Neural Network-Based State-of-Charge and State-of-Health Estimation

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FOREWORD

To deal with environmental deterioration and energy crises, developing clean and sustainable new energy has become the strategic goal of all countries in the world. Lithium-ion batteries are the best solution to provide power and energy storage in the new energy industry at present and are also the main power source of new energy vehicles. State-of-charge (SOC) and state-of-health (SOH) are important indicators to measure whether a battery management system (BMS) is safe and effective. Therefore, this book focuses on the co-estimation strategy of SOC and SOH for power lithium-ion batteries. The book describes the key technologies of lithium-ion batteries in SOC and SOH monitoring and proposes a collaborative optimization estimation strategy based on NN, which provides technical references for the design and application of a power lithium-ion battery management system.

PREFACE

State-of-charge (SOC) and state-of-health (SOH) play a key role in the safety and reliability of batteries. To improve the real-time estimation accuracy of battery state, a novel back propagation neural network-dual extended Kalman filter method for SOC and SOH co-estimation of lithium-ion batteries based on limited memory recursive least square algorithm is proposed. Aiming at the problem of poor anti-interference ability and easy data saturation of recursive least square algorithm, a limited memory recursive least square algorithm that removes the old data and uses new data with only the restricted length is designed to improve the accuracy of on-line parameter identification. Considering the coupling effect between SOC and SOH, the dual extended Kalman filter is used to achieve synergistic estimation to obtain better tracking accuracy. To compensate for the model error of the extended Kalman filter, a back propagation neural network is introduced for correction to further improve SOC and SOH estimation precision. The authors hope that the understanding and experience of predicting the SOC and SOH of a lithium-ion battery can provide some technical reference for the design, matching, and application of power lithium-ion battery management systems, and contribute to the development of new energy technology applications.

CHAPTER 1

INTRODUCTION

With the advantages of small size, high energy density, and low clean pollution, lithium-ion batteries have become an indispensable core energy storage component for the current energy storage industry and the development of new energy vehicles (Xu et al., 2023). State-of-charge (SOC) and state-of-health (SOH) are the core state parameters for the battery management system (BMS) to evaluate and manage the battery state, so it is important to obtain accurate and effective estimates of SOC and SOH in real time to improve the performance of the battery management system and promote the development of electric vehicles.

1.1. Research background and significance

In recent years, as the global climate continues to change, various kinds of extreme weather appear frequently. From torrential rains into disaster and extreme cold, to raging wildfires and high-temperature heat waves, the global "temperature disorder" has destroyed countless lives and homes. To cope with environmental degradation and energy crisis, the search and development of sustainable and clean energy have become a strategic goal for all countries in the world, and carbon neutrality has become a global trend (Cheng et al., 2021; Deng et al., 2022; Zou et al., 2022). China has made a solemn commitment to the international community, "peak carbon emissions and carbon neutrality", striving to reach peak carbon dioxide emissions by 2030 and striving to achieve the strategic goal of carbon neutrality by 2060 (Kong, 2022; Wang et al., 2022c). The White Paper on China's Policies and Actions to Address Climate Change was officially released on October 27, 2021, which is the second time since 2011 that China has released a White Paper on China's response to climate change from the national level (Lu et al., 2023a).

Under the global trend of carbon neutrality, new energy vehicles have seen booming growth (Liu et al., 2022a). Data show that during the five-year period from 2017 to 2021, China's lithium battery shipments continued to climb, maintaining a double-digit increase each year (Zheng et al., 2022b). Among them, the proportion of automotive power battery shipments is rising, accounting for 69% of the national lithium battery market in 2021, far exceeding other application terminals. In the first half of 2022, China's new energy vehicle sales achieved year-on-year growth for six consecutive months, with sales reaching a cumulative total of 2.6 million units, up 120% year-on-year (Tan et al., 2023). At the same time, China's power battery production and installation volume increased significantly by 157.9% and 90.3% respectively. According to the U.S. Department of Energy, 13 new battery gigafactories will come online in the U.S. by 2025 (Ahmed et al., 2023). Another forecast shows that by 2035 Europe may add 35 new super plants for processing lithium resources or producing lithium-ion batteries (Garcia et al., 2023a; Potrc et al., 2021). With the rapid development of new energy vehicles and the increase of intelligent consumption in daily life, lithium battery application scenarios will be more abundant (Zahoor et al., 2023). It is expected that the next 10 to 15 years will be its golden development period. This shows that lithium batteries have broad development and application prospects.

