batteries

Review

Status and Prospects of Research on Lithium-Ion Battery Parameter Identification

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Abstract: Lithium-ion batteries are widely used in electric vehicles and renewable energy storage systems due to their superior performance in most aspects. Battery parameter identification, as one of the core technologies to achieve an efficient battery management system (BMS), is the key to predicting and managing the performance of Li-ion batteries. However, due to the complex chemical reactions and thermodynamic processes inside lithium-ion batteries, coupled with the influence of the external environment, accurate identification of lithium-ion battery parameters has become an urgent problem to be solved. In addition, data-driven parameter identification can enable battery models to better understand battery behavior, which is one of the focuses of future research. For this reason, this paper comprehensively reviews the application of data-driven parameter identification methods in different scenarios. Firstly, the research briefly explains the working principle of lithium-ion batteries and the key parameters affecting their performance. Secondly, this paper deeply discusses data-driven methods for parameter identification, which are widely used nowadays, and provides improvement ideas to address the shortcomings of traditional methods. Finally, the paper discusses the challenges faced by parameter identification technology for lithium-ion batteries and envisages future prospects.

Keywords: battery management system; data-driven method; lithium-ion battery; parameter identification

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1. Introduction

With the increasing installed capacity of new energy and the increasing popularity of electronic equipment, the rational use of large-scale integrated energy storage battery cells has become a current trend, and lithium-ion batteries are widely used because of their stable performance, long life, low pollution, and fast charging speed [1,2]. According to a white paper, the total shipment of lithium-ion batteries in the world in 2023 will be 1202.6 GW·h, a year-on-year increase of 25.6%. Global shipments of lithium-ion batteries are expected to reach 1926.0 GW·h by 2025 [3], so research on lithium-ion batteries is becoming more significant as the use of lithium-ion batteries increases worldwide.

At present, lithium-ion batteries are one of the main energy sources for electrochemical energy storage power stations and new energy vehicles, but due to the complex operating conditions of lithium-ion batteries, it is necessary to establish an effective battery management system (BMS) to monitor the batteries continuously. As an integrated electronic system, in addition to effectively monitoring the health and safety of the battery and ensuring its optimal performance, its key responsibilities also include calculating the main parameters such as voltage, current, temperature, state of charge (SOC), and state of health (SOH) of the battery [4,5], as well as protecting the battery from overcharge, overdischarge, abnormal temperature, and short circuits and implementing functions such as data logging

and fault diagnosis, etc. In addition, advanced BMS may also include thermal management, energy optimization, and research on battery charging and discharging strategies [6–8]. While battery model parameter identification plays a crucial role in realizing efficient battery management systems, traditional battery parameter identification methods often rely on complex empirical models or electrochemical models (EM), which require a large amount of experimental data and computational time. The empirical model is often called Equivalent Circuit Model (ECM) [9,10], and the basic idea is to use electrical characteristics of circuit components to describe the characteristics of electrochemical systems; in other words, it can describe batteries with voltage sources, resistors, and capacitors based on the circuit. ECM has fewer parameters and a simpler structure than other models, so it is the most widely used battery model in BMS. In another aspect, electrochemical models are mainly divided into pseudo two-dimensional (P2D) models, single particle (SP) models, and enhanced single particle (ESP) models [11,12]. In recent years, some researchers have also reviewed the methods of battery parameter identification. Barcellona et al. [13] and Madani et al. [14] have comprehensively summarized different models and parameter identification techniques for lithium-ion batteries.

However, with the rise of artificial intelligence technology, especially the rapid development of deep learning, data-driven parameter identification methods provide new research ideas for battery management. And most of the existing research focuses on specific types of data-driven identification methods, lacking a comprehensive comparison and in-depth analysis. In particular, how to effectively improve the accuracy of traditional physical models and rationally use flexible data-driven models to adapt complex and diverse battery application scenarios have become urgent problems to be solved. In addition, with the development of battery requirements in the direction of higher energy density, longer life, and lower cost, more new battery types and application scenarios have emerged; therefore, the parameter identification methods are also facing new challenges and requirements. In view of this, this paper aims to systematically analyze and compare the existing data-driven battery model parameter identification methods while providing optimization ideas and improvement directions for the problems existing in different identification methods. In addition, considering the latest battery technology and application requirements, this paper also involves emerging parameter identification methods that are in line with the current development trend of science and technology, which provides a reference for the subsequent selection of appropriate parameter identification methods in different scenarios and also helps to promote the development of battery technology and BMS. Finally, this paper discusses the current challenges of parameter identification of lithium-ion batteries and predicts possible research directions in the future.

The remaining sections are organized as follows. Section 2 introduces the basic principles and key parameters of the battery. Section 3 explains the parameter identification method based on least squares and its derivative algorithms and proposes modification ideas. Section 4 presents the existing data-driven parameter identification method and summarizes the analysis. The challenges and perspectives are provided in Section 5. The conclusions are provided in Section 6.

2. Structural Characteristics of Lithium-Ion Batteries

2.1. Internal Mechanism of Lithium-Ion Battery

A lithium-ion battery is a type of secondary battery that typically contains two kinds of compounds capable of embedding and detaching Li^+, serving as the anode and cathode of the battery, using the currently commercialized lithium-ion battery with graphite as the anode and lithium cobaltate as the cathode as an example. The electrolyte adopts ethylene carbonate (EC) and dimethyl carbonate (DMC), and the charging process is as follows: During the charging process, the potential of the power supply forces Li^+ to move from lithium cobaltate to the cathode, passing through the electrolyte and diaphragm embedded in graphite. The lithium-ion moves through the electrolyte to the negative electrode, passing through the electrolyte and separator to be embedded in graphite. Simultaneously,

electrons flow from the positive electrode to the negative electrode through an external circuit to replenish the charge balance formed by the lithium-ions in the negative electrode. This process is accompanied by the oxidation of Co^{3+} in the positive electrode material. The discharge process is reversed; Li^+ is released through an internal electrochemical drive and moves through the electrolyte and becomes embedded in the negative electrode. Electrons reach the positive electrode from the external circuit and trigger the reduction of high-valent cobalt, in which the battery releases electrical energy through the external circuit to power the device [15,16]. The basic principle is shown in Figure 1. The electrochemical reaction equation of the lithium-ion battery during cycling is as follows:

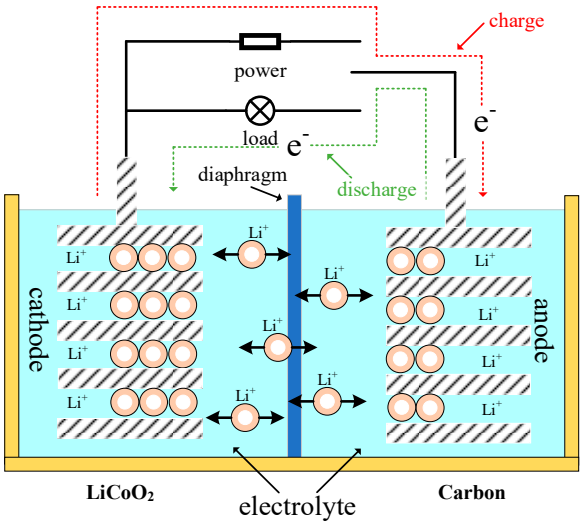

Figure 1. Working principles diagram of a rechargeable lithium-ion battery.

