TAO, J., WANG, S., CAO, W., TAKYI-ANINAKWA, P., FERNANDEZ, C. and GUERRERO, J.M. 2024. A comprehensive review of state-of-charge and state-of-health estimation for lithium-ion battery energy storage systems. *Ionics* [online], 30(10), pages 5903-5927. Available from: https://doi.org/10.1007/s11581-024-05686-z

A comprehensive review of state-of-charge and state-of-health estimation for lithium-ion battery energy storage systems.

TAO, J., WANG, S., CAO, W., TAKYI-ANINAKWA, P., FERNANDEZ, C. and GUERRERO, J.M.

2024

A comprehensive review of state-of-charge and state-of-health estimation for lithium-ion battery energy storage systems

Junjie Tao[1], Shunli Wang[1*], Wen Cao[1], Paul Takyi-Aninakwa[1,2], Carlos Fernandez[3] and Josep M. Guerrero[4]

1 School of Information Engineering, Southwest University of Science and Technology, Mianyang 621010, Sichuan, China

2 College of Electric Power, Inner Mongolia University of Technology, Hohhot 010080, China

3 School of Pharmacy and Life Science, Robert Gordon University, Aberdeen, UK

4 Department of Energy Technology, Aalborg University, Pontoppidanstraede, 111 9220, Aalborg East, Denmark

* Corresponding author: Shunli Wang (497420789@qq.com)

Abstract

With the gradual transformation of energy industries around the world, the trend of industrial reform led by clean energy has become increasingly apparent. As a critical link in the new energy industry chain, lithium-ion (Li-ion) battery energy storage system plays an irreplaceable role. Accurate estimation of Li-ion battery states, especially state of charge (SOC) and state of health (SOH), is the core to realize the safe and efficient utilization of energy storage systems. This paper presents a systematic and comprehensive evaluation and summary of the most advanced Li-ion battery state estimation methods proposed in the past 3 years, focusing on analyzing data-driven state estimation algorithms. At the same time, the latest Li-ion battery data sets and data selection methods are analyzed, and future research trends and possible challenges are proposed. This review will provide a valuable reference for future academic research in Li-ion battery state estimation.

Keywords:- Li-ion battery state estimation; Equivalent circuit model; Parameter identification; Kalman filtering; Deep learning; Based on data-driven algorithms

Introduction

At present, the climate issue has become a hot topic of global concern, and the development of clean energy and the reduction of carbon emissions are essential ways to address global warming and the frequent occurrence of extreme weather phenomena. Countries are vigorously building wind power, hydropower, nuclear power, and other new green power generation facilities and fully implementing electric vehicles instead of traditional fuel vehicles, which are committed to solving the existing environmental, climate, and ecological problems. Among them, a Li-ion battery energy storage system, as a transfer station of a clean energy grid, can play an essential role in smoothing the grid load, mitigating peak and trough fluctuations, and stabilizing the grid frequency and voltage. As a power source for new clean energy devices, it has the advantages of safety and reliability, high energy density, and long service life.

It has been a common concern of scholars to develop a set of well-functioning battery management systems (BMS) to improve Li-ion batteries' safety and energy utilization and prolong their service life. However, it takes work to estimate their state accurately due to Li-ion batteries' complex physical and chemical reaction characteristics. Currently, the main state estimation parameters realized by BMS include state of charge (SOC) [1], state of health (SOH) [2], state of energy (SOE) [3], state of power (SOP) [4], state of tem-perature (SOT) [5], and state of safety (SOS) [6]. In general, improving SOC and SOH estimation accuracy is the basis for realizing the reliability and safety improvement of the BMS system. The SOC estimation of Li-ion batteries is mainly to predict the remaining battery power to avoid the unsafe use of batteries, which may lead to the rapid reduction of the service life or even safety accidents, while the SOH estimation is to accurately predict the remaining service life of the batteries, such as the remaining charging and discharging cycles, to determine whether the batteries need to be replaced or not and to enhance the accuracy of the load balancing in the battery balancing system. Meanwhile, in the joint estimation of SOC and SOH, the improvement of SOH estimation accuracy also helps to improve the SOC estimation accuracy.

From the perspective of real-time algorithms, it is mainly divided into the online state estimation method [7] and the offline state estimation method [8]. The online state estimation method is mainly through the pre-established battery model, through the real-time collection of relevant battery operating data, input to the model, and output to obtain the current state of the Li-ion battery estimated value. Its advantage is high flexibility, can be adjusted in real-time according to environmental changes, and is more suitable for dynamic changes in the battery system; the disadvantage is that the computational complexity is high, and the estimation results are greatly affected by the sensor noise and measurement errors. The offline estimation method mainly estimates the current battery state by constructing the SOC-OCV fitting curve [9], statistics, etc. The advantages are that the cal-culation is simple, not affected by environmental changes, and historical data can improve the estimation accuracy. The disadvantages are that the state cannot be updated in real time, and there may be delays. From the perspective of algorithm functionality, it is mainly categorized into single-state estimation and multi-state joint estimation. The advantages of single-state estimation are that the algorithm structure is simple, the computation amount is small, and it is easy to use online. The disadvantages are that the algorithm could be more utilized, and the estimation accuracy is affected by other unknown state factors. The advantage of joint estimation is that it considers the relationships between multiple states, which can estimate the battery state more comprehensively and thus improve the estimation accuracy. The disadvantage is the high computational complexity, and more data and information are needed to support it. The implementation methods for Li-ion battery state estimation are divided into direct measurement, model-based, and data-driven methods. (a) The direct measurement methods are ampere-time integration [10] and open-circuit voltage [11]. The ampere-time integration method acquires Li-ion battery terminal current and terminal voltage data at high frequency, serializes the discrete data, and integrates the current and other data to obtain the estimated Li-ion battery state. The open-circuit voltage method establishes the SOC-OCV fitting curve by collecting the experimental data of the Li-ion battery under the HPPC condition. It measures the open-circuit voltage data of the battery under the long-term quiescent state to feed into the SOC-OCV fitting function to obtain the current SOC value. (b) Model-based methods mainly include various equivalent circuit models, electrochemical models, etc. Standard equivalent circuit models include the Thevenin model [12], the second-order RC equivalent circuit model [13], the PNGV model [14], and so on. The algorithm identifies the relevant parameters of the equivalent circuit model, the state and observation equations are established, and the Kalman filtering algorithm is used to establish a model-based SOC estimation simulation model to realize the battery state estimation. The electrochemical model can realize the battery state estimation of coupled electrochemical mechanisms, and then it becomes the research focus of the next-generation battery management system. (c) Data-driven methods mainly include two main parts: neural networks and machine learning. Standard neural networks include BP [15], LSTM [16], DNN [17], and so on, and standard machine learning algorithms include support vector machine [18], decision tree [19], clustering [20], and so on. Both neural networks and machine learning are trained on many samples to obtain a network model that realizes the input of the battery-related measurement parameters and the output of the state variables to be estimated.

To date, several review papers have been published by scholars on SOC and SOH estimation for Li-ion batteries. Among them, Selvaraj et al. [21] provided a more compre-hensive summary of SOC estimation methods for Li-ion batteries in electric vehicles, summarizing the existing SOC estimation methods from five aspects: direct method, model-based method, observation method, adaptive filtering method, and data-driven method. However, it is mainly an introductory theoretical exposition with insufficient expan-sion. Tian et al. [22] summarized the SOH estimation methods for Li-ion batteries, analyzing and evaluating them from four perspectives: model-based method, data-driven method, hybrid method, and other methods. However, there are more advanced methods as far as it is concerned. Yang et al. [23] summarized the health characterization, evaluation, and application of Li-ion batteries from various aspects, analyzed the battery characteristics under different models and working conditions, and analyzed the factors affecting the SOH estimation accuracy. However, the specific theoretical part of the algorithm is more general. Wang et al. [24] summarized the online joint estimation algorithm of SOC and SOH for Li-ion batteries and elaborated on the SOC and SOH estimation algorithms in detail. Liu et al. [25] summarized the multi-state estimation methods for Li-ion batteries, elaborated the definition of each state parameter, and summarized the joint estimation methods between different states, which is of solid reference significance. However, there is still the need for more expansion. Zhou et al. [26] summarized four typical state estimation algorithms and their joint estimation methods for Li-ion batteries and made a more detailed outlook on the future development trend. However, the description of the algorithms is relatively brief and needs to be more comprehensive. Du el al. [27] summarized the SOC and SOH estimation algorithms of Li-ion batteries for electric vehicles. However, it mainly focuses on the model approach, and the summary needs to be more comprehensive. Espendal et al. [28] summarized the development trend. Existing techniques for SOC estimation of Li-ion batteries for automobiles described various model-based estimation methods, simultaneously analyzed the errors from various sources, and explained how to eliminate the errors. Cui et al. [29] comprehensively analyzed a comprehensive analysis of neural network-based Li-ion battery SOC estimation algorithms, especially some less commonly used neural network algorithms. They predicted the future direction of the technology in this field. Yao et al. [30] summarized the model-based, data-driven, and statistical-based approaches and provided unique insights into future development trends. Tian et al. [31] reviewed deep learning technology's latest application and development trend in Li-ion battery SOC estimation. This paper details the architecture and applications of three major deep neural networks (fully connected neural networks, recurrent neural networks, and convolutional neural networks). It discusses advanced applications of deep learning combined with other methods, such as transfer learning and data augmentation. Deep learning has great potential to process large-scale battery data and improve SOC estimation accuracy. It also highlights future challenges and research opportunities in data collection, model interpretability, and uncertainty estimation. Ren et al. [32] focused on reviewing four major machine learning algorithms: shallow neural networks, deep learning, support vector machines, and Gaussian process regression. This paper details the basic principles, applications, and performances of these algorithms in SOC and SOH estimation in recent years. It compares their datasets, input features, hyperparameter selection, performance metrics, etc. Through a comprehensive comparison and discussion that also analyzes current challenges and future directions to inspire the development of advanced machine learning state estimation algorithms.

The above papers all reflect specific academic values. However, there are different problems, such as the summary of research status needing to be more comprehensive, being deep enough, and needing better scalability. At the same time, the early review literature cannot reflect the latest academic research results in Li-ion battery state estimation. This paper conducts a systematic and comprehensive review of the literature on state estimation of Li-ion battery SOC and SOH published in recent years. It selects the most representative papers for different algorithm types. The model-based and data-driven state estimation algorithms are expounded, and the data-driven algorithm is the mainstream direction of future develop-ment, so it is emphatically discussed. At the same time, the problem of selecting the Li-ion battery data set is summa-rized separately. Finally, the direction of future technology development and the possible challenges are prospected. Section 1 summarizes the existing definitions of Li-ion battery SOC and SOH; Sect. 2 mainly expounds on the basic theory involved in data-driven algorithms; Sect. 3 mainly classifies and summarizes the recent model-based state estimation theory; and Sect. 4 mainly classifies and summarizes the recent data-driven state estimation theory. Section 5 summarizes the selection principles of different types of algorithms and discusses future research trends and possible challenges, and Sect. 6 concludes the paper.

Definition of SOC and SOH

Definition of SOC

The SOC of a battery refers to the available state of the remaining charge in the battery, which is generally expressed as a percentage and takes a value in the range of 0 to 1. The classical definition of SOC is shown in Eq. (1).

$$SOC = \frac{Q_{remain}}{Q_{rated}} \times 100\% \tag{1}$$

where Q_{rated} is the nominal charge capacity of the battery and Q_{remain} is the total remaining charge of the battery. When $SOC = 0$ means the battery is fully discharged, and when $SOC = 1$ means the battery is fully charged.

Definition of SOH

The SOH of a battery refers to the current state of the battery relative to its original performance, which is an essential parameter for evaluating the long-term health of the battery and is usually expressed as a percentage. The standard definition of SOH is the ratio of the capacity discharged from a complete state of a power battery at a specific multiplication rate from the entire state to the cut-off voltage to the nominal capacity (the actual initial capacity) to its corresponding nominal capacity under the standard conditions. There are four main ways of defining SOH for Li-ion batteries, as shown in Table 1.

The SOH of a battery is a comprehensive indicator that reflects the health of the battery during long-term use. By monitoring the SOH of a battery, its health status can be assessed promptly, and appropriate measures can be taken to extend the battery's service life and maintain its performance.

Table 1 Li-ion battery SOH definition approach

Defining the type	Defining the formula	Clarification
Health status based on capacity definition	$\mathrm{SOH}_C = \frac{C_t}{C_0} \times 100\%$	SOH_C: Battery capacity healthiness. C_t: The rated capacity of the battery at moment. C_0: Initial rated capacity of the battery
State of health based on internal resistance definition	$SOH_R = \frac{R_{end}-R(t)}{R_{end}-R_0} \times 100\%$	SOH_R: The health of the internal resistance of the battery. R_{end}: Internal resistance of the battery at the moment of end of life. $R(t)$: Internal resistance of the battery at moment t. R_0: Initial internal resistance of the battery
Health state based on power definition	$SOH_p = (1 - \frac{P(t)}{P(0)})\times 100\%$	SOH_p: Battery power health degree. $P(0)$: Battery nameplate power. $P(t)$: Effective power that can be supplied after the tth cycle
Health states based on self-discharge definitions	$SOH_{R_d} = \frac{R_d(end)-R_d(t)}{R_d(end)-R_d(0)} \times 100\%$	SOH_{R_d}: The self-discharge health of the battery. $R_d(end)$: Self-discharge resistance at the moment of battery end-of-life. $R_d(t)$: Battery self-discharge resistance at sampling moment t. $R_d(0)$: Self-discharge resistance of the battery at the initial moment

Explanation of basic theoretical knowledge of state estimation of Li-ion battery

Direct measurement method

The direct measurement method of Li-ion batteries is to infer the battery's SOC and SOH by real-time measurement of parameters such as voltage, current, and temperature. This method does not require complex mathematical modeling or data processing but relies directly on real-time measurements for state estimation. Standard direct measurement methods include the open circuit voltage [33] and the ampere-time integration [34].

Open circuit voltage method

By measuring the terminal voltage of the battery, the SOC of the battery can be roughly estimated. In general, there is a specific linear relationship between the open circuit voltage of the Li-ion battery and its SOC, so the battery's open circuit voltage can be used to estimate the SOC of the battery. The advantage of the open-circuit voltage method is that the calculation is relatively simple, and it only needs to measure the open-circuit voltage of the battery in the long-term static state, which is not affected by the error of current sampling. The disadvantage is that it requires a long resting time and cannot realize online SOC estimation. The open circuit voltage method for SOC estimation is shown in Fig. 1.