As electric vehicles are becoming more and more accepted, their battery safety issues cannot be ignored (Huang et al., 2021c). Due to the relatively active nature of lithium, spontaneous combustion and explosion accidents related to lithium batteries occur frequently, resulting in consumers' concerns about electric vehicles gradually shifting from "mileage anxiety" to "safety anxiety" (Li et al., 2023a). According to the relevant data survey statistics, from the beginning of 2021 to date the country has occurred more than 50 electric car spontaneous combustion events, the vast majority caused by the battery thermal runaway (Gao et al., 2022b). Power lithium battery safety issues have become a "stumbling block" for the development of the electric vehicle industry. According to research studies, the main concern of Chinese consumers for electric vehicles is safety up to 29%. In addition, from the proportion of complaints about the quality of electric vehicles, battery complaints accounted for 37.1%, including power battery failure, charging failure, battery failure, etc The safety of power batteries has become a new concern for consumers, so it is urgent to further improve the safety of lithium batteries (Shi et al., 2022a; Zhang et al., 2021a).

To solve the battery safety problem and guarantee the safe application of lithium-ion batteries, an efficient, stable, and reliable BMS is crucial (Wang et al., 2022a). As the key core equipment of lithium battery energy storage, BMS integrates function and management to achieve all-round, efficient, and refined management of battery by monitoring battery parameters to estimate battery status to extend battery life, ensure battery safety and improve battery utilization (Adaikkappan and Sathiyamoorthy, 2022; Qays et al., 2022; Wang et al., 2020e). SOC and SOH are key state quantities for BMS evaluation and management, and their accuracy directly affects the safety and effectiveness of the BMS system (Park et al., 2021). SOC characterizes the remaining available capacity of the battery and its accuracy directly affects the mileage range of the electric vehicle. SOH characterizes the safety performance and capacity decay degree of the battery, which is an important parameter for battery fault diagnosis and safety warning, and has an important reference value for battery safety management and life enhancement. Therefore, accurate estimation of SOC and SOH can improve the effective control of lithium-ion batteries by BMS, which in turn can improve the driving range and driving safety of electric vehicles.

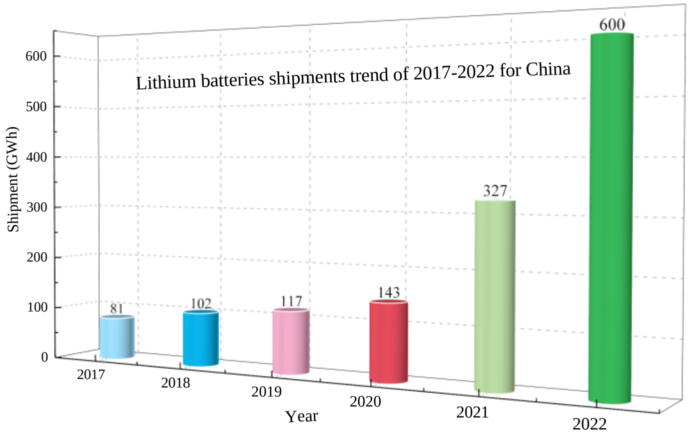

Fig. 1-1 Power lithium-ion batteries shipment trend chart for China

As can be seen visually in Fig. 1-1, from 2017 to 2020, the annual growth rate of lithium battery shipments is maintained at 15 GWh ~ 25 GWh. However, lithium battery shipments are growing rapidly from 2021 onwards, almost doubling every year, with shipments already reaching 600 GWh in 2022. China's lithium battery shipments are expected to exceed 1,000 GWh in 2023, reaching another new level (Hu et al., 2022a).