Anodic equation:

$$LiCoO_2 \underset{\text{discharge}}{\overset{\text{charge}}{\rightleftarrows}} Li_{1-x}CoO_2 + xLi^+ + xe^- \quad (1)$$

Cathode equation:

$$6C + xLi^+ + xe^- \underset{\text{discharge}}{\overset{\text{charge}}{\rightleftarrows}} Li_xC_6 \quad (2)$$

Overall reaction equation:

$$LiCoO_2 + 6C \underset{\text{discharge}}{\overset{\text{charge}}{\rightleftarrows}} Li_{1-x}CoO_2 + Li_xC_6 \quad (3)$$

2.2. Basic Parameters of a Lithium-Ion Battery

In order to understand and study the performance of lithium-ion batteries, it is necessary to start from the internal parameters of lithium-ion batteries, and the basic parameters of lithium-ion batteries are as follows:

1. Open-circuit voltage

Open circuit voltage (OCV) refers to the potential difference between the positive and negative poles of the battery when the battery is not connected to any load or power supply [17,18], which is one of the most significant indicators of the electrochemical state of the lithium-ion batteries, and it also plays an important role in evaluating the electrode materials [19] and aging state [20]. Besides, there is a nonlinear relationship between the OCV and SOC of the battery in a steady state, while different models of batteries have their

specific SOC-OCV curves, and accurate OCV values can provide a great foundation for the state estimation and study of optimization strategies of batteries [21].

2. Capacity

Battery capacity is one of the important indicators to measure the performance of the battery; it represents the amount of electricity released by the battery under certain conditions such as discharge rate, temperature, termination voltage, etc., which is generally divided into rated capacity and actual capacity [22]. The rated capacity refers to the capacity of the battery to work continuously for a long time under certain working conditions under the condition of an ambient temperature of 20 ± 5 °C, while the actual capacity refers to the actual amount of power that the battery can give under certain current density, termination voltage, and other conditions. The actual capacitance will be affected by various factors such as temperature, humidity, charge, and discharge rate during the actual use of the battery [23,24].

3. Internal resistance

The internal resistance of a lithium-ion battery is the resistance that hinders the passage of current during the conductive process of the battery. It is mainly divided into ohmic resistance and polarization resistance [25], and polarization resistance can be further classified into electrochemical polarization internal resistance and concentration polarization internal resistance. The ohmic internal resistance is affected by the electrode material, electrolyte, etc., resulting in continuous changes during the detection process, and the polarization internal resistance will change to varying degrees with the process of electrochemical reaction inside the battery, which has the dynamic characteristics of time and current [26]. The main measurement methods of battery internal resistance include the DC internal resistance method, AC impedance spectroscopy method, pulse discharge method, etc.

4. State of charge

The state of charge of a battery refers to the percentage of the battery's remaining charge, which is usually used to express the charge level of the battery. There are many ways to describe SOC; one that is widely used as in [27] is:

$$SOC(t_1) = SOC(t_0) - \frac{1}{C_r}\int_{t_0}^{t_1} I(t)dt \quad (4)$$

where the t_0 and t_1 is the start and end time, respectively. It is generally accepted that the SOC = 1 when the battery is fully charged using a standard charging method. Cr is the rated capacity of the battery. In the actual use process, the lithium-ion battery SOC will be affected by many factors such as charge and discharge current, ambient temperature, and self-discharge, which make it difficult to measure directly [28]. Accurate estimation of SOC value can ensure the stable and safe operation of related equipment; therefore, the estimation of SOC is also one of the important research directions at domestic and overseas.

5. Battery self-discharge rate

The self-discharge rate of a battery is also known as the charge retention capacity, which refers to the ability to store power under the open-circuit voltage condition [29]. It is seriously affected by temperature, and usually the lower the ambient temperature, the lower the self-discharge rate. Compared with other rechargeable batteries, lithium-ion batteries have a lower self-discharge rate, generally 2~5% at room temperature [30].

3. Parameter Identification Based on Least Squares and Its Derivative Algorithms

3.1. Least Squares

Least squares(LS) parameter identification is usually used for offline parameter identification of batteries, which is usually carried out under non-operating conditions, and its process is similar to the optimization method. The purpose is to match the measurement

curve with the target curve and find the optimal solution of the state parameters by solving the minimum value of the objective function [31,32]. The flowchart of the offline parameter identification is shown as an example in Figure 2.

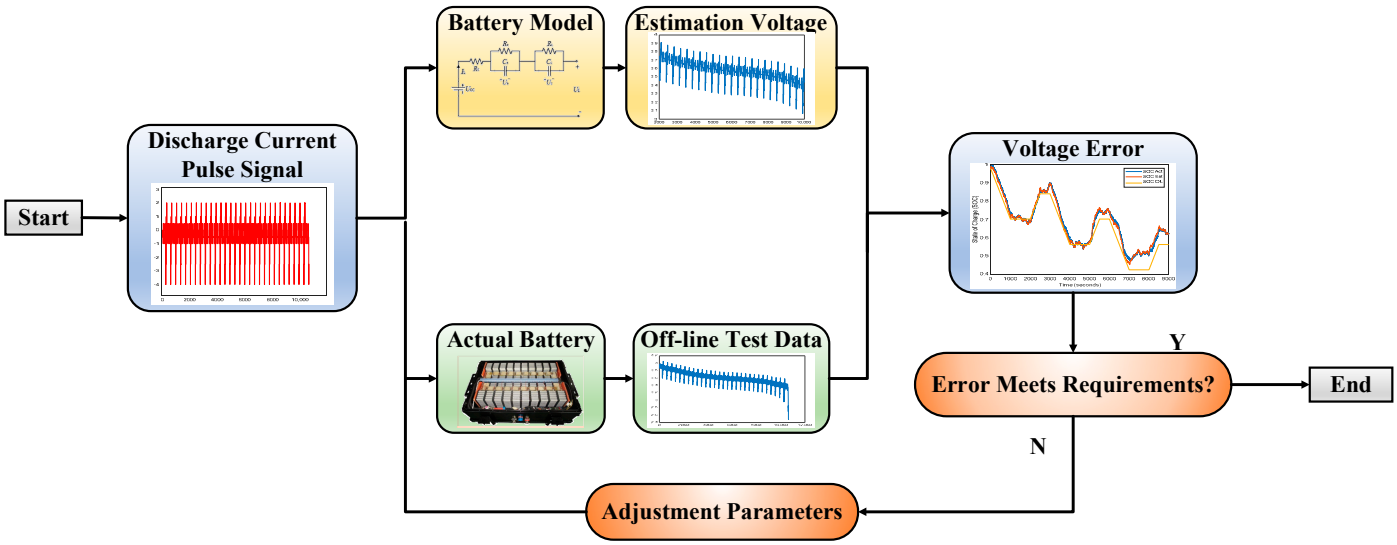

Figure 2. Flowchart of offline parameter identification.