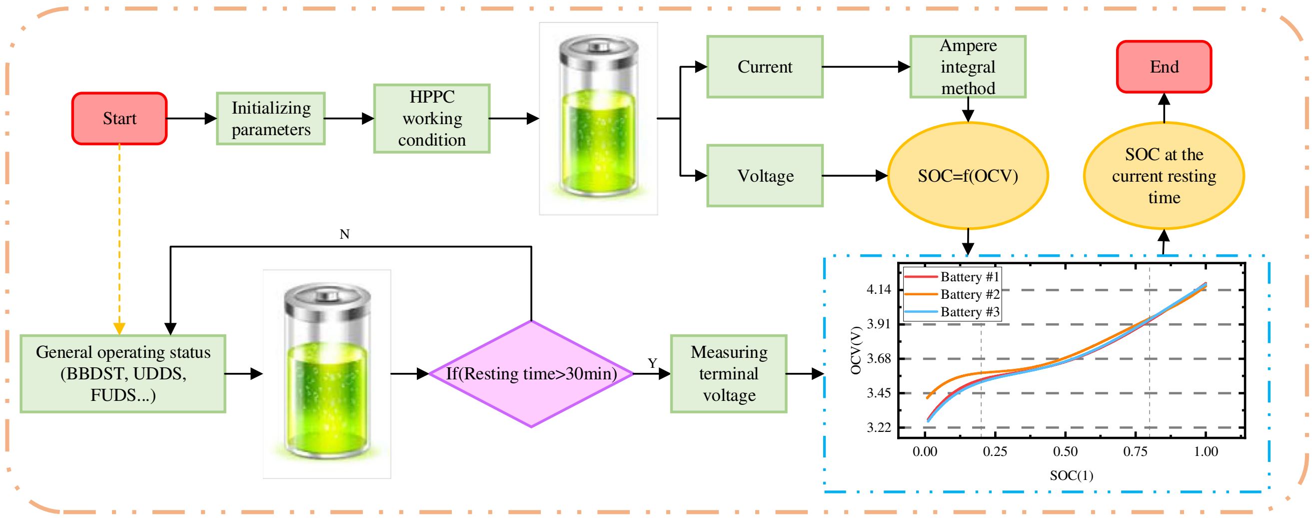


Fig. 1 Flow chart of open circuit voltage method

For the same battery, it is necessary first to obtain the corresponding open-circuit voltage value of 10% SOC interval under HPPC condition from the SOC-OCV fitting function, and then measure the terminal voltage under normal operating conditions by standing for more than 30 min and then look up the table to get the estimated value of SOC at the corresponding moment. The fitting curves of different batteries are different. However, the overall direction is the same, and the SOC-OCV fitting functions of three different Li-ion batteries are drawn, as shown in Fig. 2.

As shown in Fig. 2, the slope is slower during 20% SOC ~ 80% SOC in this period, and certain battery types have voltage plateaus, making the estimation accuracy lower. Also, the SOC estimation accuracy is highly affected by temperature and lifetime.

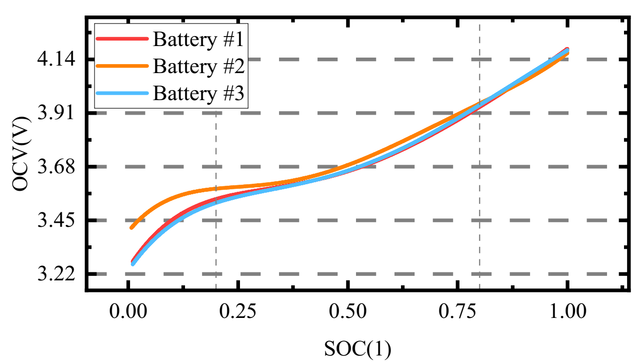


Fig. 2 Schematic diagram of SOC-OCV fitting functions for three types of batteries

Ampere integral method

The ampere-time integration method is a simple and intuitive method for estimating the remaining capacity of a battery by measuring the battery charging and discharging currents in real time and integrating them to obtain the total amount of battery charging and discharging. Its advantages are simple calculation, reliable results, low requirements on the state of the battery itself, and online real-time state estimation can be realized. The disadvantage is that the sampling accuracy and sampling interval have a significant impact on the error of the final estimation results, and at the same time, temperature changes, battery aging, different charging and discharging multipliers, and battery self-discharge phenomenon will also affect the state estimation accuracy. Since the algorithm is an open-loop algorithm with no feedback correction link, wrong initial state values will result in wrong estimated state values. A schematic diagram of the SOC estimation process for the ampere-time integration method is shown in Fig. 3.

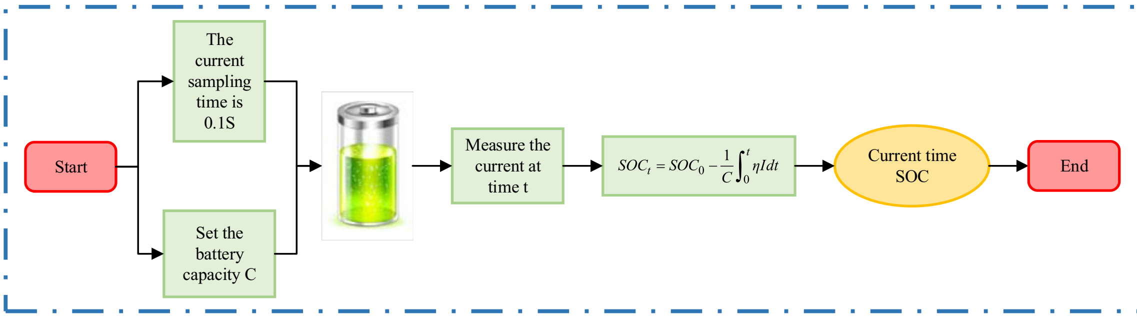


Fig. 3 Flowchart of the ampere-time integration method

Model-based state estimation method for Li-ion batteries

Model-based estimation methods are used to estimate the SOC and SOH of a battery by building a mathematical model of the battery. These methods usually use the physical and chemical properties of the battery as well as real-time measurements of parameters such as voltage, current, and temperature for estimation. Standard model-based SOC and SOH estimation methods include electrochemical models [35], equivalent circuit models [36], empirical models [37], electrochemical impedance models [38], and so on. This paper focuses on state estimation methods based on equivalent circuit models.

Electrochemical model

Electrochemical modeling of Li-ion batteries is usually based on their internal chemical reaction processes. Such models can be divided into two main types: single-particle models [39] and multi-particle models [40]. These models describe the diffusion and embedding/de-embedding processes of lithium ions between the battery's positive and negative electrodes and consider the battery's characteristics, such as current, voltage, capacity, and internal resistance. The advantages of electrochemical models are that they have better physical consistency and can accurately describe the behavior of the battery, including current, voltage, and temperature. The generalization is better and can be applied to different working conditions—more accurate battery state estimation than equivalent circuit models. The disadvantage is that the computational complexity is high, usually contains multiple equations and parameters, poses a challenge for parameter identification, and does not apply to real-time estimation. The model is imperfect and cannot capture the complex behavior of the battery, such as polarization effects and temperature variations. Figure 4 shows a schematic diagram of the electrochemical model of a Li-ion battery.

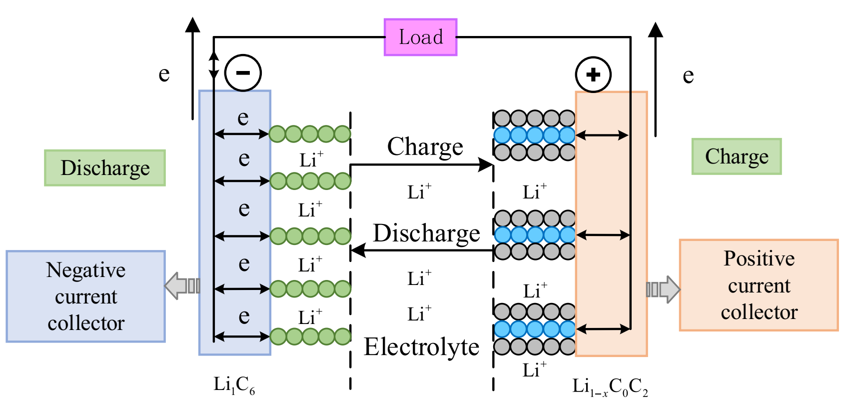


Fig. 4 Electrochemical model of Li-ion battery

Figure 4 shows that the cathode material is usually a lithium metal oxide, such as LiCoO2, LiMn2O4, and LiFePO4. Lithium ions are de-embedded during discharge from the positive electrode material and move through the electrolyte to the negative electrode. The negative electrode material is usually graphite or other forms of carbon, and there have also been studies using materials such as silicon. Lithium ions are embedded in the negative electrode material during the discharge process. An electrolyte is a liquid or solid material that can conduct electricity by transporting lithium ions. The electrolyte also contains salts that facilitate the transport of lithium ions, such as LiPF6. The diaphragm is a porous material that sits between the positive and negative electrodes, preventing them from coming into direct contact and shorting out. At the same time, it allows lithium ions to move freely through the electrolyte. Electrochemical models typically include the following vital equations and parameters.

(a) Voltage equation: Describes the relationship between the voltage response of the cell and the SOC, which is usually established by the variation of the ion diffusion rate and the cell's internal resistance.

(b) Diffusion equation: Describes the diffusion process of lithium ions between the positive and negative electrodes of the battery, taking into account the diffusion coefficient, electrode surface reaction rate, and other factors.

(c) Embedding/de-embedding equation: Describes the process of embedding/de-embedding of lithium ions in the electrode material, and the Butler-Volmer equation or other electrochemical kinetic equations are usually used to describe the reaction rate on the electrode surface.

(d) Heat equation: Describes the temperature distribution inside the cell and the effect of temperature on cell performance.

(e) Parameters: These include the internal resistance of the cell, the conductivity of the electrode material, the diffusion coefficient, the electrochemical reaction rate constant, and other parameters.

These equations and parameters are usually integrated into a set of differential equations or difference equations, which are numerically simulated or analytically solved to model the dynamic behavior of the battery and enable the estimation of states such as SOC and SOH of the battery. These models have critical applications in battery design, management, and control and can help optimize the performance and lifetime of battery systems.

Equivalent circuit model

Usually, the steps of estimating the states such as SOC and SOH of a Li-ion battery are mainly divided into the following steps.

1. Obtaining the parameters of the battery operating state.
2. Selecting an appropriate equivalent circuit model according to the state estimation algorithm.
3. Using the parameter identification algorithm to identify the parameters of the equivalent circuit model.
4. Using the state estimation algorithm to estimate the state of the Li-ion battery.

Therefore, choosing a reasonable equivalent circuit model is a prerequisite for realizing highly accurate state estimation. A conventional flowchart for state estimation of Li-ion batteries based on the equivalent circuit model is given in Fig. 5.

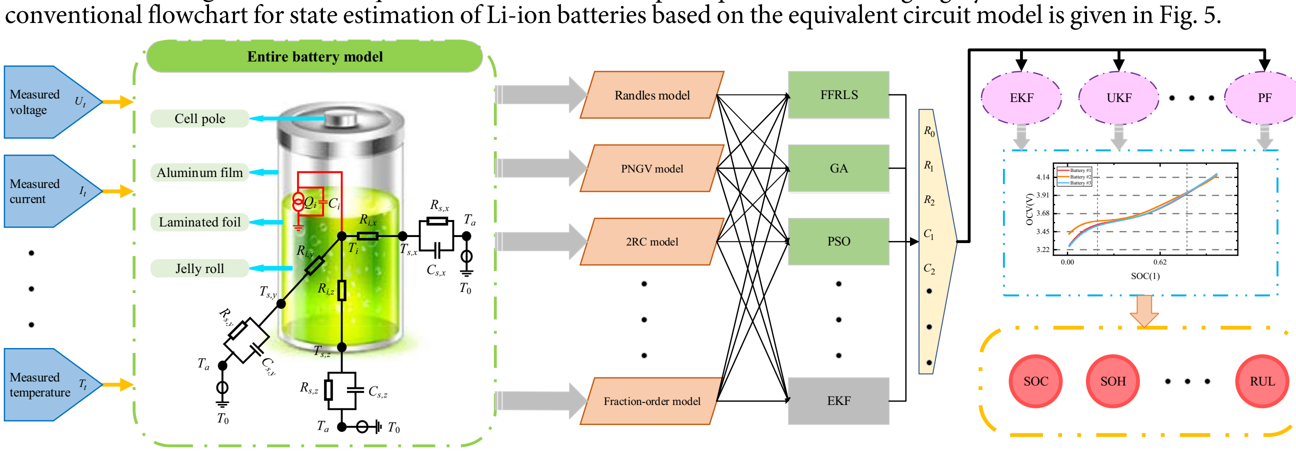


Fig. 5 Flowchart of Li-ion battery state estimation based on equivalent circuit modeling

As shown in Fig. 5, in the state estimation algorithm based on the model method, the characteristics of different state estimation algorithms combined with the characteristics of different equivalent circuit models are matched, and the most suitable pair is selected for combination. Second, parameters such as terminal voltage, terminal current, and temperature of the Li-ion battery are collected at intervals of 0.1 s, and the parameters are transferred to a parameter identification algorithm (e.g., FFRLS) for calculating the relevant parameters of the equivalent circuit model. Subsequently, the model parameters are brought into the parameter identification algorithm to establish state equations and observation equations, and appropriate state and observation variables are selected to estimate the state of the Li-ion battery, during which the SOC-OCV fitting curves are usually pre-established for parametric conversion. Finally, the relevant target estimation parameters, such as SOC, SOH, and RUL, are calculated.

A data-driven approach to Li-ion state estimation

Data-driven Li-ion battery state estimation methods rely heavily on machine learning (SVM et al.) and deep learning (CNN, LSTM, DBN) techniques for estimating key state parameters of Li-ion batteries, such as SOC, SOH, and future performance or lifetime. In contrast to model-based approaches, data-driven methods do not require complex electrochemical models but rather learn battery behavioral characteristics directly from experimental data. These methods typically require a large amount of data to train the model for highly accurate and reliable estimation, and their basic flowchart is shown in Fig. 6.