1.2. Research status

1.2.1. Research status of SOC estimation strategies

SOC is a status parameter that measures the current remaining battery power (Chen et al., 2022; Jiang et al., 2021). An accurate SOC estimate is the key to ensuring battery safety and optimizing battery life level, while providing users with the current battery power status in real time to enhance the user experience (Yang et al., 2022a; Yang et al., 2022b; Zhao et al., 2022). SOC is defined as the ratio of the remaining battery charge under standard discharge rate conditions to the rated capacity under the same conditions, and is defined as shown in Eq. (1-1).

$$SOC = \frac{Q_r}{Q_N} \times 100\% \tag{1-1}$$

In Eq. (1-1), Q_r is the remaining battery power, and Q_N is the rated capacity of the battery under the same conditions, i.e., the current maximum available battery power. The value of SOC ranges from 0 to 100%, when SOC = 100% means the current battery is fully charged, if the battery continues to be charged at this time, the battery may be damaged by overcharging. When SOC = 0, it means the current battery is fully discharged, at this time, if the battery is still discharged, it may damage the battery due to over discharge. Both overcharge and over discharge can cause irreversible damage to the battery, so an accurate SOC value is a prerequisite for preventing overcharge and over-discharge to ensure the safety and health of the battery.

Currently, the estimation methods of SOC mainly include methods based on experimental tests, methods based on model-driven, and methods based on data-driven (Meng et al., 2018; Xu et al., 2021a). The experimental test-based method calculates the lithium battery SOC by measuring physical quantities such as battery voltage, current, and temperature, and then calculating the lithium battery SOC based on known physical relationships, mainly including the discharge method, the open circuit voltage method, and the ampere-hour integration method (Liu et al., 2022b; Wang et al., 2020e; Zhou et al., 2021). The discharge method is generally used as a calibration method for battery SOC estimation or for post battery maintenance work, which is relatively simple, reliable, and has a high accuracy of results (Gao et al., 2022a; Jia et al., 2022). However, the experimental procedure of this method is time-consuming and cannot be used to calculate the battery in operating conditions.

The open circuit voltage method is to obtain the function relationship between OCV and SOC by curve fitting, and then estimate the SOC of lithium-ion battery by OCV-SOC curve (Shan et al., 2022). The method has a simple principle, high operability, and high accuracy of results. However, the measurement of OCV requires a long shelving time of lithium batteries, which is time-consuming and leads to its inability to be estimated online. The ampere-hour integration method calculates SOC based on the integration of current in time. This method focuses only on the external characteristics of the battery system, without considering the internal electrochemical reactions of the battery and the complex relationships between the various parameters (Zhang et al., 2023d; Zhou et al., 2021). Therefore, the calculation is simple and the lithium battery SOC can be estimated online in real time. However, the measurement accuracy of the initial value is required to be high, and the calculation error will gradually become larger with time accumulation because it cannot be corrected in time.

The model-driven approach is based on the working principle and reaction mechanism of lithium batteries to establish the corresponding equivalent model, which is an indirect estimation method with mainly electrochemical models and equivalent circuit models (Shrivastava et al., 2019; Wang et al., 2022e; Wang et al., 2022k). The electrochemical model is based on the principle of electrochemical reaction and describes the internal characteristics of lithium batteries in detail. Its physical meaning is clear and the model accuracy is high, which is suitable for theoretical analysis, but the model structure is too complex and has many parameters, which is extremely computationally intensive (McCarthy et al., 2022; Meng et al., 2018; Peng et al., 2022). The equivalent circuit model consists of circuit elements such as resistors, capacitors, and voltage sources, which are combined in different combinations to form a circuit network to simulate the dynamic reaction process inside a lithium-ion battery (Chen et al., 2021a; Wang et al., 2022d; Zhou et al., 2022). Its model is simple, with few parameters, a small amount of calculation, and good real-time performance, usually combined with parameter identification and state space equations to achieve the prediction and estimation of lithium battery related state

(Adaikkappan and Sathiyamoorthy, 2022; Qi et al., 2022b; Zhang et al., 2021b). The technology is quite mature and very widely used.