Before the least squares method can be used to identify parameters, the battery needs to undergo a series of tests, such as charge-discharge cycles, pulse tests, etc. Its essence is to estimate the parameters by minimizing the sum of squares of the errors between the model prediction output and the experimental data [33], which is simple, time-consuming, and easy to identify [34], and the relevant algorithm process can be summarized as follows.

The mathematical model of the battery system is assumed to be:

$$A\left(z^{-1}\right)Y(i) = B\left(z^{-1}\right)X(i) + e(i) \tag{5}$$

where the *Y(i)* and the *X(i)* is the output and input of the system, and the *e(i)* is the systematic measurement error. The difference equation of the system is expressed as:

$$Y(i) = \sum_{k=1}^{n} a_i Y(i-k) + \sum_{k=1}^{n} b_i X(i-k) + e(i) \tag{6}$$

Writing Equation (5) in least squares form can be expressed as:

$$Y(i) = \varphi^T(i)\theta + e(i) \tag{7}$$

where the model parameters vector to be estimated and the input data vector can be expressed as follows:

$$\begin{cases} \theta = [a_1\ a_2 \cdots a_n\ b_1\ b_2 \cdots b_n]^T \\ \varphi(i) = [Y(i-1)Y(i-2)\cdots Y(i-n)X(i-1)X(i-2)\cdots X(i-n)]^T \end{cases} \tag{8}$$

After m observations, let the standard function J be:

$$J = \sum_{i=1}^{m} \left(Y(i) - \varphi(i)^T\theta\right)^2 = \left(Y - \varphi^T\theta\right)^T\left(Y - \varphi^T\theta\right) \tag{9}$$

where $\varphi(i)^T\theta$ is the value predicted by the model at the ith data point by the parameter vector θ. By minimizing the standard function J, when

$$\frac{\partial J}{\partial \theta} = \frac{\partial}{\partial \theta}[(Y - \varphi^T\theta)^T(Y - \varphi^T\theta)] = 0 \tag{10}$$

The best parameter vector estimate that can be found is:

$$\hat{\theta}_{LS} = (\varphi^T\varphi)^{-1}\varphi^T Y \tag{11}$$

Then the least squares form for $Y(i)$ can be expressed as:

$$Y(i) = \varphi^T(i)\theta \tag{12}$$

The core of the LS method to identify battery parameters aims to find a set of parameters that allow the mathematical model to best fit the behavior of the actual battery, and its advantage lies in the ability to analyze and optimize the parameters in detail without affecting the performance of the battery; therefore it is usually used in battery performance evaluation or the early stage of battery design [35]. However, the disadvantages of the LS method are also very obvious in that its fixed mode cannot meet the more complex working conditions; the identification of the parameter values cannot accurately reflect the real-time changes of the battery, so it is only applicable to some fixed scenarios [36].

3.2. Recursive Least Squares

Recursive least square (RLS) is one of the most common estimation methods currently in use, which is mainly suitable for the online parameter identification of batteries. The RLS method not only reduces a large number of preliminary experiments but also largely solves the time-varying problem of battery parameters [37]. The basic principle of online parameter identification is to use a unified input u(t), input to the system to be identified to generate the output y(t), and then superimpose with the measurement noise v(t) to form the observation output Z(t), compare with the model output generated in the system model to obtain the measurement error $\tilde{Z}(t)$, and then import it into the identification algorithm to correct the error through the generated parameter estimation vector. The schematic is shown as an example in Figure 3.

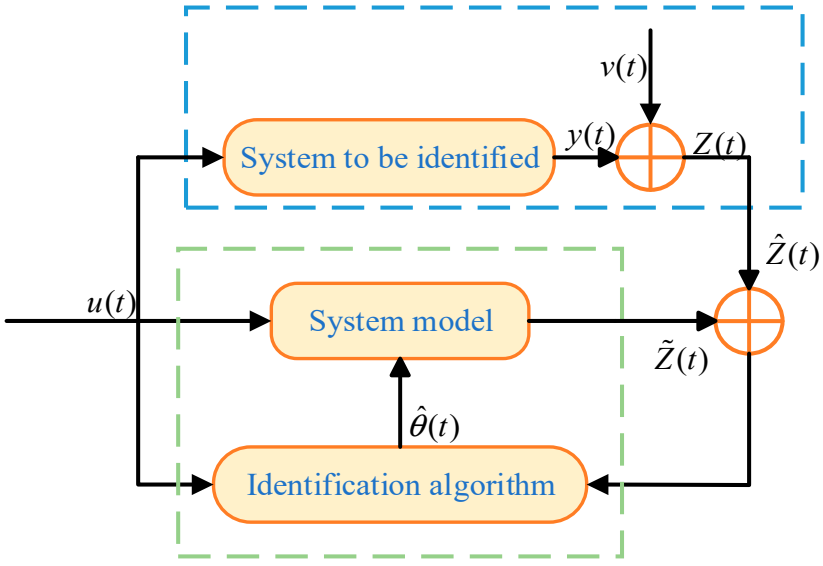

Figure 3. Basic principle of online identification.

The principle of the RLS method is to add a time-varying link on the basis of the LS method, which can update the parameter estimates in real time according to each new data

point, reducing the calculation of a large number of datasets. The nonlinear form of the RLS method is provided in Ref. [38], and the process evolves from Equation (11) to the recursive form is shown as:

$$\begin{cases} \hat{\theta}(i+1) = \hat{\theta}(i) + K(i+1) \times \left[Y(i+1) - \varphi^T(i+1)\hat{\theta}(i) \right] \\ e(i+1) = Y(i+1) - \varphi^T(i+1)\theta(i) \\ K(i+1) = \frac{P(i)\varphi(i+1)}{1+\varphi^T(i+1)P(i)\varphi(i+1)} \\ P(i+1) = P(i) - K(i+1)\varphi^T(i+1)P(i) \end{cases} \tag{13}$$

where the $\hat{\theta}$ is the parameter to be recognized, e is the estimated error of the system, K is the system gain, and P is the covariance matrix. According to the formula, the RLS method will calculate the result of the current LS according to the current new input data combined with the data calculated at the previous moment. However, in actual calculations, there are many areas that need to be improved in the process of parameter identification using the RLS method. Listed below are three aspects where the RLS method needs to be improved.

1. Data saturation

In the recursive process, as the number of cycles increases, the old data will continue to increase, and when accumulated to a certain extent, it will inevitably affect the recognition of new data, which ultimately leads to the termination of the parameter identification process. In order to reasonably allocate the proportion of old and new data and reduce the influence of old data on new data, researchers added a forgetting factor on the basis of RLS to match the parameter identification in different environments. The improved algorithm is called Forgetting Factor Recursive Least Squares (FFRLS). The recursive principle of FFRLS is based on Equation (13) and is shown as:

$$\begin{cases} \hat{\theta}(i+1) = \hat{\theta}(i) + K(i+1) \times \left[Y(i+1) - \varphi^T(i+1)\hat{\theta}(i) \right] \\ e(i+1) = Y(i+1) - \varphi^T(i+1)\theta(i) \\ K(i+1) = \frac{P(i)\varphi(i+1)}{1+\varphi^T(i+1)P(i)\varphi(i+1)} \\ P(i+1) = \frac{1}{\lambda}[P(i) - K(i+1)\varphi^T(i+1)P(i)] \end{cases} \tag{14}$$