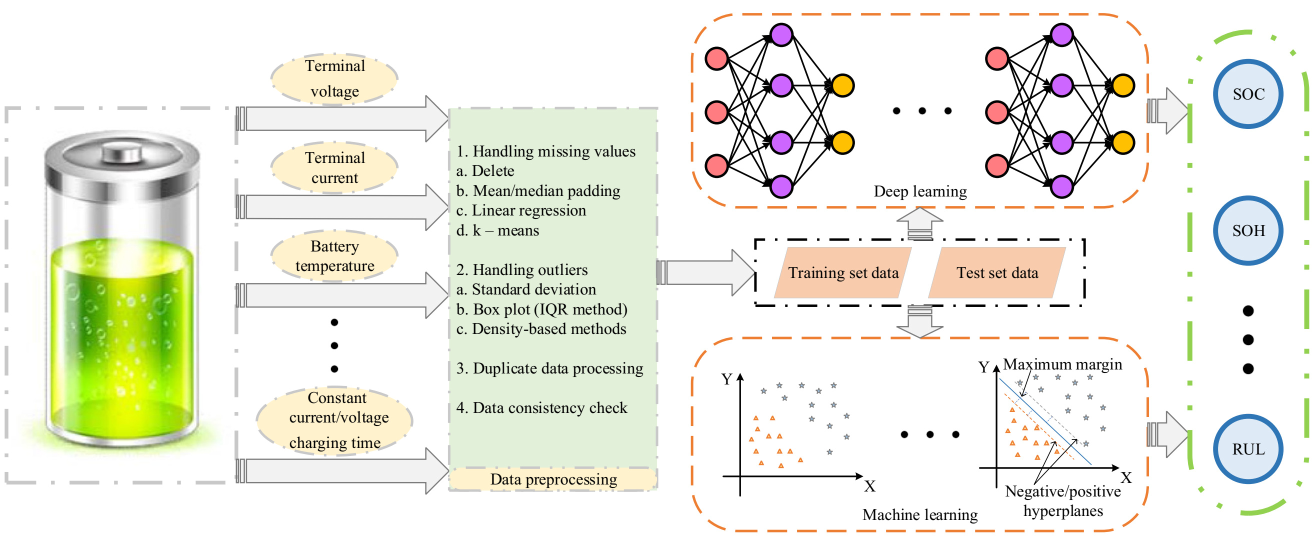


Fig. 6 Flowchart of data-driven state estimation based on Li-ion battery

As shown in Fig. 6, in a data-driven approach, more data features need to be captured relative to a model-based approach to make the trained model fit the fundamental physical and chemical properties of Li-ion batteries as closely as possible. Usually, the data needs to be cleaned first to minimize model overfitting due to problems such as errors contained in the data and data point noise. Subsequently, the cleaned data is divided into a training set and a test set, and the model is trained using the training set and validated using the test set. In data-driven-based algorithms, the loss function is usually used as an evaluation criterion, and choosing an appropriate loss function is conducive to improving the fitting accuracy of the model. A typical machine learning and deep learning-based Li-ion battery state estimation algorithms are introduced below for data-driven methods, respectively, and the rest of the algorithms have similar algorithmic structures and processes, which will not be repeated.

Long Short-Term Memory (deep learning)

LSTM (Long Short-Term Memory Network) is an algorithm that utilizes deep learning techniques to predict the performance parameters of Li-ion batteries. The LSTM network is a special kind of recurrent neural network (RNN), capable of processing and memorizing long-term dependence information, making it particularly suitable for dealing with time-series data, such as battery charging and discharging cycle data. In Li-ion battery state estimation, LSTM can help to address the complex, nonlinear, time-dependent, and battery aging mechanisms that are difficult to capture by traditional methods. The specific flow of Li-ion battery state estimation using LSTM is shown in Fig. 7.

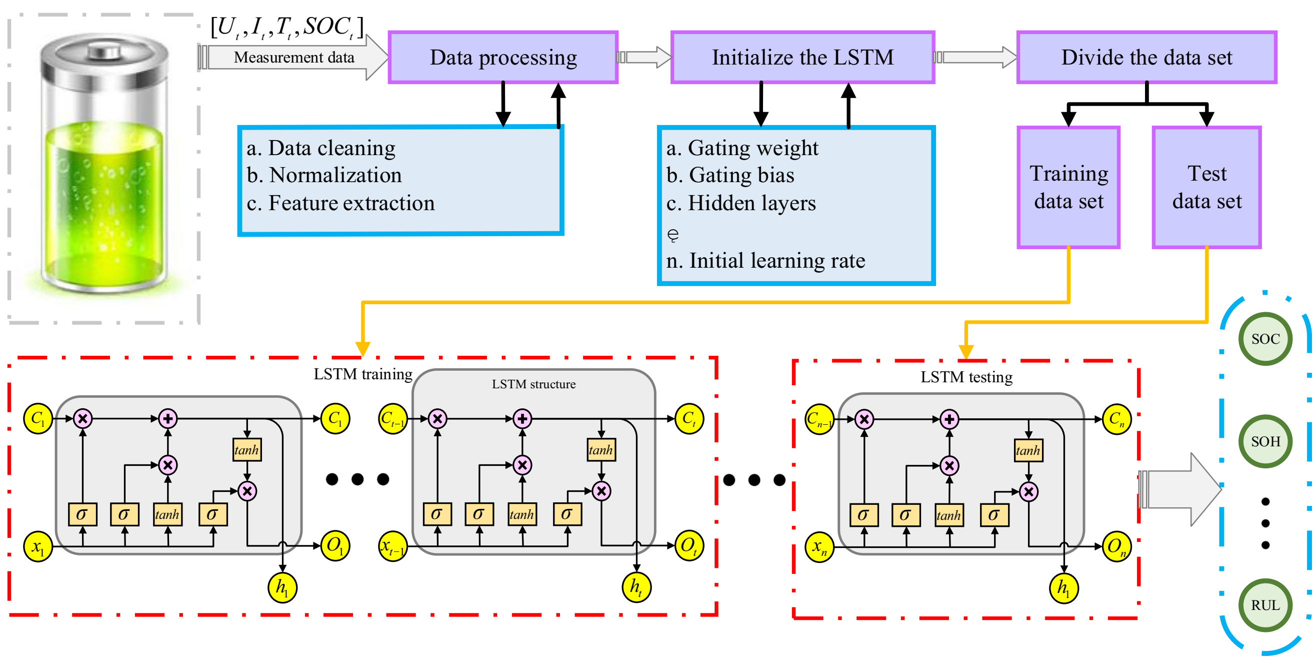


Fig. 7 Flowchart of LSTM-based Li-ion battery state estimation

As shown in Fig. 7, the data usually collected are voltage, current, temperature, etc. The data's diversity and adequacy largely determine the model's performance. The generalization ability of the model can be enhanced by collecting the operating data of the battery under different working conditions, such as HPPC [41], BBDST [42], UDDS [43], and DST [44] working conditions. In order to improve the utilization of data, it is necessary to select the features reasonably, such as assigning weights to the features through the attention mechanism and other related algorithms. The LSTM neural network is designed to process time data. The correct processing of time series data (e.g., the length of the sequence, the step size), etc., has a significant impact on the performance of the model to ensure that the time series data can effectively capture the characteristics of the changes in the state of the battery concerning the time. Meanwhile, adjusting the hyperparameters of the neural network is also an essential task, such as the learning rate, the batch size, and the number and size of neurons in the hidden layer, which can also be automatically optimization-seeking by some optimization algorithms [45].

Support vector regression (machine learning)

Support vector regression (SVR) utilizes machine-learning techniques to predict the state of Li-ion batteries. SVR is a regression method based on SVM, suitable for small samples and nonlinear and high-dimensional pattern recognition. It is especially suitable for dealing with complex problems in battery state estimation. The specific flow of Li-ion battery state estimation based on SVR is shown in Fig. 8.

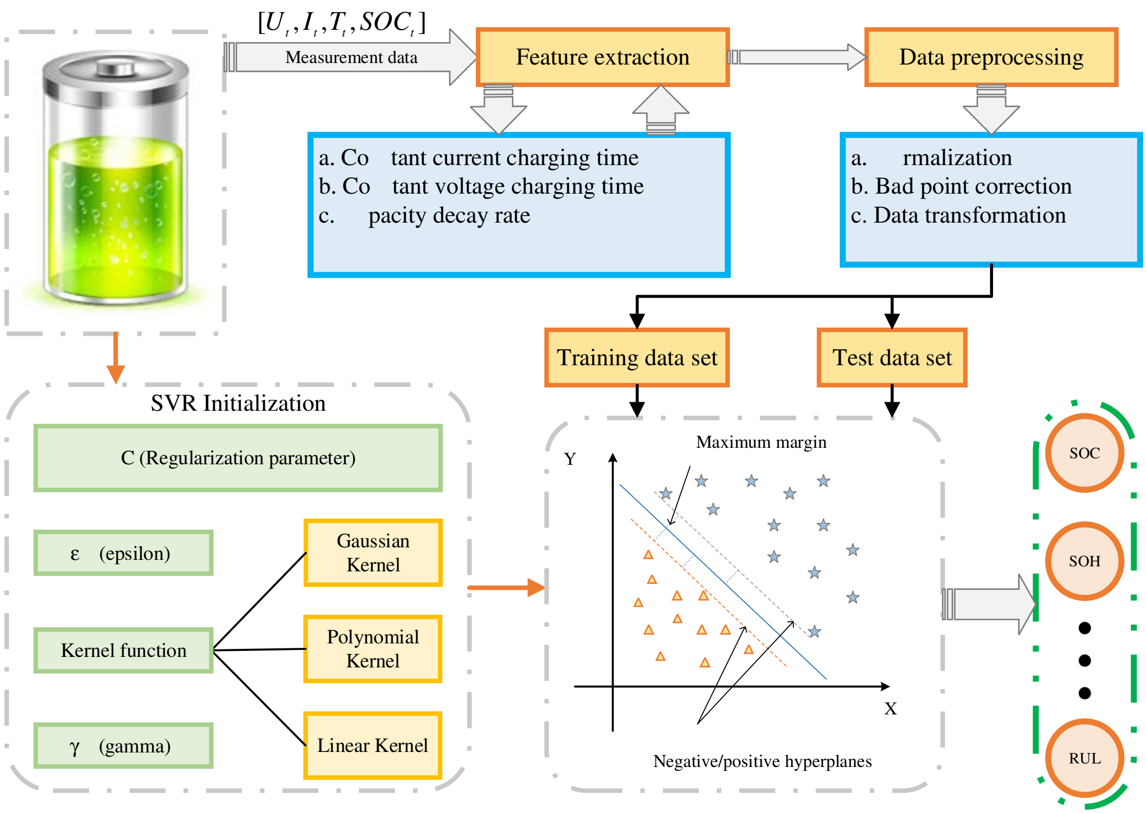


Fig. 8 Flowchart of SVR-based Li-ion battery state estimation

As shown in Fig. 8, similar to the LSTM algorithm, the antecedent steps, such as processing and feature extraction, must be completed first. The performance of the SVR model depends mainly on the choice of kernel function. Commonly used kernel functions include linear kernel, polynomial kernel, and radial basis function (RBF) kernel. Choosing an appropriate kernel function can significantly improve the model's prediction accuracy. Meanwhile, reasonable parameters of the SVR model (e.g., C, ε, and kernel function parameters) are critical. They must be finely tuned by methods such as cross-validation to achieve the best prediction performance.

In summary, when applying data-driven-based methods to estimate Li-ion battery states, the matters to be taken care of include ensuring the quality of the data, performing effective feature engineering, carefully selecting and tuning the model, and preventing overfitting to ensure that the model has a good generalization ability. These strategies help build efficient and reliable battery state estimation systems that support battery management.

Overview of recent model-based estimation methods

Many state estimation methods based on equivalent circuit models of Li-ion batteries have emerged in recent years. The basic steps of these algorithms are consistent and can be summarized in 3 steps, which are (a) model building, (b) parameter identification, and (c) state estimation. The related theories and algorithms used in each of these steps have advanced in different aspects, and this section is divided into three subsections to summarize and generalize the theories and algorithms involved in each of these steps.

Equivalent circuit model of Li-ion battery

The selection of an appropriate equivalent circuit model depends on the application requirements, the required accuracy, and the available computational resources. It can be evaluated and selected based on real-time, accuracy, and scalability. A trade-off is typically between model accuracy and computational efficiency in practical applications.

Table 2 gives a few standard equivalent circuit models available and list the literature on Li-ion battery state estimation in the last 5 years that use these models.

The choice of different equivalent circuit models for Li-ion batteries depends mainly on the required accuracy, computational complexity, and application scenario. Simple models, such as the Rint model, are suitable for essential battery performance estimation and are computationally fast but may only accurately capture some electrochemical dynamics. More complex models, such as the Randles model or the multiple RC loop model, provide higher accuracy, can simulate more details of the internal processes of the battery, and are suitable for applications with in-depth studies of battery performance and aging mechanisms. Therefore, the choice of model needs to be weighed against accuracy, computational resources, and the specific needs of the target application. The advantages and disadvantages of the various equivalent circuit models listed in Table 2 are analyzed below.

(a) Randles model.

The Randles model is an equivalent circuit model commonly used in electrochemical impedance spectroscopy (EIS) [46] analyses to describe electrochemical processes at electrolyte interfaces. It consists of a series resistance (representing the ohmic impedance of the electrolyte), a capacitor in parallel (representing the double-layer capacitance), and a Warburg impedance (representing the diffusion process). The advantages are that the model is simple, describes the basic properties of electrochemical systems, and applies to various electrochemical studies. The disadvantage is that the model assumes more ideal assumptions and may not accurately portray complex electrochemical systems' full range of properties, especially under nonlinear or non-stationary conditions.

(b) PNGV model.

The PNGV (Partnership for a New Generation of Vehicles) model is a US government initiative to develop fuel-efficient vehicles in the automotive industry. While not a direct "model" for battery or circuit modeling, the PNGV initiative is focused on advancing fuel-efficient technologies, including hybrid and electric vehicles. Advantages of PNGV include fostering technological innovation in automobiles and promoting more environmentally friendly vehicles. However, its disadvantages may include the high cost of research and development and the challenge of commercializing advanced technologies within a limited time frame.

(c) Thevenin model.

The Thevenin model of a Li-ion battery is an equivalent circuit model that reduces the battery to a voltage source (representing the open circuit voltage) and a series resistor (representing the internal resistance). The model is suitable for simulating battery behavior under various load conditions and is relatively simple to implement, making it widely used in basic battery management systems. However, an oversimplified model can be a drawback because it may need to accurately capture the complex dynamics or aging effects of the battery, limiting its accuracy and effectiveness in estimating its state of charge or health.