The method based on the equivalent circuit model first needs to collect information such as battery voltage, circuit, and temperature through experiments, then establish a suitable equivalent model to construct the state space equation, carry out model parameter identification, and finally use a suitable control theory algorithm to estimate SOC (Wang et al., 2022f; Wang et al., 2022g; Zhang et al., 2022a). Currently, the Kalman Filter (KF) and Particle Filter (PF) are more widely used (Pu et al., 2022; Takyi-Aninakwa et al., 2022a; Wang et al., 2022i). Naseri et al. proposed an enhanced equivalent circuit model based on the Wiener structure to improve the nonlinear capability of capturing lithium-ion batteries (Naseri et al., 2022). The results showed that the accuracy of the EKF algorithm to estimate SOC is improved by 1.5% compared to the conventional second-order equivalent circuit model. Duan et al. used a robust EKF method with correlated entropy loss for SOC estimation to improve the estimation accuracy in non-Gaussian environments, and the results show that the mean square error of the proposed method is reduced by 0.849% (Duan et al., 2020). Qiao et al. proposed a firefly algorithm based on intelligent weight decay to improve the particle wave method for estimating SOC (Qiao et al., 2022). This method avoids the algorithm from falling into local optimum by introducing a linear weighting strategy, and data with different complexity conditions are used to verify the feasibility of the proposed algorithm. The experimental results showed that the root mean square error of the calculation is around 1%.

The data-driven method is based on using data to estimate SOC directly by mining the mapping relationship between the own characteristics of battery measurement parameters such as current, voltage, temperature, and internal resistance and the battery SOC (Cui et al., 2022; Wang et al., 2022h; Zhang et al., 2022c). Its advantage is that it does not need to build a battery model, but it must be backed by high-quality measurement data to obtain accurate estimation results (Liu et al., 2023b; Takyi-Aninakwa et al., 2022b; Wang et al., 2022j). At present, neural networks and deep learning are the most common, and they provide a novel solution for SOC estimation.

Hong et al. proposed a multi-step forward online joint SOC prediction method based on the long short term memory (LSTM) neural network and multiple linear regression algorithm, and the experimental validation showed that the method has good stability, flexibility, and robustness (Hong et al., 2020). To overcome the shortcomings of the black box principle and thus fully exploit the performance of deep learning, Tian et al. proposed to integrate two kinds of domain knowledge into a deep learning-based approach (Tian et al., 2022). First, the voltage and current sequences are decoupled into open-circuit voltage (OCV), ohmic response, and polarization voltage to enhance the input of deep neural networks (DNN). Second, a combined framework is proposed to adaptively fuse SOC estimation results from DNN and short-term ampere-hour integral prediction. The results show that this method can significantly reduce the root mean square error and maximum absolute error of SOC estimation by 30.89% and 64.88%, respectively, with a slight increase in the amount of calculation. To overcome the general deep learning models that ignore the changes between battery cells or focus on short-term estimation, Oyewole et al. proposed a controllable deep transfer learning (CDTL) network for short-term and long-term SOC estimation in the early stages of degradation (Oyewole et al., 2022). The experimental results show that the proposed CDTL outperforms existing deep and transfer learning benchmarks, where the RMSE is improved by 50%~60% and the computation time is reduced by about 39%.

1.2.2. Research status of SOH prediction algorithms

SOH is an important indicator to evaluate the degree of battery aging or decline, reflecting the health of the battery, commonly expressed as a percentage, and the new battery is 100% when it leaves the factory (Long et al., 2023; Yang et al., 2021; Zhang et al., 2022b). The accurate SOH value provides the basis for real-time monitoring of the health information of the lithium-ion battery (Fan et al., 2022; Hu et al., 2022b; Ren et al., 2022a). When SOH is lower than 80%, it reaches the end-of-life standard (Huang et al., 2021a; Xiong et al., 2021). At this time, the battery should be replaced in time to ensure the safe and stable operation of the electric vehicle. There are two main definitions of SOH, namely capacity-based definition and internal resistance-based definition (Huang et al., 2021b; Ren et al., 2022b; Tian et al., 2020).

When capacity decay is used as the definition, SOH is the ratio of the current remaining battery capacity to the rated capacity, which is defined as shown in Eq. (1-2).

$$SOH = \frac{Q_{now}}{Q_{new}} \times 100\% \tag{1-2}$$

In Eq. (1-2), Q_{new} is the rated capacity of the battery when it leaves the factory, and Q_{now} is the capacity at the current moment after the battery has been cyclically charged and discharged, that is, after being used. When the capacity is lower than 80% of the rated capacity at the time of delivery, the battery fails and is no longer used as a power source.