where the λ is the forgetting factor, usually between 0.95 and 1, and different λ corresponds to different forgetting speeds; when $\lambda = 1$, it means no forgetting, and when $\lambda = 0$, it means all forgetting. Many scholars have tried to apply the FFRLS algorithm to different scenarios and found that the identification results are significantly improved compared with the traditional RLS algorithm. Xia et al. [39] used the FFRLS algorithm to continuously update the parameters in the battery model and then used the Kalman filter to estimate the SOC of the battery and verified the algorithm under different ambient temperatures and driving conditions, proving that the RLS algorithm can show good adaptability and accuracy in different scenarios. In addition, the selection of the forgetting factor in the FFRLS algorithm is also very important; different forgetting factors will affect the time-varying and accuracy of parameter identification. Based on this, Shi et al. [40] adjusted the forgetting factor by using the mean square value of the difference between the battery OCV and the terminal voltage in the sliding window mode. Lao et al. [41] proposed a variable forgetting factor least squares method Recursive Least Squares (AFFRLS), the principle of which is to adjust the size according to the error, and its relationship to the error can be expressed as:

$$\begin{cases} \lambda(k) = \lambda_{\min} + (1 - \lambda_{\min})^{\alpha(k)} \\ \alpha(k) = 2^{\rho e^2(k)} \end{cases} \tag{15}$$

where the $e(k)$ is the measurement error, $\alpha(k)$ is the intermediate variable, ρ is the undetermined coefficient, and its value range is within $[10^4, 5 \times 10^4]$. The most suitable λ-value is determined by adjusting the values of $e^2(k)$, but the convergence speed of this method is affected by the value of ρ, so the requirements for the adjustment of the coefficients are high. At the same time, considering the instability of the parameter results and the inaccuracy

of the initial state, Fan et al. [42] proposed an Adaptive Forgetting Factor Recursive Least Squares (AFFRLS) method based on Equation (15), which has both accuracy and stability, and it can make $e(k)$ quickly converge to the minimum value when λ is larger values, and when $e(k)$ is within the allowable error range, λ can rapidly approach the maximum. Its principle can be expressed as:

$$\begin{cases} \lambda(k) = \lambda_{\max} - (\lambda_{\max} - \lambda_{\min}) \cdot \arctan(\mu(k)) \cdot \frac{\pi}{2} \\ \mu(k) = round(\left|\frac{e(k)}{e_0}\right|^n) \end{cases} \tag{16}$$

where the $\lambda_{\max}$ and $\lambda_{\min}$ are the expected maximum and minimum values of λ, e_0 is the benchmark error. When $e(k)$ is smaller than e_0, the ratio by n exponentiation is scaled down, so that λ can quickly close to the $\lambda_{\max}$; when $e(k)$ is greater than e_0, the ratio expands and λ can more quickly converge to the $\lambda_{\min}$. Where the n is generally taken as 2 or 4, and the rounding function $round(\ \ )$ is used to reduce the intermediate of the transition value.

2. Unequal supply and demand

When using the LS method for parameter identification, the most obvious problem is the "inequality of supply and demand" caused by the incentive and identification parameters. In short, the excitation provided for parameter identification is less than the number of parameters that need to be identified. Taking the second-order RC equivalent circuit as an example, we need to identify five parameter results by only two inputs of voltage and current as the model excitation; in the higher order equivalent circuit, this problem will be more obvious, and in the actual process, we also need to consider the influence of various environmental factors, which results in a more complicated process. Therefore, it is very important to select the appropriate excitation input in order to fully reflect the internal characteristics of the lithium-ion battery. Considering that the parameter discrimination ability of lithium-ion batteries is poor when the input and output data are not suitable, Song et al. [43] found that the data selected for battery state estimation needs to have certain adaptability, while analyzing the accuracy of single-parameter and multi-parameter identification schemes, and verified that the recognition accuracy can be further improved when the current excitation meets certain criteria.

3. Different time scales

The dynamic characteristics of the battery are distributed in a wide frequency range. It contains both fast and slow response processes under the action of excitation, so the second-order RC circuit model will set two different time constants to correspond to different response links [44]. However, this lead to the result that the process of parameter identification cannot be ensured to take the corresponding links of each time constant into account at the same time, and when identifying one of the links, the other link may cause information loss or data saturation, which will greatly affect the accuracy of parameter identification [45,46]. In order to solve the above problems, relevant scholars propose a multi-time scale identification method. Taking ECM as an example, the basic principle is to apply different time constants to different time scales for identification, and its improvement idea is shown in Figure 4.

At present, many scholars use this method to improve the accuracy of ECM. Yang et al. [47] used a combination of the fixed memory recursive least squares method and fading extended Kalman filter method to obtain the parameters of the fast and slow dynamic links of the ECM, respectively, and the experimental results showed that the method had high consistency under different working conditions. In addition, many parameters of lithium-ion batteries change over time, so they can be improved along this line. Based on this, Shi et al. [48] established a multiple-time scales characteristics model for on-board lithium-ion batteries and distinguished between fast and slow changes in the model parameters of the resistance-capacitance links. Furthermore, Zou et al. [39] proposed a multi-time scale estimator that can adjust parameters on different time scales and verified the effectiveness of the method in verifying SOC and SOH. In general, multi-time-scale

identification allows the model to react sudden changes on fast time scales while adapting to sluggish changes on slow scales. This allows the model to have better responsiveness and flexibility while maintaining high accuracy.

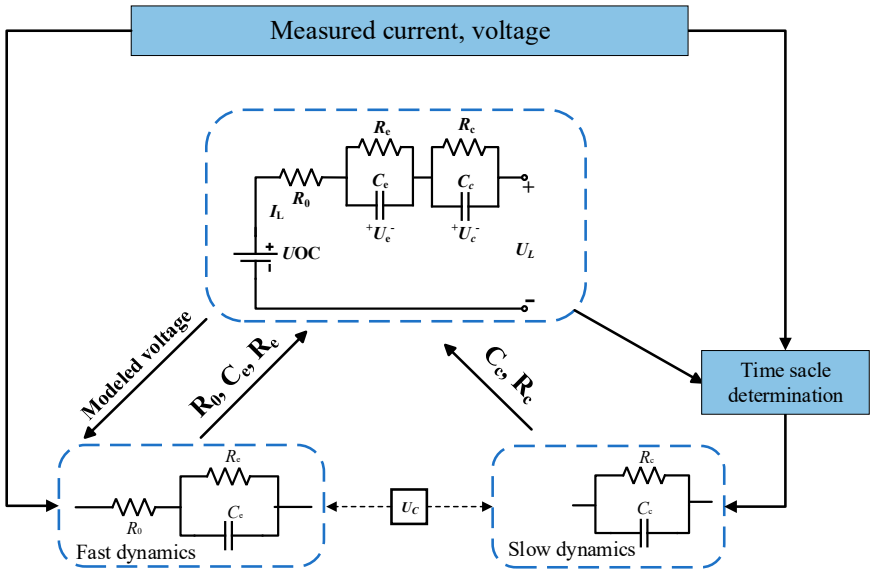

Figure 4. Improvement idea based on ECM with multiple time scales.