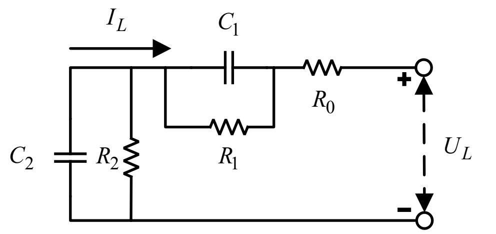
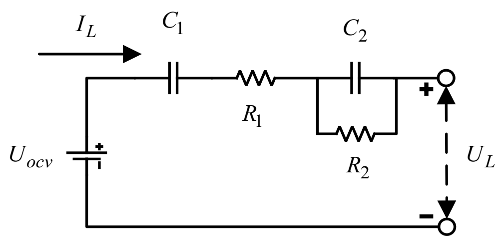
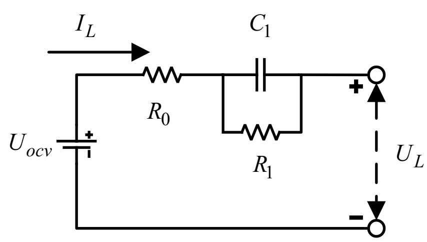
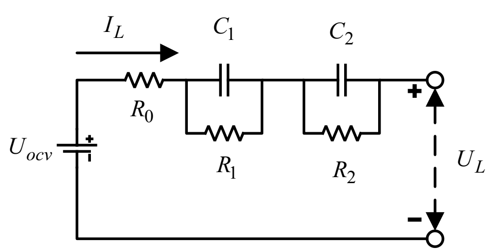
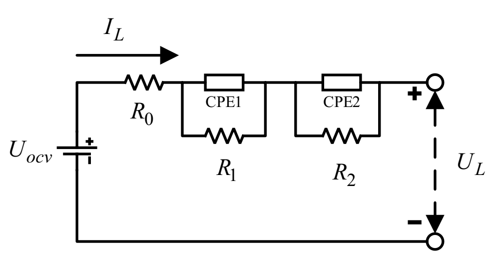
(d) 2RC model.

The 2RC model is a type of equivalent circuit model for Li-ion batteries that simulates the dynamic electrochemical behavior of the battery using two series-connected resistance–capacitance (RC) networks. This model captures the transient response of the battery during charging and discharging more accurately than a single RC network model, thus providing a more precise estimate of the battery state. The advantage is that it can better reflect the actual operating state of the battery and is suitable for applications that require high battery performance. The disadvantage is that the model is relatively complex and requires more data to accurately determine parameters, which may increase the difficulty and cost of model calibration.

(e) Fraction-order model.

The fractional order model is an advanced mathematical model for describing the electrochemical behavior of Li-ion batteries, which is used to simulate the charging and discharging processes and aging phenomena of the batteries more accurately by introducing fractional order derivatives. The advantage is that its description of the battery behavior is closer to reality, and it can capture the complex processes inside the battery that are difficult to express by other models. The disadvantage is that the mathematical processing of the model is more complicated and requires specific mathematical tools and algorithms to solve, which increases the difficulty of model implementation and computational cost.

Table 2 Equivalent circuit model and its associated references and publication date

Equivalent circuit model and its associated references and publication date		
Equivalent circuit model	Circuit diagram	References and year of publication
Randles model		Simić et al. (2022) [102], Hasan et al. (2020) [103], Moye et al. (2019) [104], Poonam et al. (2021) [105], Zhang et al. (2023) [106], Han et al. [107]
PNGV model		Geng et al. (2022) [108], Zhou et al. (2022) [109], Liu et al. (2022) [34], Lin et al. (2021) [110], Jiang et al. (2022) [111], Zheng et al. (2023) [14]
Thevenin model		Fatoorehchi et al. (2022) [112], Wang et al. (2021) [113], Tian et al. (2020) [114], Suti et al. (2022) [115], Seo et al. (2021) [116], Shen et al. (2023) [117]
2RC model		Cao et al. (2023) [118], Sugumaran et al. (2023) [119], Shrivastava et al. (2022) [120], Tahir et al. (2021) [121], Lai et al. (2020) [122], Saqli et al. (2023) [123]
Fractional-order model		Wang et al. (2020) [124], Zhang et al. (2022) [125], Zhu et al. (2023) [126], Yu et al. (2020) [127], Ruan et al. (2021) [128], Wang et al. (2023) [129]

Parameter identification algorithm of the model

After selecting an appropriate equivalent circuit model, the relevant parameters of the model need to be identified for application in the state estimation algorithm. The model's accuracy largely depends on the accuracy of the parameter identification algorithm, which further affects the accuracy of the state estimation algorithm, so the improvement of the parameter identification algorithm is essential. According to their working principle and application background, the parameter identification algorithms can be classified into several categories, and the specific classification and recent references of related improved algorithms are given in Table 3.

Table 3 Improved algorithms and references related to parameter identification

Types of algorithms	Specific algorithm name	Relevant references and year of publication	Detailed description of the algorithm
Based on the least squares method	IA-MAFF-RLS	Guo et al. (2023) [47]	FFRLS based on information Analysis
	FMRLS	Yang et al. (2023) [48]	Fixed memory recursive least squares
	PCFFRLS	Zhu et al. (2023) [49]	Proportional control forgetting factor recursive least square
Based on filtering algorithms	CF-PF	Qiao et al. (2023) [45]	Chaotic firefly-particle filtering method
	SPF	El-Dalahmeh et al. (2023) [50]	Physics-informed smooth particle filter
Based on swarm intelligence algorithms	IMCCPSO	Tang et al. (2023) [51]	Incomplete multi-context cooperatively coevolving PSO
	CBSO	Zhang et al. (2023) [52]	Complex-order beetle swarm optimization
Based on statistical algorithms	Bayesian (math.)	Kim et al. (2023) [53]	Bayesian inference
Based on artificial intelligence algorithms	INFO	Merrouche et al. (2024) [54]	Innovative weighted mean of vectors

As shown in Table 3, the Li-ion battery parameter identification algorithms are mainly divided into five major categories based on least squares, filtering algorithms, swarm intelligence algorithms, statistical algorithms, and artificial intelligence algorithms, and the table lists 1–3 recently published papers of improved algorithms for each of these five major categories of algorithms. Currently, various improved algorithms based on RLS are predominant, which are preferred for equivalent circuit model parameter discrimination due to their broad applicability, good dynamic properties and robustness, and concise algorithmic structure. The IA-MAFF-RLS algorithm proposed by Guo et al. [47] is improved in several aspects. First, the information analysis based on the Cramér-Rao lower bound was carried out for each model parameter, and the constant informatics theory was introduced to update the related estimation error covariance with CRLB [55]. Second, a switch-based adap-tive strategy is proposed to fine-tune multiple FFs online using two rules, which trade-offs between the information richness of the memory window and the traceability of the current–voltage distribution. Finally, an IA-MAFF-RLS method is established to identify different model parameters associated with FFs, respectively. This method provides a more accurate and interference-resistant technological path for parameter identification of Li-ion batteries in electric vehicles through information analysis, adaptive forgetting factor tuning, and targeted element-level strategies. The FMRLS algorithm proposed by Yang et al. [48] obtains the fast-dynamic (FD) and slow-dynamic (SD) parameters of the equivalent circuit models (ECM), respectively. Due to the slow dynamic nature of the open circuit voltage, the algorithm recognizes it as a component of the SD part. By accurately identifying the fast and slow dynamic parameters, the algorithm improves the predictive performance and reli-ability of the battery model. However, at less than 10% SOC, especially at very high or low temperatures, the OCV iden-tification still suffers from specific errors and fluctuations, indicating that the adaptability of the algorithm for extreme conditions needs to be further improved. Zhu et al. [49] proposed the PCFFRLS algorithm, which aims to reduce the steady-state error by adding a proportional control link based on the forgetting factor recursive least squares algorithm and further reduce the effect of random noise on the estimation results using the Monte Carlo method. However, its complexity increases compared to the traditional EKF or AEKF algorithms. In particular, the Monte Carlo method requires many samples to be resampled, which may lead to an increased computational burden, especially in real-time or resource-constrained application scenarios. The paper should further explore the algorithms' computational efficiency and optimization strategies.

Secondly, particle filtering and swarm intelligence-based optimization algorithms also occupy a non-negligible position in parameter identification. For filtering algorithms, the CF-PF algorithm proposed by Qiao et al. [45] achieves high-precision joint estimation of SOC and SOH by adjusting the battery parameters to reflect the dynamic characteristics of Li-ion batteries in different aging states in real time. It utilizes simulation of the behavior of fireflies attracting to each other and mapping a set of particles to different solution spaces through chaotic mapping to find a new optimal solution. However, the study did not consider the effect of temperature on battery state estimation, which is a direction for future research. El-Dalahmeh et al. [50] proposed a RUL prediction method based on a physically-informed Smoothed Particle Filtering (SPF) framework, which extracts the loss of active material in the positive and negative electrodes of Li-ion batteries and loss of lithium inventory, which are the three main degradation mechanisms to estimate the parameters of the single particle model (SPM), which can more accurately quantify the degradation mechanisms and predict the capacity decline trend. In the future, the accuracy and reliability of the model can be further improved by considering more physical degradation mechanisms in the prediction process and possible changes in battery operating conditions. For swarm intelligence optimization algorithms, an adaptive multi-context co-evolutionary parallel differential evolutionary algorithm (AMCC-PDE) for Li-ion battery parameter identification proposed by Tang et al. [51] constructs a new offline identification model for the Li-ion battery parameter identification problem, which transforms the battery parameter identification problem into a large-scale global optimization (LSGO) [56] problem. The AMCC-PDE algorithm, which effectively handles the high-dimensional parameter identification problem by combining the segmented parameter identification (SPI) method and the new context vector update strategy, is proposed. However, the application of the algorithm also has specific challenges and limitations, such as the increase in computational complexity, the need for parameter adaptation, the possible local optimum problem, the need for validation in practical application scenarios, and the potential for further optimization. The CBSO algorithm proposed by Zhang et al. [52] combines the concept of complex-order (CO) operator and the mutation strategy into the traditional Beetle Swarm Optimization (BSO) [57] algorithm in the traditional beetle swarm optimization (BSO) algorithm, which may have better performance in searching for globally optimal solutions by capturing the historical memory of the particles and avoiding the algorithm from prematurely converging to the local optimum through mutation operations. There is still room for further research and validation on the algorithm's adaptability, efficiency, stability, and performance in practical applications.

In addition, a few parameter identification algorithms based on statistics and artificial intelligence have recently emerged, with some academic value in terms of theoretical expansion and innovation. Kim et al. [53] proposed ‘Bayesian-based parameter identification for electrochemical models of Li-ion batteries,” which explored in detail the process of parameter identification using the Bayesian frame-work for parameter identification. This approach focuses on estimating the distribution of electrochemical model parameters using observed voltage data from Li-ion batteries, emphasizing the quantification of parameter uncertainty and parameter identifiability. The methodology employed in this study provides a robust and comprehensive strategy for parameter estimation, offering valuable insight into parameter uncertainty and model sensitivity. While this approach demonstrates strong potential for enhancing model accuracy and reliability, its computational demands and the expertise required in Bayesian analysis may be a barrier to the practical implementation of the algorithm. Future research could explore ways to simplify the computational process by developing more efficient sampling techniques or applying machine learning algorithms to approximate the posterior distributions, thus broadening the methodology’s application and ease of use in various battery technology domains. Merrouche et al. [54] described the use of a vector-weighted averaging algorithm for the estimation of ECM parameters of Li-ion batteries in an application. The INFO algorithm optimizes the ECM parameters by minimizing the difference between the estimated and actual battery voltages, showing higher accuracy and convergence speed than other state-of-the-art optimization algorithms. The INFO algorithm can be further improved and explored for more accurate parameter identification hybrid methods.

Table 4 Model-based state estimation algorithms and related references

Types of algorithms	Specific algorithm name	Relevant references and year of publication	Detailed description of the algorithm
Improvements based on EKF	AMCCEKF	Liu et al. (2023) [58]	EKF based on the adaptive maximum correntropy criterion
	MM-EKF	Lv et al. (2024) [59]	A multi-model extended Kalman filtering algorithm considering the effects of temperature and current rate
Improvements based on UKF	ISRUKF	Peng et al. (2023) [60]	Avoid algorithm divergence
	ADUKF	Hosseininasab et al. (2023) [61]	Adaptive dual spherical UKF
	FRTSUKF	Rezaei et al. (2023) [62]	Fuzzy robust two-stage unscented Kalman filtering
Improvements based on CKF	AWSCKF	Takyi-Aninakwa et al. (2023) [63]	Adaptive weighted square-root cubature Kalman filtering
	AFOBS-SRCKF	Zhou et al. (2023) [64]	Adaptive fractional-order backward smoothing square root cubature Kalman filtering
	SVD-AECKF	Zhou et al. (2023) [65]	Based on singular value decomposition with adaptive embedded cubature Kalman filtering
Improvements based on PF	HIPF	Chen et al. (2023) [66]	H-infinity particle filter
	FTC-APF	Luan et al. (2023) [67]	A Fast Temperature Correction Adaptive Particle Filter
Hybrid algorithm	MIEKPF- EKPF	Zhou et al. (2023) [68]	Multi-innovative extended Kalman particle filter combined with extended Kalman particle filte
	EKF-LSTM	Li et al. (2023) [69]	Combining neural networks with model-based methods

State estimation methods for Li-ion batteries

After the equivalent circuit model is obtained by a parameter identification algorithm, it is brought into suitable state estimation algorithms (e.g., EKF, UKF, PF), which can estimate the internal state of the battery based on the battery's input and output data. Recently, model-based state estimation methods for Li-ion batteries have undergone several significant improvements to enhance the estimation's accuracy, efficiency, and applicability. Table 4 lists some of the recent typical state estimation algorithms for the reader's reference.

As shown in Table 4, model-based state estimation methods for Li-ion batteries are mainly filtering algorithms, which include, but are not limited to, extended Kalman filtering, unscented Kalman filtering, cubature Kalman filtering, particle filter algorithms, and some hybrid algorithms based on model and data-driven. The most common of these are the various improved algorithms based on Kalman filters, and the following will introduce the innovations and room for improvement in the literature listed in the table.

For the EKF improvement algorithm, a new method for SOC estimation of Li-ion batteries based on the adaptive iterative extended Kalman filtering (AIEKF) combined with the adaptive maximum correlation entropy criterion (AMCC) [70] and the Levenberg–Marquardt (L-M) [71] principle was proposed by Liu et al. [58]. AMCC was introduced to replace the Minimum Mean Square Error (MMSE) criterion in the traditional EKF to enhance the robustness to abnormal data and non-Gaussian noise. Specifically, an adaptive kernel width update strategy is designed so that the filter can dynamically adjust to adapt to different noise environments. At the same time, by analyzing the relationship between OCV and SOC, an OCV correction strategy based on terminal voltage innovation is proposed, which uses the terminal voltage deviation to correct the OCV estimation error and further improves the accuracy of SOC estimation. Lv et al. [59] proposed a multi-model extended Kalman filtering (MM-EKF) based algorithm. The Li-ion battery system is decomposed into two sub-models considering the effect of temperature and the effect of current, which can select the appropriate model according to different operating conditions, has better environmental adaptability than the single-model approach, and is more suitable for estimating the state of Li-ion batteries under complex operating conditions. Future research can further explore and improve the model generalization ability, optimize the computational efficiency, improve the accuracy of parameter identification, consider more environmental factors, and improve the weight determination method.