When defined by the increase of internal resistance, the definition of SOH is shown in Eq. (1-3).

$$SOH = \frac{R_{aged} - R_{now}}{R_{aged} - R_{new}} \times 100\% \tag{1-3}$$

In Eq. (1-3), R_{new} is the rated ohmic internal resistance of the battery when it leaves the factory, that is, the ohmic internal resistance when the battery is in a new state, and R_{aged} is the corresponding ohmic internal resistance when the battery reaches the scrapping standard, that is, the ohmic internal resistance when SOH is equal to 80%. R_{now} is the ohmic internal resistance corresponding to the current moment after the battery has been used for some time.

At present, the three main types of SOH estimation methods at home and abroad are experimental test methods, model-driven methods, and data-driven methods (Lipu et al., 2018; Qiu et al., 2022; Shen et al., 2021). The experimental test method obtains the SOH value based on the definition of SOH by directly measuring the characteristic parameters of the characterized power cell such as cell capacity, internal resistance, etc (McCarthy et al., 2022; Tan et al., 2021). The experimental test method is simple but requires strict experimental conditions and complex and accurate experimental equipment, and the measurement cycle is long, which is not suitable for online estimation of SOH, and is difficult for practical application (Zhao et al., 2023). It is generally used as a benchmark value to verify the effectiveness of other related estimation methods.

The model-driven method needs to establish a battery model and obtain parameters such as internal resistance and capacity of the battery through the corresponding model mechanism to realize the estimation of SOH (Park et al., 2020). Commonly used models include equivalent circuit models and electrochemical models. The equivalent circuit model is similar to the SOC estimation method, which usually requires a combination of parameter identification and various filtering algorithms to achieve an online estimation of SOH. Due to better accuracy and convergence, equivalent circuit models are widely used and mature, and the more common ones are recursive least squares, $H\infty$ observer, Kalman filter, and particle filter (Hong et al.; Wang et al., 2020e).

Rossi et al. proposed a GO-EKF algorithm for estimating the SOH value of lithium batteries (Rossi et al., 2022). The method optimally adjusts the covariance matrix of the EKF employing a genetic algorithm to solve the minimization problem of the nonlinear function, to avoid falling into local minima and thus determine the covariance matrix coefficients of the EKF. The experiments show that the method has good accuracy. For the problems of low accuracy and poor convenience of existing SOH estimation methods, Liu et al. proposed an improved cuckoo search particle filter (ICS-PF) algorithm (Liu et al., 2021b). The method proposes an improved cuckoo search particle filter algorithm to estimate capacity attenuation based on the traditional particle filter (PF) and cuckoo search (CS) algorithms by enhancing the search step size and discovery probability. The experimental results show that the maximum error of the method is less than 2%. To solve the problems of insufficient fit of a single health index and difficulty of online measurement of battery internal resistance, Yu et al. proposed a multi-dimensional health indicator (HI) battery state of health (SOH) prediction method (Yu et al., 2023). The method is based on the equivalent circuit model to extract the polarization resistance, polarization capacitance, and initial discharge resistance values through the constant current discharge characteristic curve as health indicators, and the optimal equal voltage drop discharge time selected by the retention strategy genetic algorithm (e-GA) as an indirect health indicator, and finally the PSO-LSTM model is established to realize SOH prediction based on the above health indicators. The experimental results show that the accuracy of this optimization strategy is improved by 0.79% compared to the prediction model with a single health indicator input.

To address the problem of low accuracy of SOH estimation for lithium-ion batteries under complex stress conditions, Yang et al. proposed a method for SOH estimation of lithium-ion batteries using an adaptive dual extended Kalman filter-based fuzzy inference system (ADEKF-FIS) (Yang et al., 2020). The experimental results show that the ADEKF-FIS algorithm effectively improves the prediction accuracy of SOH and has better convergence. Zhu et al. proposed a SOH estimation method for lithium-ion batteries based on the traceless Kalman filter and Improved Unscented Particle Filter (IUPF) (Zhu and Fu, 2021). The experimental results show that the UKF-IUPF algorithm can obtain higher SOH estimation accuracy and faster estimation speed compared with the IUPF method.