4. Data-Driven Parameter Identification

4.1. Heuristic Algorithms

Heuristic algorithms (HAs) are a kind of solution method constructed on the basis of specific empirical rules, which are often used to solve global optimal problems [49], but the traditional HA needs to evaluate the performance of the system by deriving all nonlinear constraint functions when solving practical problems [50], which is a very complex process. To solve this problem, relevant scholars have proposed meta-heuristic algorithms (MHA). This algorithm has better global search ability and higher robustness and has been effectively applied to constraint optimization problems in various fields [51–53], so it is also suitable for parameter identification of lithium-ion batteries, which can find the parameters closest to the actual data of the battery through iteration. Taking the most typical Genetic Algorithms (GA) [54] and Particle Swarm Optimization (PSO) in MHA as an example [55,56], when identifying battery parameters, the basic principle is to setting the parameters to be identified as the initial population, setting the error between the output of the battery model and the actual measured data as the fitness function, by evaluating the individuals separately through the fitness function and iterating continuously until the algorithm stop condition is satisfied, and then finding the optimal solution and output the optimal model parameters [57]. The process of GA and PSO is shown as an example in Figure 5.

Similar methods also include Tabu Search (TS) [58], Simulated Annealing (SA) [59], and Ant Colony Optimization (ACO) [60]. However, when using these algorithms, researchers have found that the convergence speed is relatively slow when used alone, and it is possible for GA and PSO to converge in the local optimal solution before reaching their global optimal solution. To face this problem, Srinivas et al. [61] applied adaptive probability to the intersection and mutation links of genetic algorithms, which effectively optimized the population diversity and convergence ability of genetic algorithms, but the method was limited to some links of GA and did not analyze from the whole part. In order to overcome this challenge, San et al. [62] applied adaptive links to all links of GA and proposed an Adaptive Genetic Algorithm (AGA), which provides an improved way to solve the identification problem of nonlinear systems. Moreover, considering that individual algorithms have obvious advantages and disadvantages when used, in order to maximize

the optimization ability of the algorithm, Garg H [50] proposed a PSO-GA hybrid algorithm to deal with nonlinear problems. The basic idea is to optimize the vector by using the PSO while using the genetic operator of GA to modify the decision vector, and it is considered as an effective algorithm that is suitable for various optimization problems. In addition, MHA is also suitable for model-specific optimization. Ren et al. [63] used PSO to optimize the key parameters of the long short-term memory (LSTM) network to match the data features of the lithium-ion battery with the network topology and experimentally verified that the method can effectively reduce the error. Recently, Nouri et al. [64] established an intelligent charge and discharge management system for electric vehicles and adopted a new method combining ANN and PSO to achieve data collection under different conditions, which greatly improved the robustness of the system.

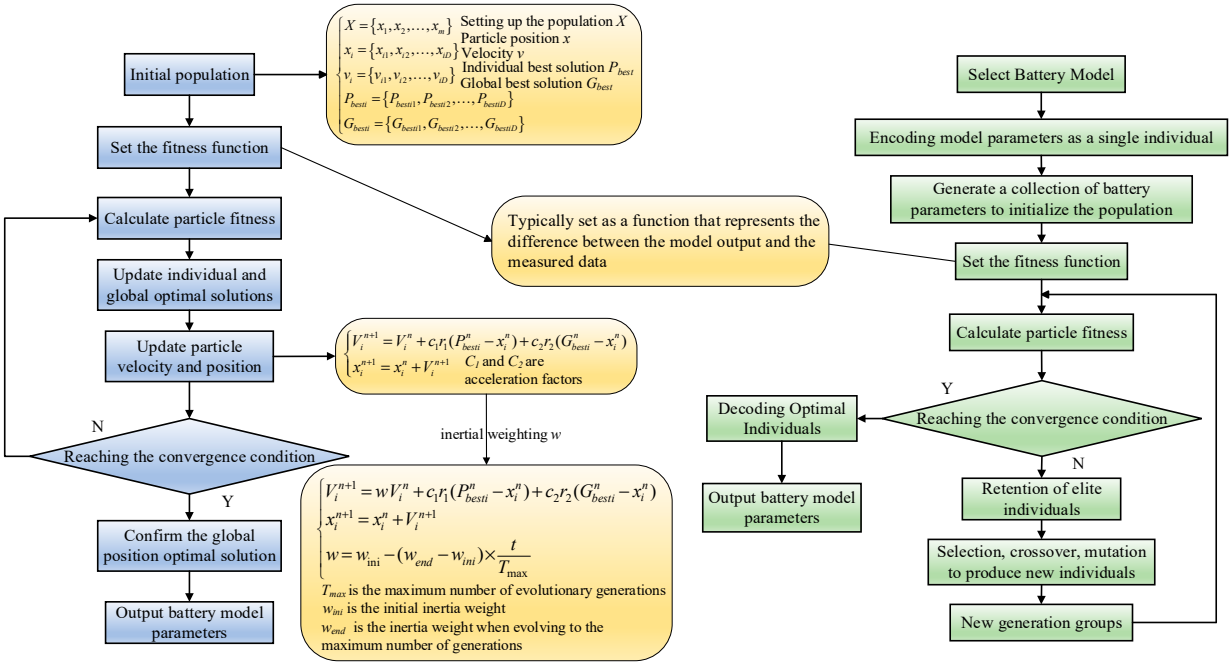

Figure 5. Flowchart of GA and PSO identification parameters.

4.2. Kalman Filter and Its Derivative Algorithms

Kalman filtering (KF) is an algorithm capable of estimating the state of a dynamic system from a series of noisy measurements. It was first proposed by E. Kalman in his paper on solving the linear filtering problem, which was published in 1960 [65]. The process mainly includes defining the equation of state and the equation of observation, initializing the state, predicting, updating, and iterating. The schematic diagram of KF is shown as an example in Figure 6.

EKF Most of the traditional KF algorithms are only applicable to state vectors in linear systems and cannot deal with the nonlinear equations in battery models. In order to solve this problem, researchers added a real-time linear Taylor approximation process to the estimation of the previous state of the system equation in the steps of state estimation and prediction and proposed an extended Kalman filtering (EKF) algorithm [66]. Based on this, Plett of the University of Colorado (Boulder, CO, USA), firstly applied it to the SOC estimation and parameter identification of lithium-ion batteries [67,68] and obtained good results. However, considering that the monotonic EKF algorithm cannot well solve the uncertainty and system noise of complex lithium-ion battery models, to address this challenge, He et al. [69] proposed an adaptive extended Kalman filter (AEKF) and verified that this algorithm can greatly improve the dependence of traditional filtering algorithms on the battery model. At the same time, in order to reduce the error caused by incorrect prior covariance in the EKF algorithm, Jaehyun et al. [70] also adaptively modified the

covariance by using the AEKF method, which improves the reliability and accuracy of the measurement process. Recently, with the gradual development of cloud platforms, Wang et al. [71] proposed a noise matrix self-adjustment-extended Kalman filter (NMSA-EKF) algorithm based on the powerful computing power and huge storage capacity of the cloud platform to estimate the SOC of cloud-based discharging fragments and verified its accuracy.