For the improved UKF algorithm, Peng et al. [60] proposed a dual coefficient tracking improved square root unscented Kalman filtering (ISRUKF), which integrates an improved square root unscented Kalman filtering based on the QR decomposition to maintain the positive characteriza-tion of the covariance matrix and a dual coefficient tracker. Effectively addressing the limitations of traditional Kalman filtering-based methods, it provides better accuracy and more robust robustness. However, the literature does not discuss the impact of battery aging and long-term degradation on the performance of the ISRUKF method, which is critical for long-term battery management. Hosseininasab et al. [61] proposed an adaptive dual unscented Kalman filtering. Compared with the EKF, the UKF has more advantages in dealing with nonlinear systems because it avoids using the Jacobian matrix to approximate nonlinear functions, thus reducing the linearization error. In addition, due to the high computational complexity of the traditional UKF, the spherical simplex method is introduced in this paper, which significantly reduces the computational cost by reducing the number of sigma points. The algorithm can dynamically adjust the parameters of the battery model (e.g., resistance and capacity) to adapt to changes in the battery state, which is particularly important to cope with the battery's aging and changes in its performance under different operating conditions. Rezaei et al. [62] proposed an improved robust unscented Kalman filtering (FRTSUKF) that improves the accuracy of the SOC by compensating for the uncertainty of the model of unknown statistical properties. In addition, the algorithm uses a fuzzy system to recursively adjust the covariance matrix of the measurement noise, making the estimation process more accurate and practical. However, the design and parameter selection of fuzzy logic systems themselves require optimization based on empirical or trial-and-error methods, which limits their general application without sufficient expertise.

For the CKF improvement algorithm, the study by Takyi-Aninakwa et al. [63] introduces a nonlinear autoregressive external input (NARX) network based on the optimization of adaptive weighted square root cubature Kalman filtering (AWSCKF) [72]. The critical innovation is the introduction of an adaptive sliding update mechanism to optimize the process noise and measurement noise covariance matrices, as well as innovative updates to the state estimation and error covariance matrices to improve the accuracy of the method. This study demonstrates the NARX-AWSCKF model's validity under laboratory conditions and emphasizes its potential for application in EV battery management systems. This is demonstrated by the high accuracy and robustness of the model under a wide range of battery chemistries, different charging and discharging conditions, and temperatures. Zhou et al. [64] proposed an improved adaptive fractional-order backward-smoothing square root cubature Kalman filtering algorithm (AFOBS-SRCKF), which combines Sage Husa's adaptive filtering [73] and backward smoothing process to square root cubature Kalman filtering is optimized to enhance the algorithm's ability to handle the nonlinearities and uncertainties inherent in SOC estimation, improving the accuracy and adaptability of SOC estimation in real-time in complex environments. Another paper [65] published in 2023 proposed a new high-precision method based on improved singular value decomposition and adaptive embedded Cubature Kalman fltering (SVD-AECKF) algorithm. It is used to jointly estimate the SOC and SOE of the Li-ion battery of new energy electric vehicles online. The dualpolarization equivalent circuit model and the Time-varying forgetting factor recursive least squares (TVFFRLS) algorithm were used for online parameter identifcation, and the embedded Cubature criterion and SVD matrix decomposition technology were combined to improve the filtering accuracy, efciency, and numerical stability.

For the PF improvement algorithm, Chen et al. [66] proposed the H-infinity particle filter (HIPF) algorithm, which combines the advantages of particle filter (PF) and H-infinity filter (HIF) and introduces a new mechanism of particle weight adjustment in the algorithm, which maintains the particles by compromising their weights in order to maintain the particle diversity and prevent particles from concentrating on a few particles, thus improving the accuracy of the estimation. Considering the nonlinearity and complexity of the battery behavior, combining the HIPF algorithm with machine learning methods can be explored further to improve the accuracy and robustness of the estimation. Luan et al. [67] proposed a fast temperature-corrected adaptive particle filtering (FTC-APF) SOC estimation strategy, which not only updates the actual capacity, open-circuit voltage, and double-pole (DP) model in real-time parameters to adapt to rapid temperature changes but also attenuates the effect of external disturbances or sensor-generated uncertainty noise on the SOC estimation of Li-ion batteries by predicting the process noise and updating the observation noise. Future research directions include considering the effect of cell inconsistency on SOC estimation and considering the variability of the charging and discharging processes when designing cell capacity experiments and OCV experiments.

In addition to the single type of state estimation algorithms mentioned above, some hybrid algorithms exist, which realize their complementary advantages through the fusion of the same or different algorithms. Zhou et al. (2023) [68] proposed the MIEKPF-EKPF fusion algorithm for the joint estimation of SOC and SOH of Li-ion batteries, which entirely takes into account the influence of historical observation data on the current estimation value by combining the multi-innovation theory and extended Kalman particle filtering, and improves the estimation accuracy and robustness by dynamically adjusting the weights and particle sampling. The algorithm considers the influence of historical observation data on the current estimation value. It improves the accuracy and robustness of the estimation by dynamically adjusting the weights and particle sampling [69]. In response to the problem that the traditional second-order equivalent circuit model can not fully capture the complex electrochemical reactions and state changes inside the battery, the proposed hybrid methods of EKF-LSTM and LSTM-EKF, combined with the EKF algorithm for real-time dynamic estimation of the SOH and SOC, are used to estimate the SOC and SOH of Li-ion batteries in real-time. The real-time dynamic estimation capability of the EKF algorithm and the nonlinear learning capability of the LSTM use WOA to optimize the preset parameters of the EKF and LSTM models to improve the model performance effectively. Future research can further explore the SOC estimation methods for different types of batteries and their different operating conditions, as well as how to optimize the model parameter selection and algorithm combination methods to adapt to the practical application requirements in EV battery management systems.

Model-based estimation methods provide a powerful tool for accurately estimating the battery state through a deep understanding of the physical and electrochemical processes of the battery. With the advancement of computational techniques and the development of model optimization algorithms, these methods play an increasingly important role in improving the performance of BMS, extending battery life, and ensuring safe battery operation. Future research may further explore more efficient model parameter identification methods, develop more accurate electrochemical models, and design more flexible hybrid estimation strategies to adapt to the needs of battery state estimation under different types and operating conditions. In addition, combining advanced optimization algorithms and artificial intelligence techniques to improve models' adaptive ability and prediction accuracy will be an important direction for future research.

Overview of recent data-driven based estimation methods

In recent years, with the rapid development of machine learning and deep learning technologies, data-driven methods based on Li-ion battery state estimation have been widely used and deeply studied, such as LSTM, CNN, DNN, and integrated learning methods, which rely on a large amount of battery usage data to predict the battery state by learning patterns and features from the data. In particular, the hybrid use of different types of network models combined with transfer learning and optimization algorithms, such as the WOA [74], further optimizes the model parameter selection and improves the estimation accuracy.

Lithium-ion battery dataset

A reasonable data set for machine learning algorithms can improve the whole system's performance. Its typical characteristics are low noise, high precision, multiple operating conditions, large scale, etc. From the dimension perspective, it usually includes voltage, current, temperature, charging time, battery internal resistance, and appropriate features are selected according to different estimation targets. There is a specific time correlation from the data series, usually in the form of time series. In terms of sampling frequency, the data used for SOC estimation is usually sampled at high frequency, which is convenient for the model to learn the characteristics of the data thoroughly. The data used for SOH estimation are usually sampled at a low frequency and reflect the macroscopic characteristics of Li-ion batteries. In terms of the diversity of operating conditions, the data collection covers a variety of operating conditions, usually including but not limited to HPPC, BBDST, DST, UDDS, and standard constant current and constant voltage charge and discharge cycles. Different test conditions are designed according to different states to be estimated. Han et al. [75] highlighted the importance of three fundamental data types: laboratory, field, and synthetic data in battery health estimation. Ma et al. [76] developed a physical model to extract aging-related parameters from charging curves, which were then used to guide a DNN for high-precision and efficient RUL prediction. Tang et al. [77] proposed a few-shot learning-based method to detect battery life anomalies by analyzing the first cycle of battery aging data. The proposed method utilizes a 215 commercially available Li-ion battery dataset and develops a few-shot learning network to detect lifetime anomalies without prior knowledge of degradation mechanisms. This literature fully illustrates the importance of dataset selection for machine learning, and Table 5 lists a series of dataset selection schemes from the perspective of SOC and SOH estimation of Li-ion batteries, respectively.

Table 5 Different dataset selection schemes for Li-ion batteries

Types of datasets	Relevant references and year of publication	Detailed description of the dataset
Run-to-failure	Wang et al. (2024) [78]	Contains operational fault data for 6 batteries under 55 charging and discharging strategies. Some unique charging and discharging strategies are included, such as those for satellites in geosynchronous orbit (GEO)
Incremental capacity	Tang et al. (2021) [79]	IC trajectories are reconstructed from complex load curves, including those with large noise or non-constant current curves
Electrochemical impedance spectroscopy	Tang et al. (2023) [80]	A novel approach combining fractional order circuit models and machine learning techniques. To solve the challenge of using 10 s sampling time and 10 Hz sampling rate to predict the electrochemical impedance spectrum of Li-ion batteries
Battery degradation	Vilsen et al. (2024) [81]	Contains second-level measurements of three Li-ion battery units aged at three different temperatures (45 °C, 40 °C, and 35 °C) using realistic forklift load curves
Cyclic aging	Kirkaldy et al. (2024) [82]	Forty commercial 21,700 Li-ion batteries (LG M50T) were cycled under 15 different operating conditions (temperature and state of charge)
Different discharge levels	Taş et al. (2023) [83]	Contains the temperature variation, discharge time, capacity loss and performance characteristics of Li-ion batteries at 2C, 4C, 5C, 6C, 10C, 15C, and 20C discharge levels
Electrochemical impedance spectroscopy	Rashid et al. (2023) [84]	Electrochemical impedance spectroscopy (EIS) was performed at temperatures of 15 °C, 25 °C, and 35 °C at 5%, 20%, 50%, 70%, and 95% state of charge (SOC)
Accelerated aging	Tang et al. (2021) [85]	Comprehensive dataset containing 8947 burn-in cycles for 15 modes of operation

As shown in Table 5, eight recent papers on Li-ion battery data sets are listed, most of which are public data sets, reflecting the data characteristics of Li-ion batteries from different perspectives. Wang et al. [78] aimed at the problem that most of the current public datasets are laboratory simulation environments and lack real usage scenarios. The data preprocessing methods used in different studies are inconsistent, leading to unfair comparisons between dif-ferent models and an unobvious improvement effect. The run-to-failure dataset of Li-ion batteries based on real-use scenarios was published. These data can help researchers evaluate Li-ion batteries' SOC and SOH estimation models in real-use scenarios and have practical value. Tang et al. [79] studied how to estimate the SOC and SOH of batteries in Li-ion battery management and introduced a new method based on incremental capacity analysis (ICA) to handle data under complex load conditions. The proposed method can reconstruct ICA trajectories under complex load conditions, such as three complex operating conditions: constant current charging (with noise), pulse charging, and battery pack charging with active equalization. Tang et al. [80] proposed a system to predict the EIS of a Li-ion battery using a 10-s pulse test and a 10-Hz sampling rate. By using more than 1000 sets of load curves under different SOC and SOH, the study shows that the RMSE of the proposed method can be controlled within 1.1 mU and 2.1 mU under the 3-min dynamic curve and 10-s dynamic curve, respectively. Vilsen et al. [81] proposed a Li-ion battery degradation dataset based on forklift operating curves, containing degradation data measured at a frequency of seconds for three batteries at three different temperatures (45 °C, 40 °C, and 35 °C). This data under realistic load conditions helps to more accurately model and verify battery behavior in applications such as electric vehicles. Such high-frequency data are precious for SOC and SOH modeling, estimation, and short and long-term prediction in multi-temperature natural environments. Kirkaldy et al. [82] studied the cyclic aging data of a commercial model 21,700 Li-ion battery (LG M50T, LG GBM50T2170) and its impact on the battery state (SOC and SOH) estimation. In the experiments, the battery was cycled in different SOC ranges (0–30%, 70–85%, 85–100%, 0–100%). The results show that batteries in the 70–85% SOC range age the slowest, while those in the extreme SOC range (0–30% and 85–100%) age the fastest. Through the cycle aging data, the capacity fade (CF) and resistance increase (RI) of the battery can be analyzed. The study also calculated the loss of active material (LAM) for the positive and negative electrodes and their active materials, such as graphite and silicon, and the loss of lithium inventory (LLI). These metrics can help to estimate the battery health status accurately. Taş et al. [83] developed a dataset for lithium polymer batteries containing current, voltage, and temperature parameters at different discharge levels. The research team used a CNN deep learning model for SOC estimation and studied their impact on SOC estimation accuracy by varying the network's dense layers and batch size. The results show that more extensive dense layers and smaller batch sizes produce more minor errors in SOC estimation. Rashid et al. [84]

introduced a method to rapidly estimate the SOH of Li-ion batteries using EIS and machine learning. It has been shown that the SOH of the battery can be quickly estimated by analyzing the EIS data. EIS data can provide detailed information about the internal state of the battery, especially impedance changes that are highly correlated with the health state of the battery. The influence of EIS test data under different SOC and temperature conditions on SOH estimation was also explored. Training machine learning models with data from various conditions can improve the adaptability and robustness of the model to uncertain factors in practical use. Tang et al. [85] proposed a transfer learning and machine learning method to generate high-quality battery aging datasets by combining industrial data with accelerated aging experimental data. This way, high-accuracy datasets with less than 1% error can be generated with up to 90% experimental time savings. These datasets can be used not only to train other data-driven battery aging models but also for more complex application scenarios such as fault prediction, lifetime evaluation, fast charging optimization, and battery "second life" utilization.

