the joint estimation method is increasingly widely used. After setting up the initial model through parameter identification, it is often combined with state estimation algorithms, such as filtering algorithms and sliding membrane observers, to simplify computational complexity and improve estimation accuracy. The combination of equivalent circuit models and electrochemical models can accurately reflect their physical significance and real-time changes in working conditions. The amalgamation of the model method and data-driven approach ensures that different influencing factors are considered in the model, ensuring the completeness of the dataset. At the same time, machine learning algorithms significantly improve estimation efficiency and effectiveness.

(4) The various application scenarios and characteristics of LIBs have led to significant differences in the selection of SOC estimation methods. The ampere-hour integration approach and the Coulomb method are suitable for consumer electronics because they do not need to consider the internal mechanism of the battery, the starting capacity setting is more flexible, and the operation is easy and straightforward. Because of their quick convergence speed and excellent noise reduction capacity, the Kalman series algorithms are ideal for use in electric car applications. In the realm of communication base stations, neural networks and SVMs are both more appropriate. The neural network technique has significant nonlinear processing capabilities that can effectively predict the state of charge of LIBs without the need for high-precision battery models. It can be very useful in high-dimensional pattern recognition, nonlinear regression, and other tasks. In the field of energy storage in the power system, the joint estimation method can accurately and reliably estimate various parameters of lithium batteries such as voltage, current temperature, aging coefficient, and so on, as well as preprocess the data by creating a comprehensive battery charging and discharging database.

6.2. Outlook for Future Research on SOC

(1) It is essential to establish an accurate model in model-based SOC estimation methods. LIBs are a nonlinear time-varying system, and if the electrochemical model describes each ion reaction in detail, it will inevitably lead to complex models and complicated calculations. Considering that single-particle motion cannot truly simulate the internal responses of batteries, the electrochemical model needs to consider both its simplification and accuracy. The equivalent circuit model has a solid real-time performance and can reflect the dynamic characteristics of LIBs well; concurrently, it must also consider the true reflection of the physical characteristics of lithium batteries.

(2) Self-discharge, aging, internal temperature changes, environmental temperature, and other factors of the battery can affect the accuracy of SOC estimation for LIBs. Moreover, many existing research results are based on laboratory experiments and simulations, which do not fully comply with actual production and application situations. Therefore, it is necessary to strengthen lithium battery experiments in complex environments with multiple operating conditions to improve the adaptability of the proposed method to changing environments.

(3) Machine learning plays a pivotal role in data-driven methods for estimating SOC of LIBs, offering sophisticated tools to handle the complexities and nonlinearities inherent in battery behavior. These methods leverage historical and real-time data to learn patterns and predict the SOC with high accuracy, overcoming the limitations of traditional model-based approaches. Currently, the databases are still limited to specific applications. The success of data-driven methods in SOC estimation depends on the quality and quantity of the data, objectives, and model complexity. Therefore, it is necessary to establish a database of LIB operating conditions with multiple types, regions, seasons, modes, and durations to promote the research of machine learning algorithms for battery state estimation without overfitting, interpretability, or the need for substantial computational resources.

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