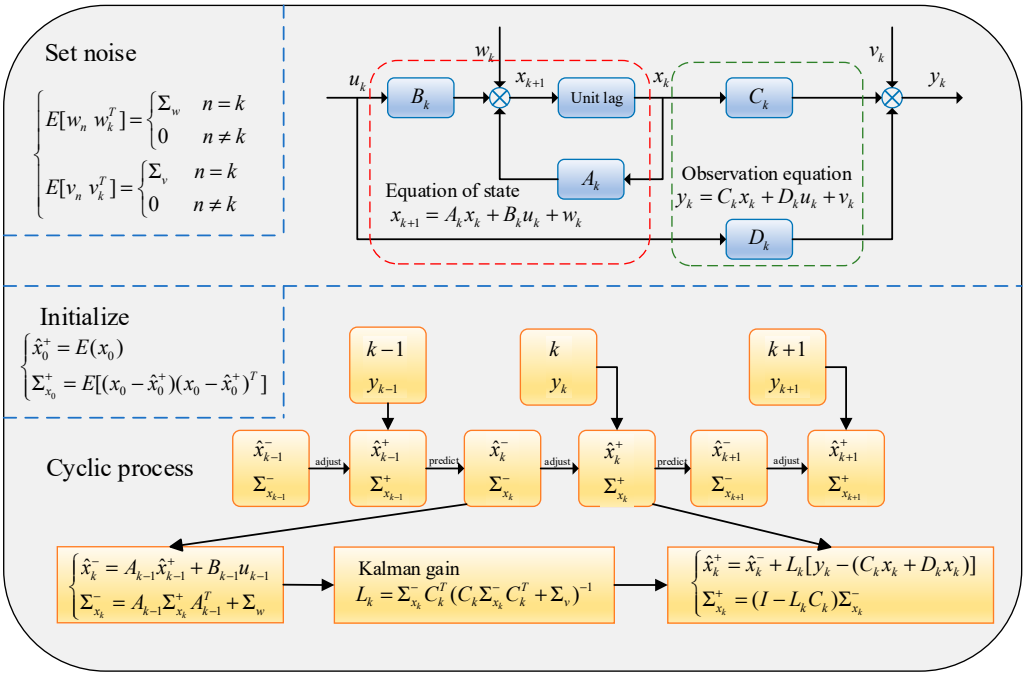

Figure 6. Schematic diagram of Kalman filtering.

UKF The traditional EKF only uses the first- or second-order terms of the Taylor series to approximate the nonlinear model. In order to solve the problem that the EKF produces a large error when facing a highly nonlinear system, Tian et al. [72] proposed unscented Kalman filtering (UKF) to estimate the SOC of the battery and verified that the UKF can capture the distribution characteristics of the nonlinear system through a series of carefully selected sigma points, which improves the accuracy of prediction. At the same time, He et al. [73] compared the EKF and UKF methods experimentally and further verified that the UKF algorithm has high accuracy and convergence in SOC estimation. Based on this, Meng et al. [74] proposed an adaptive unscented Kalman filter (AUKF) to adaptively adjust the process measurement noise and noise covariance, reducing the computational burden when updating the covariance matrix. Of course, the UKF is not without its weaknesses; for example, in the case of high measurement noise, the UKF can lose stability and cause divergence problems. In addition, due to the uncertainty of the battery electrochemical model, the UKF may not be able to produce good robustness [75].

PF In 1993, Gordon et al. [76] proposed a SIS-based bootstrap nonlinear filtering method, which laid the foundation for the particle filter (PF) algorithm. PF is also a nonlinear state estimator based on the Bayesian model, but the algorithm eliminates the constraint that the random quantity must meet the Gaussian distribution when solving the nonlinear filtering problem, so it is also suitable for parameter identification of lithium-ion battery models. Schwunk et al. [77] used PF to estimate lithium-iron phosphate batteries. In addition, considering that the classical PF technique may have a lack of samples or a decrease in prediction accuracy when the weight of the simulated sample is small or the diversity of sampled particles is reduced, Li et al. [78] proposed a mutated particle filter (MPF) algorithm for predicting the Remaining Useful Life (RUL) of the battery, which utilizes mutated particles to search for the extended region of a priori Probability Density

Function (PDF) thus exploring the posterior PDF more comprehensively. Other than that, Lai [79] proposed the combination of PF and EKF, which enables the omission of calculating the Jacobi matrix of battery model and reduces the complexity of the identification process. At present, the research on the PF algorithm is relatively scarce, and it is still a major challenge for battery parameter identification in practical applications. Recently, Wang et al. [80] used PSO to solve the degradation and diversity reduction of the PF algorithm and then proposed a double-scale dual particle filter (D-PF) method to adjust parameters in real time during battery aging and temperature changes, which has certain practical value.

4.3. New Algorithms Based on Machine Learning

With the rapid development of machine learning and artificial intelligence technologies, it has become a research hotspot to apply these advanced methods to the field of battery parameter identification and further optimize model performance and improve the identification accuracy by improving algorithms and calculation strategies. These new methods can not only process a large amount of complex data but also learn the deep characteristics of battery behavior, which is of great significance for the development of battery management systems in the future.

ANN The neural network (NN), also known as the artificial neural network (ANN), is a type of machine learning algorithm that achieves learning from experience by simulating the transmission of signals between neurons or interconnected nodes in the hierarchical structure of the human brain [81], and its schematic diagram is shown as an example in Figure 7. It was first proposed by neurophysiologist Warren McCulloch and mathematician Walter Pitts in 1943 [82]. In 1986, David Rumelhart et al. used the backpropagation (BP) algorithm to train multi-layer neural networks, which greatly improved the learning ability of neural networks [83]. Its ability to describe nonlinear relationships between inputs and outputs has been recognized in various fields. Related derived neural networks also include the recurrent neural network (RNN) [84,85], the convolutional neural network (CNN) [86,87], and long short-term memory (LSTM) [88,89], etc. Therefore, researchers have gradually discovered the potential of ANN in the field of batteries, which can achieve accurate estimation of various battery states without considering the internal electrochemical state of the battery due to the feature extraction and fitting ability of neural networks [90,91]. Cui et al. [92] provided an introduction to the use of different types of neural networks for estimating the SOC of lithium-ion batteries and summarized the principles, advantages, disadvantages, and current status. Based on this, Yang et al. [93] used the parameters obtained from the Hybrid Pulse Power Characterization (HPPC) test to train a three-layer BP neural network to verify its accuracy in SOH estimation. However, with the increasing requirements for battery prediction accuracy, more and more researchers are improving on classic neural network algorithms. In order to eliminate the influence of battery degradation on the estimation accuracy of the original training model, Kang et al. [94] proposed a new radial basis function neural network (RBFNN) and compared it with the traditional neural network through experiments. The results show that the model can effectively improve the accuracy of system SOC estimation and has better robustness for different battery aging cycles, temperatures, and load curves. In addition, in order to solve the dependence of traditional neural network systems on Kalman filtering, Chemali et al. [95] proposed a deep feedforward neural network (DFNN), which can directly map observable signals such as voltage and current to the battery SOC and can learn to estimate the SOC at different ambient temperatures through learning algorithms such as gradient descent. Recently, considering the increasing importance of studying the thermal behavior of batteries such as temperature change and heating rate, Pang et al. [96] integrated the positive and negative electrode surface concentrations in the thermodynamic single event model (SPMT) as physical information into bidirectional long short-term memory networks (BiLSTM) and constructed a new physics-based information neural network (PINN) while verifying its effectiveness under different driving conditions

and ambient temperatures, which opens up a new research direction for neural networks in the field of battery state estimation.