Based on data-driven algorithms

In recent years, many Li-ion battery experimental datasets have been developed to support data-driven algorithms. These advances indicate that data-driven approaches are becoming a critical technological pathway to enhance the performance of Li-ion battery management systems, extend battery life, and ensure battery safety. Table 6 lists a series of articles published in recent years on deep learning and machine learning applied to the field of Li-ion battery state estimation, respectively, in order to summarize and summarize the essential and prominent recent advances in this field. As shown in Table 6, for related algorithms based on the field of deep learning, including but not limited to deep CNN, LSTM, DNN, and their composite algorithms. For DNNs and their related extended composite algorithms, an innovative approach proposed by Kannan et al. [86] estimates the SOC of Li-ion batteries by combining DNN and time-series neural-based extended analysis (N-BEATS). The proposal of this novel hybrid architecture, which is targeted at improving the accuracy and reliability of SOC estimation for Li-ion batteries, along with experiments using low-cost microcontrollers, not only demonstrates the utility of the architecture but also shows the potential for application in resource-constrained environments. Considering the "black-box" nature of DNNs, the research could explore model interpretation methods to understand the model decision-making process better and improve user trust. Li et al. [87] proposed an algorithm that is an innovative hybrid model designed to accurately predict the RUL of Li-ion batteries. This model combines a Temporal Convolutional Network (TCN) [97], Gated Recurrent Unit (GRU), DNN, and Dual Attention Mechanism to significantly improve the prediction accuracy of the remaining useful life of Li-ion batteries. Introducing the feature and temporal attention mechanisms further enhances the model's understanding of the battery performance degradation patterns, giving the model significant potential for application in battery health management and prediction. Considering the complexity and challenges of practical applications, future work requires further efforts to optimize the model performance, reduce the complexity, and improve the generalization ability. Chang et al. (2024) [88] proposed an electrochemical impedance spectroscopy (EIS) prediction method based on the Sparrow Search Algorithm Optimized Deep Neural Networks (SSA-DNN) by extracting features from the middle and high-frequency bands and predicting the more time-consuming middle and low-frequency bands, significantly reducing the overall measurement time. The prediction method is also used to estimate the SOH of the battery, showing the broad applicability of this EIS prediction method in various application scenarios based on EIS technology.

There has been a considerable accumulation of literature on LSTM algorithms in Li-ion battery state estimation, and many improved algorithms based on LSTM have appeared recently. Chen et al. [89] proposed an innovative LSTM-RNN model for SOC estimation of Li-ion batteries, which improves the accuracy and stability of SOC estimation by extending the input (EI) and limiting the output (CO) to improve the accuracy and stability of SOC estimation. This approach focuses on the significant fluctuations in the output SOC of a single network. It proposes a strategy that combines a slow variable (e.g., sliding average voltage) as the input to the network and restricts the variation in the output SOC of the network by an Ampere-hourly integration-based state-flow strategy to improve the performance of the SOC estimation. Xu et al. [16] introduced an improved SOH estimation method for Li-ion batteries based on a convolutional neural network and short-term memory model, with a core focus on ensuring the accuracy of the prediction through effective data feature extraction. The study proposes a feature selection method by removing useless features from the input data during the data preparation stage. In addition, Skip Connection was added to the CNN-LSTM model in the study to address the problem of neural network degradation caused by multi-layer LSTM. Although the model performs well on specific datasets, its ability to generalize to different types of batteries from different manufacturers needs to be further verified. Wang et al. [90] proposed a composite model (DRSN-CW-LSTM) based on deep residual shrinkage network (DRSN) and LSTM for the SOC and SOH joint prediction. For the DRSN-CW model, channel-specific thresholds are introduced to achieve adaptive soft thresholding of data noise in the residual shrinkage layer, improving feature extraction accuracy. Combined with the LSTM model, the time-series features of the battery data are effectively captured, which improves the model's ability to understand the trend of battery performance changes. Gao et al. [91] proposed a hybrid network model combining the Hierarchical Feature coupling Module (HFCM) and LSTM to improve the accuracy and versatility of Li-ion battery SOH estimation. The HFCM module extracts different semantic information from the original data through the deep feature extraction flow and the shallow feature extraction flow, which solves the problem of insufficient feature extraction of time series. The LSTM module effectively models time series information by introducing input gate, forget gate, and output gate, which overcomes the limitations of traditional RNN in dealing with long-term memory. The whole HFCM-LSTM network structure performs ini-tial data processing through the 1D-CNN module, cascades the HFCM and LSTM modules, and achieves high-precision battery SOH estimation through the fully connected layer. Guo et al. [92] proposed a framework for predicting the health state of Li-ion batteries based on the complete integrated empirical modal decomposition (CEEMDAN) and LSTM neural networks. CEEMDAN decomposes the original battery capacity degradation curves to remove the high-frequency subsequences unrelated to the primary degradation trend and then predicts using bidirectional LSTM and LSTM network groups. Experimental results show that the framework can predict batteries' SOH more accurately than previous mainstream methods.

Table 6 *Based on the data-driven state estimation algorithm and its related references*

Types of algorithms	*Specific algorithm name*	*Relevant references and year of publication*	*Detailed description of the algorithm*
Based on deep learning	*DNN-NBEATS*	*Kannan et al. (2023) [86]*	*A new hybrid architecture combining Deep Neural Network (DNN) and Neural Basis Expansion Analysis for Time Series (N-BEATS)*
	TCN-GRU-DNN	*Li et al. (2023) [87]*	*A hybrid model based on temporal convolutional network (TCN)-gated recurrent unit (GRU)-deep neural network (DNN) and dual attention mechanism*
	SSA-DNN	*Chang et al. (2024) [88]*	*A sparrow search algorithm optimized deep neural network (SSA-DNN)*
	LSTM-RNN	*Chen et al. (2023) [89]*	*A novel long short-term memory recurrent neural network (LSTM-RNN) with extended input (EI) and constrained output (CO)*
	CNN-LSTM	*Xu et al. (2023) [16]*	*The skip connection is added to the convolutional neural network-long short-term memory model*
	DRSN-CW-LSTM	*Wang et al. (2023) [90]*	*A method is based on long-short-term memory (LSTM) and Deep Residual Shrinkage Networks with Channel-wise Thresholds (DRSN-CW)*
	HFCM-LSTM	*Gao et al. (2023) [91]*	*A novel hybrid network, called HFCM (Hierarchical Feature Coupled Module)-LSTM (long-short-term memory)*
	CEEMDAN-LSTM	*Guo et al. (2024) [92]*	*A LSTM neural network with the complete ensemble empirical mode decomposition with adaptive noise*
Based on machine learning	*PSO-LS-SVM*	*Zhou et al. (2024) [18]*	*A combined data-driven modeling approach based on Least squares support vector machine based on particle swarm optimization and unscented Kalman filtering*
	WLS-SVM	*Xiong et al. (2023) [93]*	*A method for early predicting Li-ion batteries cycle life based on weighted least squares support vector machine (WLS-SVM) with health indicators (HIs)*
	ABC-MK-SVR	*Chen et al. (2023) [94]*	*A hybrid method based on artificial bee colony (ABC) algorithm and multi-kernel support vector regression (MK-SVR)*
	PSO-RF	*Wu et al. (2023) [95]*	*A Particle Swarm Optimization Random Forest (PSO-RF) prediction method*
	EMD-VCR-GRU-RF	*Wang et al. (2024) [96]*	*A method combining Empirical Modal Decomposition (EMD), Random Forest (RF) and Gated Recurrent Unit (GRU)*

Machine learning-based algorithms mainly include SVM, decision trees and random forests, K-mean clustering and their composite algorithms, etc. In this paper, a series of literature on improved algorithms based on support vector machines and random forest algorithms for estimating the state of Li-ion batteries are listed in order to show the recent developments in this field. Zhou et al. [18] proposed a data-driven modeling method that combines the Least Squares Support Vector Machine (LS-SVM) and UKF data-driven modeling approach using LS-SVM to establish a nonlinear link between the current, voltage, and SOC. PSO is used to optimize LS-SVM parameters to improve the model's accuracy for voltage estimation. Unscented Kalman filtering is used for SOC estimation using the state and measurement equations established by LS-SVM. Xiong et al. [93] proposed a method for early prediction of the cycle life of Li-ion batteries based on the Weighted Least Squares Support Vector Machine (WLS-SVM) algorithm. WLS-SVM improves the traditional SVM algorithm's robustness and prediction accuracy when dealing with abnormal data. Although the area change of the battery's voltage-capacity discharge curve ($\Delta A10 - 100$) was shown to have a strong correlation with the battery's cycle life, this metric may not be the only or optimal health indicator, and other unconsidered metrics can be further considered in the future to provide more comprehensive or earlier information about the battery's health. Chen et al. 2024) [94] proposed a method based on the Artifcial Bee Colony (ABC) [98] algorithm and the Multi-Kernel Support Vector Regression (MK-SVR) hybrid method for predicting the capacity degradation of Li-ion batteries. In the paper, the capacity degradation prediction model of Li-ion battery under diferent conditions is established by MK-SVR, and ABC optimizes the penalty factor and kernel function parameters of SVR to improve the efectiveness of SVR for Li-ion battery capacity degradation prediction. The acquisition and processing of real-time data and the practical feasibility of model updating and maintenance must be further explored in future work. Wu et al. [95] proposed a method to improve the accuracy of the RUL prediction of Li-ion batteries by constructing a particle swarm-optimized random forest (PSO-RF) algorithm. The PSO-RF model optimizes the tree in the random forest algorithm by optimizing the PSO-RF model solves the problem of parameter selection of the random forest algorithm by optimizing two parameters: the number of trees and the number of random features used for segmentation in the random forest algorithm, which improves the accuracy and robustness of the prediction. The study was compared with the traditional random forest and BP neural network algorithms, but the comparative analysis may need to be more comprehensive. Comparison with other advanced machine learning and deep learning methods, such as CNN and extended LSTM, which perform well in time series prediction, can also be considered. Wang et al. [96] proposed a combination of empirical modal decomposition (EMD) [99], random forests

combination of empirical modal decomposition (EMD) [99], random forests (RFs), and GRU for Li-ion battery SOH estimation method. The method starts by analyzing the time intervals between equal voltage increases and decreases of the battery as HIs. Then, it analyzes the correlation between these HIs and SOH using Pearson's coefficient. Next, the battery SOH data were decomposed using EMD, and the variance contribution ratio (VCR) [100] was introduced to measure the relationship between the intrinsic modal function (IMF) [101] components and SOH. Ultimately, an EMD-VCR-GRU-RF-based SOH estimation model was developed. However, the construction and training of the model are still relatively complicated, and further simplification of the model structure is needed. In practical applications, real-time estimation of battery SOH is a crucial requirement. Future research can explore how to reduce the computation time and realize real-time or near real-time estimation of battery SOH.

Challenges faced by data-driven estimation methods based on data include data quality and availability, model interpretability, overfitting, and generalization ability. To improve the performance of estimation methods, common strategies include data preprocessing, feature engineering, model selection and tuning, and model fusion. In addition, with the rapid development of data science and artifcial intelligence technologies, new data-driven estimation methods and tools are emerging, providing more possibilities for solving practical problems.

Discussion

Selection principles for different methods

This paper focuses on the estimation of Li-ion battery SOC and SOH. Furthermore, it discusses the model-based and data-driven estimation methods. Model-based estimation algorithms are suitable for scenarios where some knowledge of the physical or chemical processes of the system is known. For example, in the state estimation of Li-ion batteries, equivalent circuit models (such as Thevenin model, 2RC model, and Randles model) and electrochemical models are often used. These methods use the understanding of the internal reactions of the battery, establish mathematical models, and combine the Kalman filter algorithm and its various improved algorithms to achieve state estimation. Data-driven methods are suitable for scenarios with a large amount of historical data but insufficient knowledge about the system's internal processes. Data-driven approaches rely on machine learning and deep learning techniques to make predictions and estimates by learning patterns in the data. For example, the application of LSTM, SVR, DNN, etc., in SOC and SOH estimation of Li-ion batteries. Table 7 summarizes the advantages and disadvantages of model-based versus data-driven approaches.

Currently, the existing research mainly focuses on the state estimation of a single model, which uses equivalent circuit, electrochemical, machine learning, and neural network models separately. The advantages of different models are not thoroughly combined, which is also a challenge for the algorithm's complexity. The choice of the state to be estimated is usually a single state or a joint estimation of two states. At the same time, the fusion of different state estimates is not tight in the design of the specific algorithm structure, and the known effective information is not maximized to improve the algorithm's accuracy. It is also a challenge to design the model. It is challenging to fully use the existing technology to design a set of simple and accurate models for Li-ion battery state estimation.

Table 7 Comparison of model-based and data-driven approaches

Features	Model-based approach	Based on a data-driven approach
Usage scenario	Initial stage, physical characteristics analysis, stable working environment	Large-scale application, dynamic environment, rapid deployment
Advantages	Strong physical interpretation, versatility, high accuracy	Strong adaptive ability, good real-time, high robustness
Disadvantages	High model complexity, poor real-time performance, and strong parameter dependence	High data demand, poor interpretation, and risk of overfitting

Future research directions and challenges

Future research directions can be developed from the following perspectives. (a) Multi-state joint estimation method: Future research should pay more attention to the joint estimation of multi-states (such as SOC, SOH, and SOP). The accuracy of the overall estimation can be improved by considering the interrelations between multiple states. (b) Hybrid modeling approach: Combining model-based and data-driven approaches to form a hybrid modeling approach to leverage both strengths. For example, the equivalent circuit model is combined with deep learning algorithms to improve prediction accuracy through the structured information provided by the physical model and the nonlinear fitting ability of deep learning. (c) Advanced machine learning and deep learning techniques: Explore and apply new machine learning and deep learning algorithms, such as graph neural networks (GNNS) and variational autoencoders (VAE), to better capture the complex dynamic behavior and characteristics of batteries. (d) Application of big data and cloud computing: Big data technology and platforms process and analyze large-scale battery data to extract more valuable information and features for state estimation and prediction. Cloud computing can provide powerful resources and flexible data storage and processing capabilities. (e) Integration of smart sensors and Internet of Things technologies: Smart and Internet of Things technologies are integrated to realize real-time monitoring and remote management of battery status. With the high-frequency data collected by the sensor network, state estimation, and fault prediction can be performed more precisely.

While exploring more advanced algorithms, the following challenges may be faced. (a) Data quality and quantity: High-quality and diverse data are the basis of data-driven methods. However, practical applications often face the problem of insufficient data and poor data quality. Data augmentation techniques and synthetic data generation methods must be developed to compensate for the lack of accurate data. (b) Model complexity and computational burden: As the complexity of the model increases, the computational burden increases significantly. Especially in real-time applications, it is necessary to balance accuracy and computational efficiency, which is one of the most urgent problems to solve. (c) Generalization ability and robustness of the model: The generalization ability and robustness of the model under different application scenarios and operating conditions is a significant challenge. There is a need to develop general models that can adapt to different battery types and working conditions while enhancing the robustness of the model to noise and abnormal data. (d) Complexity of battery degradation mechanism: The battery degradation mechanism is complex and variable, involving various physical and chemical processes. These mechanisms need to be studied and understood more deeply to improve the accuracy and reliability of the model.