Thanks to the development of big data and artificial intelligence, the data-driven method has developed rapidly and is widely used in recent years (Jin et al., 2021a; Shu et al., 2021; Wang et al., 2023b). Its advantage is that it does not need to establish a battery model and clarify the electrochemical mechanism of the battery, but requires high-quality data and high-performance computing power to be used as a support, which is similar to the data-driven method of SOC estimation (Chang et al., 2021; Wang et al., 2021b).

Lin et al. proposed a novel SOH estimation method based on an attentional long short-term memory network (LSTM) with multi-source features (Lin et al., 2023a). The method extracts eight features by analyzing IC, DT, and DTV curves, introduces Wasserstein distance to complement the description of battery aging characteristics, and employs a modified LSTM network structure based on an attention mechanism to estimate the SOH of lithium-ion batteries. The experimental results show that the MAE and RMSE of the proposed LSTM model with local attention mechanism based on multi-source features are less than 0.7%, which has higher accuracy and better robustness. However, LSTM has a large amount of calculation and requires a relatively long training time. The current method of predicting the SOH of lithium-ion batteries by health indicators only considers temporal characteristics and ignores the relationship between different characteristics, especially in the case of limited data in applications. Yao et al. proposed a new graph neural network (GNN)-based SOH prediction framework that considers both temporal features and spatial features of health indicators under limited data (Yao et al., 2023). The experimental results show that the SOH error under this prediction framework is the smallest and the accuracy is higher compared with RNN, LSTM, and CNN-LSTM. To achieve accurate SOH prediction in a unified framework of single-step prediction, multi-step prediction, and long-term prediction, Cai et al. proposed a data-driven approach for lithium-ion battery health state prediction in a unified framework (Cai et al., 2022). The experimental results show that the method achieves a unified prediction framework for lithium-ion batteries with uncertainty characterization, and the effectiveness and superiority are more prominent.

Considering the long training time and large computational effort of some neural networks, some researchers have combined the more traditional neural networks with other algorithms, which not only takes into account the nonlinear advantages of the neural network but also makes up for its defect of a large amount of calculation. A simulated annealing-backpropagation (SA-BP) model is proposed by Xiong et al., which can estimate the long-term state-of-health (SOH) of lithium-ion batteries online by combining them with the battery single-particle (SP) model (Xiong et al., 2023). The experimental results show that the SOH estimation results show significant improvements in various performance evaluation metrics. Xue et al. proposed a joint SOH estimation algorithm based on particle filtering, quantum genetic algorithm (QGA), and generalized regression neural network (GRNN) (Xue et al., 2022). Experimental results based on the NASA dataset and data from real vehicles show that the algorithm has the advantages of high estimation accuracy and low computational cost, which is of great significance to the estimation of SOH of electric vehicle batteries under practical working conditions.

1.2.3. Research status of SOC and SOH co-estimation

Due to the coupling effect between SOC and SOH, it is difficult to guarantee an accurate estimation of the real state of the battery by estimating one state alone (Park et al., 2021; Qi et al., 2022a; Qian and Liu, 2021). Therefore, some researchers have proposed a collaborative estimation strategy for SOC and SOH.

Xu et al. proposed a co-estimation algorithm of SOC and SOH based on an adaptive dual extended Kalman filter (Xu et al., 2021c). The experimental results show that the maximum error of SOC estimation is

2.03%, and the maximum error of ohmic resistance is 15.3%. Ren et al. introduced the forgetting factor into the particle wave algorithm and proposed a dual particle wave algorithm based on the forgetting factor for the co-estimation strategy of SOC and SOH (Ren et al., 2022c). The experimental investigation indicates that the estimation results of SOC and SOH are accurate and the convergence speed is fast. Qiao et al. introduced a bias-compensated recursive least square for parameter identification and proposed a multiple-weighted dual Kalman filtering algorithm (Qiao et al., 2021). The method not only improves the accuracy of parameter identification but also can make full use of the multiple time information to achieve the synergistic estimation of SOC and SOH.