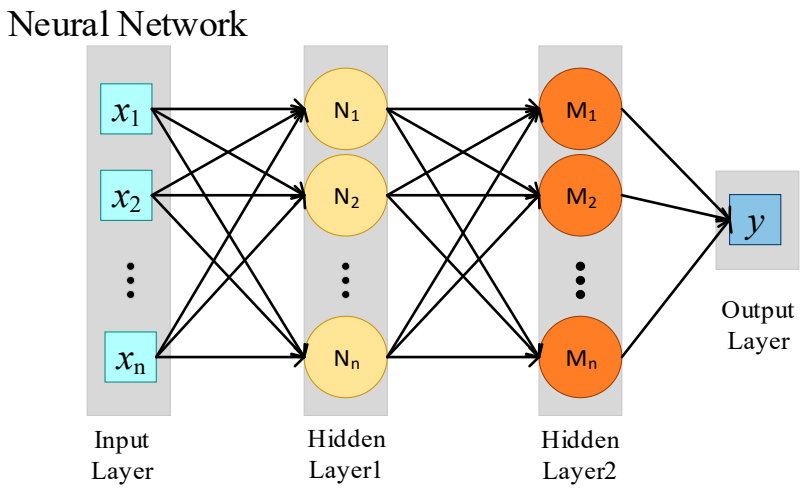

Figure 7. Schematic diagram of ANN.

SVM Support Vector Machines (SVM) is also one of the most popular machine learning algorithms, and its core idea is to find a hyperplane in the feature space based on the principle of statistical structured risk minimization to maximize the separation of different classes of data points. The schematic diagram of SVM is shown as an example in Figure 8. When dealing with nonlinear problems, SVM can map data to high-dimensional spaces through kernel functions and find separating planes in high-dimensional spaces [97]. Compared with the ANN, SVW has advantages in solving the problem of high-dimensional data model construction under the limited samples conditions, and because of its good generalization ability, it can perform better on small sample datasets [98]. Besides, it can effectively deal with nonlinear problems with the help of suitable kernel functions, so there are more scholars who have gradually have tried to use SVM for the parameter identification of lithium-ion batteries and found that SVM has excellent performance on battery life prediction. Based on this, Patil et al. [99] used SVM to establish a classification and regression model for the RUL of batteries and used the Support Vector Regression (SVR) to predict the accurate RUL of the battery. The results showed that the method could improve the prediction accuracy and calculation speed. In addition, in order to address the problem of long SVR training time, Hu et al. [100] used a two-step search to improve the training efficiency of SVR, avoiding the behavior of blindly searching for parameters over a wide range and improving the accuracy and robustness of battery SOC estimation when using SVR under more complex working conditions. Recently, considering the problem of data anomalies in the training of SVM models, Xiong et al. [101] proposed a weighted least squares SVM-based method for early prediction method for the life of lithium-ion batteries, which improved the prediction results through the error square term and weight coefficient, and verified the effectiveness of the method through experiments. It provides a theoretical basis for the battery system faults hierarchical management strategy.

ANN and SVM are essentially data-driven algorithms, and similar algorithms include Gaussian regression [102,103], logistic regression [104,105], gradient enhancement algorithms [106,107], and other machine learning algorithms. These algorithms show very good adaptability in the face of nonlinearity and relative complexity and can find the optimal model and parameters in a large amount of data. The use of appropriate learning algorithms in the BMS is often effective in improving the performance of the battery.

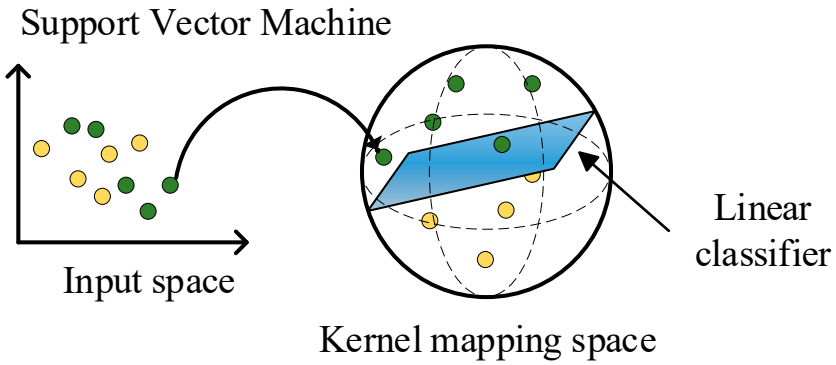

Figure 8. Schematic diagram of Support Vector Machines.

4.4. Comparison of Parameter Identification Methods

In an in-depth discussion of lithium-ion battery management and optimization strategies, it is essential to fully understand and accurately identify the key parameters of the battery. These parameters not only directly affect the performance, lifetime, and safety of the battery but also serve as the basis for optimizing the design of the battery management system and implementing efficient energy utilization strategies. Since different parameter identification methods have their own unique advantages and application scenarios, choosing the most appropriate method has become a prerequisite for achieving efficient battery management. To this end, Table 1 summarizes the current parameter identification methods for lithium-ion batteries, analyzes their disadvantages, and discusses their improvement directions, which provides a reference for the development and optimization of battery technology and subsequent research on parameter identification.

In addition to the improvement directions of each method discussed above, the application scenarios of different parameter identification methods are also different. The current application scenarios that are widely used can be summarized as small-medium capacity battery systems mainly for portable electronic devices and electric vehicles and large-scale battery systems used as energy storage devices in power systems. In one aspect, regarding small-medium capacity systems, linear regression methods based on RLS and algorithms based on KF can exert effective results, while these methods have excellent performance in real-time monitoring and basic performance prediction and can effectively estimate the state variables of the batteries in dynamic systems. Besides, it is also possible to simulate the charging and discharging behavior of small-capacity batteries by establishing smaller neural networks, which can also achieve good results. Moreover, SVM is suitable for the case of small feature spaces, so it can effectively monitor the health condition of small-scale batteries. In another aspect, large-scale neural networks such as LSTM have the ability to deal with high-dimensional and high-nonlinear problems and thus can effectively deal with richer and more complex data sets in large-scale energy storage battery systems. In addition, heuristic algorithms such as GA and PSO are able to show better accuracy in optimizing battery management strategies and life prediction in large-scale battery systems. In actual use, the most appropriate parameter identification methods should be selected according to the different battery sizes and application scenarios. If necessary, different methods also can be used in combination to complement each other in order to maximize the effect of each method to achieve a more efficient battery management system.

Table 1. Summary comparison of parameter identification methods.