Conclusion

This paper focuses on the key challenges and advanced methods for state estimation of Li-ion batteries, especially for SOC and SOH estimation in battery management systems, and proposes a series of innovative strategies by comprehensively analyzing the limitations of current estimation techniques. These include data preprocessing, feature engineering, model selection and optimization, and model fusion techniques to improve the estimation performance. In this paper, the battery data are first analyzed in depth, and the critical roles of data preprocessing and feature engineering in state estimation are identified. The quality of model input data can be improved through preprocessing measures, such as outlier handling, data normalization, and feature selection and extraction, to provide a more accurate and stable basis for subsequent state estimation models. In particular, machine learning techniques can be employed simultaneously to identify and construct features that significantly impact state estimation, and these methods have shown significant results in improving estimation accuracy. During the model development phase, various statistical and machine learning models were considered to identify the most suitable algorithms for battery state estimation. The comparative analysis of different models' performance reveals each model's advantages and limitations in specific scenarios. It explores a series of model fusion strategies to combine the advantages of different models to improve the overall estimation accuracy and robustness. Considering the rapid development in data science and artificial intelligence, this study also explores the potential applications of these advanced techniques in Li-ion battery state estimation. We emphasize the importance of leveraging methods such as big data and deep learning to enhance the estimation methodology further and point out several directions to focus on in future research, including the development of more accurate electrochemical models, effective identification methods for model parameters, and the design of flexible hybrid estimation strategies. All in all, our research results contribute to advancing state estimation techniques for Li-ion batteries and provide a theoretical foundation and practical guidance for future research and applications in this field.

Acknowledgements Carlos Fernandez expresses his profound gratitude to Robert Gordon University for its support.

Author contributions Junjie Tao: Conceptualization, Formal Analysis, Methodology, Validation, Writing - Original Draft Shunli Wang: Funding Acquisition, Resources, Writing - Review & Editing Wen Cao: Investigation, Software Paul Takyi-Aninakwa: Data Curation Carlos Fernandez: Visualization Josep M. Guerrero: Supervision

Funding The work is supported by the National Natural Science Foundation of China (No. 62173281, 52377217, U23A20651), Sichuan Science and Technology Program (No. 23ZDYF0734, 23NSFSC1436), Dazhou City School Cooperation Project (No. DZXQHZ006), and Technopole Talent Summit Project (No. KJCRCFH08).

References

1. Ghaeminezhad N, Ouyang Q, Wei J, Xue Y, Wang Z (2023) Review on state of charge estimation techniques of lithium-ion batteries: a control-oriented approach. J Energy Storage 72:108707
2. Sun X, Zhang Y, Zhang Y, Wang L, Wang K (2023) Summary of health-state estimation of lithium-ion batteries based on electrochemical impedance spectroscopy. Energies 16:5682
3. Zhang C, Zhang Y, Li Z, Zhang Z, Nazir MS, Peng T (2024) Enhancing state of charge and state of energy estimation in lithium-ion batteries based on a TimesNet model with Gaussian data augmentation and error correction. Appl Energy 359:122669
4. Li R, Li K, Liu P, Zhang X (2023) Research on Multi-Time Scale SOP estimation of lithium–ion battery based on H∞ filter. Batteries 9:191
5. Liu J, Liu X (2023) An improved method of state of health prediction for lithium batteries considering different temperature. J Energy Storage 63:107028
6. Yu X, Chen R, Gan L, Li H, Chen L (2023) Battery safety: from lithium-ion to solid-state batteries. Engineering 21:9–14
7. Ramezani-al MR, Moodi M (2023) A novel combined online method for SOC estimation of a Li-Ion battery with practical and industrial considerations. J Energy Storage 67:107605
8. Yang B, Wang D, Sun X, Chen S, Wang X (2023) Offline order recognition for state estimation of lithium-ion battery using frac-tional order model. Appl Energy 341:120977
9. Kadem O, Kim J (2023) Real-time state of charge-open circuit voltage curve construction for battery state of charge estimation. IEEE Transactions on Vehicular Technology 72:8613–8622
10. Liu Z, Li Z, Zhang J, Su L, Ge H (2019) Accurate and efficient estimation of lithium-ion battery state of charge with alternate adaptive extended Kalman filter and ampere-hour counting meth-ods. Energies 12:757
11. Xiong R, Duan Y, Zhang K, Lin D, Tian J, Chen C (2023) State-of-charge estimation for onboard LiFePO4 batteries with adaptive state update in specific open-circuit-voltage ranges. Appl Energy 349:121581
12. Xia Y (2023) Comparison and analysis of SOC estimation based on first-order and second-order Thevenin battery models based on EKF. Acad J Sci Technol 6:10–18
13. Chen B-H, Chen P-T, Yeh YL, Liao H-S (2023) Establishment of second-order equivalent circuit model for bidirectional voltage regulator converter: 48 V-aluminum-ion battery pack. Energy Rep 9:2629–2637
14. Zheng C, Zhide W, Wenbiao M, Peiwang Z, Gang X (2023) State-of-charge estimation of lead-carbon batteries based on the PNGV model and an adaptive Kalman filter algorithm. Energy Storage Sci Technol 12:941
15. Fan Z, Zi-xuan X, Ming-hu W (2023) State of health estimation for Li-ion battery using characteristic voltage intervals and genetic algorithm optimized back propagation neural network. J Energy Storage 57:106277
16. Xu H, Wu L, Xiong S, Li W, Garg A, Gao L (2023) An improved CNN-LSTM model-based state-of-health estimation approach for lithium-ion batteries. Energy 276:127585
17. Zafar MH, Mansoor M, Abou Houran M, Khan NM, Khan K, Moosavi SKR et al (2023) Hybrid deep learning model for efficient state of charge estimation of Li-ion batteries in electric vehicles. Energy 282:128317
18. Zhou Y, Wang S, Xie Y, Zhu T, Fernandez C (2024) An improved particle swarm optimization-least squares support vector machine-unscented Kalman filtering algorithm on SOC estimation of lithium-ion battery. Int J Green Energy 21:376–386
19. Pan R, Liu T, Huang W, Wang Y, Yang D, Chen J (2023) State of health estimation for lithium-ion batteries based on two-stage features extraction and gradient boosting decision tree. Energy 285:129460
20. Wang C, Chen Y, Zhang Q, Zhu J (2023) Dynamic early recognition of abnormal lithium-ion batteries before capacity drops using self-adaptive quantum clustering. Appl Energy 336:120841
21. Selvaraj V, Vairavasundaram I (2023) A comprehensive review of state of charge estimation in lithium-ion batteries used in electric vehicles. Journal of Energy Storage 72:108777
22. Tian H, Qin P, Li K, Zhao Z (2020) A review of the state of health for lithium-ion batteries: research status and suggestions. J Clean Prod 261:120813
23. Yang S, Zhang C, Jiang J, Zhang W, Zhang L, Wang Y (2021) Review on state-of-health of lithium-ion batteries: characterizations, estimations and applications. J Clean Prod 314:128015
24. Wang Z, Feng G, Zhen D, Gu F, Ball A (2021) A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles. Energy Rep 7:5141–5161
25. Liu F, Yu D, Shao C, Liu X, Su W (2023) A review of multi-state joint estimation for lithium-ion battery: research status and suggestions. J Energy Storage 73:109071
26. Zhou L, Lai X, Li B, Yao Y, Yuan M, Weng J et al (2023) State estimation models of lithium-ion batteries for battery management system: status, challenges, and future trends. Batteries 9:131
27. Du C-Q, Shao J-B, Wu D-M, Ren Z, Wu Z-Y, Ren W-Q (2022) Research on co-estimation algorithm of SOC and SOH for lithium-ion batteries in electric vehicles. Electronics 11:181
28. Espedal IB, Jinasena A, Burheim OS, Lamb JJ (2021) Current trends for state-of-charge (SoC) estimation in lithium-ion battery electric vehicles. Energies 14:3284

29. Cui Z, Wang L, Li Q, Wang K (2022) A comprehensive review on the state of charge estimation for lithium-ion battery based on neural network. Int J Energy Res 46:5423–5440
30. Yao L, Xu S, Tang A, Zhou F, Hou J, Xiao Y et al (2021) A review of lithium-ion battery state of health estimation and prediction methods. World Electric Veh J 12:113
31. Tian J, Chen C, Shen W, Sun F, Xiong R. (2023) Deep learning framework for lithium-ion battery state of charge estimation: recent advances and future perspectives. Energy Storage Mater 102883:102899
32. Ren Z, Du C (2023) A review of machine learning state-of-charge and state-of-health estimation algorithms for lithium-ion batteries. Energy Rep 9:2993–3021
33. Zhou M-Y, Zhang J-B, Ko C-J, Chen K-C (2023) Precise prediction of open circuit voltage of lithium ion batteries in a short time period. J Power Sources 553:232295
34. Liu D, Wang S, Fan Y, Xia L, Qiu J (2022) A novel fuzzy-extended Kalman filter-ampere-hour (F-EKF-Ah) algorithm based on improved second-order PNGV model to estimate state of charge of lithium-ion batteries. Int J Circuit Theory Appl 50:3811–3826
35. Gholami J, Barzoki MF (2021) Electrochemical modeling and parameter sensitivity of lithium-ion battery at low temperature. Journal of Energy Storage 43:103189
36. Tran M-K, Mathew M, Janhunen S, Panchal S, Raahemifar K, Fraser R et al (2021) A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters. J Energy Storage 43:103252
37. Voigt S, Sträubig F, Kwade A, Zehfuß J, Knaust C (2023) An empirical model for lithium-ion battery fires for CFD applications. Fire Saf J 135:103725
38. Iurilli P, Brivio C, Wood V (2021) On the use of electrochemical impedance spectroscopy to characterize and model the aging phenomena of lithium-ion batteries: a critical review. J Power Sources 505:229860
39. Li L, Ren Y, O'Regan K, Koleti UR, Kendrick E, Widanage WD et al (2021) Lithium-ion battery cathode and anode potential observer based on reduced-order electrochemical single particle model. J Energy Storage 44:103324
40. Li X, Hua W, Tian J, Tian Y (2021) A multi-particle physics-based model of a lithium-ion battery for fast-charging control application. World Electric Veh J 12:196
41. Sun J, Kainz J (2023) Optimization of hybrid pulse power characterization profile for equivalent circuit model parameter identification of Li-ion battery based on Taguchi method. J Energy Storage 70:108034
42. Shen X, Wang S, Yu C, Qi C, Li Z, Fernandez C (2023) A hybrid algorithm based on beluga whale optimization-forgetting factor recursive least square and improved particle filter for the state of charge estimation of lithium-ion batteries. Ionics 29:4351–4363
43. Sun X, Zhou F, Fu J, Liu J (2024) Experiment and simulation study on energy flow characteristics of a battery electric vehicle throughout the entire driving range in low-temperature conditions. Energy 292:130542–130556
44. Takyi-Aninakwa P, Wang S, Zhang H, Yang X, Fernandez C (2023) A hybrid probabilistic correction model for the state of charge estimation of lithium-ion batteries considering dynamic currents and temperatures. Energy 273:127231
45. Qiao J, Wang S, Yu C, Yang X, Fernandez C (2023) A chaotic firefly-particle filtering method of dynamic migration modeling for the state-of-charge and state-of-health co-estimation of a lithium-ion battery performance. Energy 263:126164
46. Lazanas AC, Prodromidis MI (2023) Electrochemical imped-ance spectroscopy─ a tutorial. ACS Meas Sci Au 3:162–193
47. Guo R, Shen W (2023) An information analysis based online parameter identification method for lithium-ion batteries in electric vehicles. IEEE Trans Ind Electron 71:7095–7105
48. Yang Z, Wang X (2023) An improved parameter identification method considering multi-timescale characteristics of lithium-ion batteries. J Energy Storage 59:106462–106472
49. Zhu C, Wang S, Yu C, Zhou H, Fernandez C (2023) An improved proportional control forgetting factor recursive least square-Monte Carlo adaptive extended Kalman filtering algorithm for high-precision state-of-charge estimation of lithium-ion batteries. J Solid State Electrochem 27:2277–2287
50. Al-Greer M, Bashir I (2023) Physics-based model informed smooth particle filter for remaining useful life prediction of lithium-ion battery. Measurement 214:112838
51. Tang R, Zhang S, Zhang S, Zhang Y, Lai J (2023) Parameter identification for lithium batteries: model variable-coupling analysis and a novel cooperatively co-evolving identification algorithm. Energy 263:125762
52. Zhang X, Li H, Zhang W, Lopes AM, Wu X, Chen L (2023) Improved parameter identification for lithium-ion batteries based on complex-order beetle swarm optimization algorithm. Micromachines 14:413
53. Kim S, Kim S, Choi YY, Choi J-I (2023) Bayesian parameter identification in electrochemical model for lithium-ion batteries. J Energy Storage 71:108129
54. Merrouche W, Lekouaghet B, Bouguenna E, Himeur Y (2024) Parameter estimation of ECM model for Li-Ion battery using the weighted mean of vectors algorithm. J Energy Storage 76:109891
55. Srinivas S, Welker S, Herschfelt A, Bliss DW (2023) Cramér-Rao lower bounds on 3D position and orientation estimation in distributed ranging systems. Appl Sci 13:2008
56. Kelkawi A, El-Abd M, Ahmad I (2023) GPU-based co-operative co-evolution for large-scale global optimization. Neural Comput Appl 35:4621–4642
57. Yu L, Ren J, Zhang J (2023) A quantum-based beetle swarm optimization algorithm for numerical optimization. Appl Sci 13:3179
58. Liu Z, Zhao Z, Qiu Y, Jing B, Yang C, Wu H (2023) Enhanced state of charge estimation for Li-ion batteries through adaptive maximum correntropy Kalman filter with open circuit voltage correction. Energy 283:128738
59. Lv H, Liao Y, Zhao C, Shang X, Zhang F (2024) State of charge estimation of lithium-titanate battery based on multi-model extended Kalman filter considering temperature and current rate. J Energy Storage 77:109890
60. Peng S, Zhang A, Liu D, Cheng M, Kan J, Pecht M (2023) State-of-charge estimation of lithium-ion batteries based on dual-coefficient tracking improved square-root unscented Kalman filter. Batteries 9:392
61. Hosseininasab S, Momtaheni N, Pischinger S, Günther M, Bauer L (2023) State-of-charge estimation of lithium-ion batteries using an adaptive dual unscented Kalman filter based on a reduced-order model. J Energy Storage 73:109011
62. Rezaei O, Rahdan A, Sardari S, Dahmardeh M, Wang Z (2023) A fuzzy robust two-stage unscented Kalman filter method for uncertainty and state of charge estimation of lithium-ion batteries. J Energy Storage 68:107883
63. Takyi-Aninakwa P, Wang S, Zhang H, Xiao Y, Fernandez C (2023) A NARX network optimized with an adaptive weighted square-root cubature Kalman filter for the dynamic state of charge estimation of lithium-ion batteries. J Energy Storage 68:107728
64. Zhou J, Wang S, Cao W, Xie Y, Fernandez C (2023) Improved backward smoothing square root Cubature Kalman filtering and fractional order—battery equivalent modeling for adaptive state of charge estimation of lithium-ion batteries in electric vehicles. Energ Technol 11:2300765