Algorithms	Problems	Improving Directions	Literature
LS	Cannot deal with non-linear conditions	Combine with online models	[31–36,108]
RLS	Data saturation	Add the forgetting factor	[39–42]
	Unequal supply and demand	Choose the right incentive	[43]
	Different time scales	Segment at different time scales	[44–48]
GA	Slower convergence	Combine with local search algorithms	[109]
	Difficult to find the global optimal solution when facing high-dimensional problems	Combine with specific heuristic algorithms	[50,110]
	Higher requirements for parameterization	Use adaptive parameter tuning strategies	[61,62]
PSO	May fall into local optimization in solving complex problems	combine local search algorithms	[111]
	Convergence speed may drop when approaching the global optimal solution	Introduce a convergence factor	[112]
	Higher requirements for parameterization	Use adaptive parameter tuning strategies	[111]
EKF	Jacobi matrices increase computational complexity	Combine new algorithms to simplify EKF calculations	[79,113]
	Algorithm performance is more dependent on the initial state estimate	Optimize initial state estimation by preprocessing data or using a priori estimation	[114]
	The accuracy is affected by noise	Add an adaptive mechanism to adjust the noise	[69,70]
UKF	The performance depends heavily on the selection of the Sigma point	Add an adaptive mechanism to adjust the distribution of sigma points based on estimated performance	[74]
PF	The reduction in diversity creates sample impoverishment	Use resampling techniques to increase the diversity of particles	[77]
	Reduction of effective particles will affect the efficiency of the filter.	Add an adaptive mechanism adjust the number of particles	[115]
ANN	Complicated process, long time needed, large amount of calculation	Use efficient neural network architectures	[84–87]
	Difficult to adjust due to too many parameters	Apply automated machine—learning frameworks or adding hyperparametric optimization techniques	[116–119]
SVM	Higher requirements for kernel function setup	Add optimization algorithms to select parameters	[120,121]
	Kernel function cannot deal with non-linear conditions	Visualization of support vectors and decision boundaries	[122]

5. Challenges and Perspectives

As one of the core industries in the current new energy field, lithium-ion batteries have gradually revealed their key influence in many fields. With the rapid improvement and innovation of science and technology, the demand for performance stability, safety, and economy of lithium-ion battery continues to increase, which increases the reliance on battery management systems. As the core components of a BMS, battery modeling and parameter identification are important means to ensure its accuracy and reliability. Although current researchers have achieved many important results in this field, accurate and efficient studying of lithium-ion batteries still faces serious challenges. Therefore, this section focuses on three aspects to look forward to the research trend of battery modeling and parameter identification, hoping to provide more in-depth theoretical support for battery performance optimization, service life extension, and the guarantee of safety.

5.1. Efficient and Accurate Parameter Identification

Currently, there are relatively mature parameter identification methods for simple ECM models such as least squares algorithms, filtering algorithms, and heuristic algorithms such as genetic algorithms and particle swarm algorithms. However, when it comes to higher-order or complex electrochemical models, we still need to continuously improve the efficiency and accuracy of the model parameter identification. One approach is to apply artificial intelligence techniques to parameter identification, such as the deep learning models DNN, CNN, etc., which can learn from the battery operation data and reduce the computation time while maintaining the identification accuracy. In addition, with the development of chip technology, using emerging technologies such as cloud computing and edge computing for parameter identification can take advantage of more powerful computing resources and more efficient data processing capabilities while realizing the rapid deployment of practical applications and is also gradually becoming a popular area of current research.

5.2. Integration of Multiple Identification Methods

In practical applications, different identification methods are suitable for specific scenarios and requirements due to their inherent advantages and limitations. For example, although physical model-based approaches can provide in-depth insights into the interior of the battery, they have higher computational complexity and may not be suitable for situations that require fast response. In contrast, data-driven approaches are more suitable for real-time monitoring and control applications due to their lower computational requirements and rapid adaptability. By integrating multiple algorithms, such as combining the accuracy of the physical models with the fast responsiveness of data-driven models, the respective deficiencies can be complemented to a certain extent to achieve better identification results. This multi-method fusion strategy can not only improve the accuracy of the model but also enhance the adaptability of the model to different operating conditions. Therefore, future research will pay more attention to algorithms innovation and the development of multi-algorithm fusion technology while strengthening the analysis of the requirements of different application scenarios to guide the selection and optimization of the battery parameter identification methods and further enhance the overall performance and reliability of the battery management system.

5.3. Consideration of Multiple Categories of Influences

In the process of actual parameter identification, how to comprehensively consider the impact of temperature changes, battery aging, and other factors on the performance of lithium-ion batteries is also one of the challenges faced. The following are three aspects of the current research trend:

(1) The integration of multi-physical field models

In the multi-scale model, the combination of microscopic electrochemical models and macroscopic thermal and mechanical models can be achieved through the formation of multi-scale, multi-physical field comprehensive models in order to comprehensively reflect the behavior of the battery under different working conditions; under multiple environmental conditions, a model identification framework that can accurately perform parameter identification under various conditions such as different temperatures, humidity, pressure, etc., can be developed to improve the applicability and robustness of the model.

(2) Consideration of the battery aging phenomenon

The study of the battery aging model and the integration of battery aging mechanisms into the parameter identification model can improve the reliability of the parameter identification results and provide the basis for the health management and timely maintenance of lithium-ion batteries.

(3) Consideration of multiple aspects

Combining the research results of many disciplines, such as chemistry, material science, electronic engineering, computer science, etc., can systematically solve the problems in the process of lithium-ion battery parameter identification and improve the comprehensive performance and application scope of identification. For example, among the selection of cathode materials for lithium-ion batteries, Ni-rich cathodes materials (NCM) are becoming increasingly dominant in the field of lithium-ion batteries, while future research will continue to be directed towards high-nickel batteries that can significantly increase energy density [123]. In addition, lithium-sulfur is becoming a popular battery system due to its high capacity and excellent cycle efficiency [124]. Besides, comprehensively considering the voltage, capacity, and temperature sensitivity of the battery will further enable higher performance, cost efficiency, and sustainability.

6. Conclusions

Lithium-ion batteries are a widely used energy source in electric vehicles and renewable energy storage systems, and the parameter identification of these batteries is essential for achieving an efficient BMS. With the continuous development of technology, data-driven parameter identification methods have attracted more attention in recent years. However, most of the current studies are only for specific data-driven methods; this type of method has not been comprehensively reviewed. To this end, this paper mainly summarizes the applications of data-driven parameter identification methods in different scenarios, and advantages and limitations of each method are also discussed while exploring the challenges and future research directions of these methods.

Upon analyzing and reviewing the related literature, it has been found that in the face of higher-order or more complex electrochemical models, effectively improving the accuracy and stability of model parameter identification is still an important research direction. In addition, although the RLS method is more mature, there is still much room for improving the adaptive ability, reducing the computational complexity, and improving the robustness of the algorithm. For the filtering algorithm, how to flexibly deal with the strong nonlinearity of the electrochemical model and adjust the system noise efficiently is still an urgent problem to be solved. Furthermore, with the rapid development of machine learning and artificial intelligence technology, the reasonable use of deep learning models can effectively reduce the computation time and maintain the accuracy of recognition.

Combining the future perspectives, it is realized that although existing research has made remarkable achievements in battery parameter identification, lithium-ion battery parameter identification still faces many challenges and opportunities compared with the complex and changing application scenarios and continuously increasing performance requirements. This paper provides research scholars with a reference for battery parameter identification in the hope of realizing the development of more advanced and efficient battery management systems.

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