65. Zhou J, Wang S, Cao W, Xie Y, Fernandez C (2023) High-precision joint estimation of the state of charge and state of energy for new energy electric vehicle lithium-ion batteries based on improved singular value decomposition-adaptive embedded cubature Kalman filtering. J Solid State Electrochem 27:3293–3306
66. Chen Y, Li R, Sun Z, Zhao L, Guo X (2023) SOC estimation of retired lithium-ion batteries for electric vehicle with improved particle filter by H-infinity filter. Energy Rep 9:1937–1947
67. Luan Z, Qin Y, Hu B, Zhao W, Wang C (2023) Estimation of state of charge for hybrid unmanned aerial vehicle Li-ion power battery for considering rapid temperature change. J Energy Stor-age 59:106479
68. Zhou H, Luo J, Yu Z (2023) Co-estimation of SOC and SOH for Li-ion battery based on MIEKPF-EKPF fusion algorithm. Energy Rep 10:4420–4428
69. Li Z, Liao C, Zhang C, Wang L, Li Y, Wang L (2023) State-of-charge estimation of lithium-rich manganese-based batteries based on WOA LSTM and extended Kalman filter. J Electrochem Soc 170:050540
70. Zhao H, Xiang W, Lv S (2023) A variable parameter LMS algorithm based on generalized maximum correntropy criterion for graph signal processing. IEEE Trans Signal Inf Processing Over Networks 9:140–151
71. Sabir Z, Umar M (2023) Levenberg-Marquardt backpropagation neural network procedures for the consumption of hard water-based kidney function. Int Journal Math Comput Eng 1:127–138
72. Cheng A, Low YM (2023) Improved generalization of NARX neural networks for enhanced metamodeling of nonlinear dynamic systems under stochastic excitations. Mech Syst Signal Process 200:110543
73. Wang Z, Liu Z, Tian K, Zhang H (2023) Frequency-scanning interferometry for dynamic measurement using adaptive Sage-Husa Kalman filter. Opt Lasers Eng 165:107545
74. Nadimi-Shahraki MH, Zamani H, Asghari Varzaneh Z, Mirjalili S (2023) A systematic review of the whale optimization algorithm: theoretical foundation, improvements, and hybridizations. Arch Comput Methods Eng 30:4113–4159
75. Han T, Tian J, Chung C, Wei YM (2024) Challenges and opportunities for battery health estimation: bridging laboratory research and real-world applications. J Energy Chem 89:434–436
76. Ma L, Tian J, Zhang T, Guo Q, Hu C (2024) Accurate and efficient remaining useful life prediction of batteries enabled by physics-informed machine learning. J Energy Chem 91:512–521
77. Tang X, Lai X, Zou C, Zhou Y, Zhu J, Zheng Y et al (2024) Detecting abnormality of battery lifetime from first-cycle data using few-shot learning. Adv Sci 11:2305315
78. Wang F, Zhai Z, Liu B, Zheng S, Zhao Z, Chen X (2024) Open access dataset, code library and benchmarking deep learning approaches for state-of-health estimation of lithium-ion batteries. J Energy Storage 77:109884
79. Tang X, Wang Y, Liu Q, Gao F (2021) Reconstruction of the incremental capacity trajectories from current-varying profiles for lithium-ion batteries. Iscience 24:103103–103125
80. Tang X, Lai X, Liu Q, Zheng Y, Zhou Y, Ma Y, et al (2023) Predicting battery impedance spectra from 10-second pulse tests under 10 Hz sampling rate. IScience 26:106821–106831
81. Vilsen SB, Stroe D-I (2024) Dataset of lithium-ion battery degradation based on a forklift mission profile for state-of-health estimation and lifetime prediction. Data Brief 52:109861
82. Kirkaldy N, Samieian MA, Offer GJ, Marinescu M, Patel Y (2024) Lithium-ion battery degradation: comprehensive cycle ageing data and analysis for commercial 21700 cells. J Power Sources 603:234185
83. Taş G, Uysal A, Bal C (2023) A new lithium polymer battery dataset with different discharge levels: SOC estimation of lithium polymer batteries with different convolutional neural network models. Arab J Sci Eng 48:6873–6888
84. Rashid M, Faraji-Niri M, Sansom J, Sheikh M, Widanage D, Marco J (2023) Dataset for rapid state of health estimation of lithium batteries using EIS and machine learning: training and validation. Data Brief 48:109157
85. Tang X, Liu K, Li K, Widanage WD, Kendrick E, Gao F (2021) Recovering large-scale battery aging dataset with machine learning. Patterns 2:100302–100311
86. Kannan M, Sundareswaran K, Nayak PSR, Simon SP (2023) A combined DNN-NBEATS architecture for state of charge estimation of lithium-ion batteries in electric vehicles. IEEE Trans Veh Technol 72:7328–37
87. Li L, Li Y, Mao R, Li L, Hua W, Zhang J (2023) Remaining use-ful life prediction for lithium-ion batteries with a hybrid model based on TCN-GRU-DNN and dual attention mechanism. IEEE Trans Transp Electrif 9:4726–40
88. Chang C, Pan Y, Wang S, Jiang J, Tian A, Gao Y et al (2024) Fast EIS acquisition method based on SSA-DNN prediction model. Energy 288:129768
89. Chen J, Zhang Y, Wu J, Cheng W, Zhu Q (2023) SOC estimation for lithium-ion battery using the LSTM-RNN with extended input and constrained output. Energy 262:125375
90. Wang X, Hao Z, Chen Z, Zhang J (2023) Joint prediction of Li-ion battery state of charge and state of health based on the DRSN-CW-LSTM model. IEEE Access 11:70263–70273
91. Gao M, Bao Z, Zhu C, Jiang J, He Z, Dong Z et al (2023) HFCM-LSTM: a novel hybrid framework for state-of-health estimation of lithium-ion battery. Energy Rep 9:2577–2590
92. Guo L, He H, Ren Y, Li R, Jiang B, Gong J (2024) Prognostics of lithium-ion batteries health state based on adaptive mode decomposition and long short-term memory neural network. Eng Appl Artif Intell 127:107317
93. Xiong W, Xu G, Li Y, Zhang F, Ye P, Li B (2023) Early prediction of lithium-ion battery cycle life based on voltage-capacity discharge curves. J Energy Storage 62:106790
94. Chen K, Liao Q, Liu K, Yang Y, Gao G, Wu G (2023) Capacity degradation prediction of lithium-ion battery based on artificial bee colony and multi-kernel support vector regression. J Energy Storage 72:108160
95. Wu J, Cheng X, Huang H, Fang C, Zhang L, Zhao X et al (2023) Remaining useful life prediction of lithium-ion batteries based on PSO-RF algorithm. Front Energy Res 10:937035
96. Wang X, Hu B, Su X, Xu L, Zhu D (2024) State of health estimation for lithium-ion batteries using random forest and gated recurrent unit. J Energy Storage 76:109796
97. Dudukcu HV, Taskiran M, Taskiran ZGC, Yildirim T (2023) Temporal convolutional networks with RNN approach for chaotic time series prediction. Appl Soft Comput 133:109945
98. Wang J, Liu Y, Rao S, Zhou X, Hu J (2023) A novel self-adaptive multi-strategy artificial bee colony algorithm for coverage optimization in wireless sensor networks. Ad Hoc Netw 150:103284
99. Yang J, Fu Z, Zou Y, He X, Wei X, Wang T (2023) A response reconstruction method based on empirical mode decomposition and modal synthesis method. Mech Syst Signal Process 184:109716

100. Tu W, Zhang L, Sun D, Mao W (2023) Evaluating high-tech industries' technological innovation capability and spatial pattern evolution characteristics: evidence from China. J Innov Knowl 8:100287
101. Bisheh HB, Amiri GG (2023) Structural damage detection based on variational mode decomposition and kernel PCA-based support vector machine. Eng Struct 278:115565
102. Simić M, Stavrakis AK, Jeoti V, Stojanović GM (2022) A Ran-dles circuit parameter estimation of Li-ion batteries with embedded hardware. IEEE Trans Instrum Meas 71:1–12
103. Hasan R, Scott J (2020) Extending randles's battery model to predict impedance, charge–voltage, and runtime characteristics. IEEE Access 8:85321–85328
104. Moye D, Moss P, Chen X, Cao W, Foo S (2019) A design-based predictive model for lithiumion capacitors. J Power Sources 435:226694
105. Poonam, Vyas M, Jangid DK, Rohan R, Pareek K (2022) Investigation of supercapacitor cyclic degradation through impedance spectroscopy and Randles circuit model. Energy Storage 4:355–360
106. Zhang F, Wu S, Li Y, Lin H, Bai W, Liu J, et al (2023) Parameter identification of Randles impedance model using sweep-phase measurements and non-iterative least squares estimation. IEEE Trans Instrum Meas 73:12254–12263
107. Han D, Kwon S, Lee M, Kim J, Yoo K (2023) Electrochemical impedance spectroscopy image transformation-based convolutional neural network for diagnosis of external environment classification affecting abnormal aging of Li-ion batteries. Appl Energy 345:121336
108. Geng Y, Pang H, Liu X (2022) State-of-charge estimation for lithium-ion battery based on PNGV model and particle filter algorithm. J Power Electron 22:1154–1164
109. Zhou H, Wang S, Yu C, Xia L, Fernandez C (2022) Research on SOC estimation for lithium ion batteries based on improved PNGV equivalence model and AF-UKF algorithm. Int J Elec-trochem Sci 17:220836
110. Lin P, Jin P, Zou A, Wang Z (2021) Real-time identification of partnership for a new generation of vehicles battery model parameters based on the model reference adaptive system. Int J Energy Res 45:9351–9368
111. Jiang Z, Li J, Li L, Gu J (2022) Fractional modeling and parameter identification of lithium-ion battery. Ionics 28:4135–4148
112. Fatoorehchi H, Ehrhardt M (2022) Numerical and semi-numerical solutions of a modified Thévenin model for calculating terminal voltage of battery cells. J Energy Storage 45:103746
113. Wang C, Xu M, Zhang Q, Feng J, Jiang R, Wei Y et al (2021) Parameters identification of Thevenin model for lithium-ion batteries using self-adaptive Particle Swarm Optimization Differential Evolution algorithm to estimate state of charge. J Energy Storage 44:103244
114. Tian N, Wang Y, Chen J, Fang H (2020) One-shot parameter identification of the Thevenin's model for batteries: methods and validation. J Energy Storage 29:101282
115. Suti A, Di Rito G, Mattei G (2022) Development and experimental validation of novel Thevenin-based hysteretic models for Li-Po battery packs employed in fixed-wing UAVs. Ener-gies 15:9249
116. Seo M, Song Y, Kim J, Paek SW, Kim G-H, Kim SW (2021) Innovative lumped-battery model for state of charge estimation of lithium-ion batteries under various ambient temperatures. Energy 226:120301
117. Shen D, Ding J, Hao T (2024) Elman neural network and Thevenin equivalent circuit model based multi-measurement Kalman filter for SOC estimation. Ionics 30:833–845
118. Cao J, Wang S, Xie Y, Fernandez C (2023) Research on the state of charge estimation method of lithium-ion batteries based on novel limited memory multi-innovation least squares method and SDE-2-RC equivalent model. Int J Circuit Theory Appl 51:1902–1917
119. Sugumaran G (2023) An extended Kalman-Bucy filter for state of charge estimation of 2-RC network modelled Li-ion battery. e-Prime-Advances in Electrical Engineering, Electronics and Energy 6:100362–100374
120. Shrivastava P, Soon TK, Idris MYIB, Mekhilef S, Adnan SBRS (2022) Model-based state of X estimation of lithium-ion battery for electric vehicle applications. Int J Energy Res 46:10704–10723
121. Tahir MU, Anees M, Khan HA, Khan I, Zaffar N, Moaz T (2021) Modeling and evaluation of nickel manganese cobalt based Li-ion storage for stationary applications. J Energy Stor-age 36:102346
122. Lai X, Wang S, Ma S, Xie J, Zheng Y (2020) Parameter sen-sitivity analysis and simplification of equivalent circuit model for the state of charge of lithium-ion batteries. Electrochim Acta 330:135239
123. Saqli K, Bouchareb H, M'sirdi NK, Bentaie MO (2023) Lithium-ion battery electro-thermal modelling and internal states co-estimation for electric vehicles. J Energy Storage 63:107072
124. Wang Y, Li M, Chen Z (2020) Experimental study of fractional-order models for lithium-ion battery and ultra-capacitor: modeling, system identification, and validation. Appl Energy 278:115736
125. Zhang L, Wang X, Chen M, Yu F, Li M (2022) A fractional-order model of lithium-ion batteries and multi-domain parameter identification method. J Energy Storage 50:104595
126. Zhu G, Kong C, Wang JV, Kang J, Yang G, Wang Q (2023) A fractional-order model of lithium-ion battery considering polariza-tion in electrolyte and thermal effect. Electrochim Acta 438:141461
127. Yu M, Li Y, Podlubny I, Gong F, Sun Y, Zhang Q et al (2020) Fractional-order modeling of lithium-ion batteries using additive noise assisted modeling and correlative information criterion. J Adv Res 25:49–56
128. Ruan H, Sun B, Jiang J, Zhang W, He X, Su X et al (2021) A modified-electrochemical impedance spectroscopy-based multi-time-scale fractional-order model for lithium-ion batteries. Elec-trochim Acta 394:139066
129. Wang Y, Zhao G (2023) A comparative study of fractional-order models for lithium-ion batteries using Runge Kutta optimizer and electrochemical impedance spectroscopy. Control Eng Pract 133:105451