Ma et al. established a fractional second-order RC model that can reflect the main electrochemical behavior of lithium batteries, and realized the model parameter identification through an adaptive genetic algorithm (Ma et al., 2022b). Then the multi-innovative unscented Kalman filter (MIUKF) is used to estimate SOC, and the unscented Kalman filter (UKF) is used to estimate SOH, and finally, a new method for the collaborative estimation of SOC and SOH based on the multi-scale FOMIUKF-UKF is realized. The experimental results show that the proposed method has good adaptability and high accuracy under different test cycles and different aging degrees. To improve the accuracy and convergence speed of SOC estimation, Qiu et al. proposed the backward smoothing square root cubature Kalman filter (BS-SRCKF), and then adopted the multiscale hybrid Kalman filter (MHKF) composed of BS-SRCKF and extended Kalman filter to achieve the joint estimation of SOC and SOH (Qiu et al., 2020). The experimental results show that the algorithm can effectively improve the accuracy of SOC and SOH estimation. Wu et al. employed an improved firefly algorithm to replace the resampling of traditional particle filtering to suppress the particle loss during the execution of the standard particle filtering algorithm (Wu et al., 2022). Then the ohmic resistance is taken as a characteristic parameter of the battery health status, and finally, an IFA-PF algorithm is proposed to realize the joint estimation of SOC and SOH. The experiments show that the joint IFA-PF estimation algorithm has better superiority. Some researchers have proposed a joint SOC and SOH prediction algorithm based on the LSTM neural network, which provides higher accuracy and stability of SOC and SOH estimates compared to predicting one state alone (Jo et al., 2021).

In summary, traditional methods are more applied and mature, such as literature [55]-[57] and literature [85]-[88]. However, most researchers focus only on one aspect of SOC or SOH. Some scholars have designed a fractional order model, adopting an adaptive dual square root cubature Kalman filter (ADSRCKF) to achieve an online estimation of SOC and SOH, and some scholars have proposed a data-driven model framework based on deep learning to estimate SOC and SOH (Gong et al., 2022; Li et al., 2023b). However, this type of method simply realizes the prediction of SOC and SOH without considering the coupling relationship between the two, so there are certain defects in the scheme.

At present, only a few researchers have conducted research on the co-estimation of SOC and SOH. Although some scholars have introduced deep learning and neural network methods for SOC or SOH estimation, such as reference [64]-[66] and literature [95]-[99]. However, these networks have high complexity, poor accuracy and stability, and high application cost. Therefore, considering the complexity and application cost, accuracy, and robustness, combining traditional methods with simple and effective neural networks is a proven solution. In addition, due to the coupling effect between SOC and SOH, the collaborative estimation will definitely become a trend for future research. However, most of the current collaborative estimations are based on traditional methods, such as in the literature [102]-[107].

Since the model defects of the algorithms in the traditional methods can indirectly affect the accuracy of SOC and SOH, a robust back propagation neural network (BPNN)-dual extended Kalman filter (DEKF) method for co-estimation based on a limited memory recursive least square (LMRLS) algorithm, also named an LMRLS-BPNN-DEKF collaborative algorithm estimation model, is proposed in this study. Firstly, a novel LMRLS algorithm is designed to overcome the defects of traditional parameter identification and improve online parameter identification accuracy. Secondly, a dual Kalman filter is constructed to achieve the cooperative estimation of SOC and SOH to obtain better tracking accuracy. Finally, the BP neural network is introduced to compensate for the model error of the Kalman filter to further improve the accuracy and robustness of SOC and SOH.

1.3. Research lines and contents

SOC and SOH are important indicators for evaluating battery status, so accurate and real-time acquisition of both pieces of information is crucial to improving battery life and safety. This book takes the ternary lithium-ion battery as the research object. Firstly, the internal mechanism and charging and discharging characteristics of the lithium-ion battery are studied through experiments to analyze the working principle of the lithium-ion battery. Secondly, a second-order RC equivalent circuit model is established according to the characteristic analysis, taking into account the accuracy and complexity of the model, and a limited memory recursive least squares algorithm is designed for online parameter identification. Then, a dual extended Kalman filter is constructed to realize the cooperative estimation of SOC and SOH. Finally, a BP neural network is introduced to correct the estimation error of DEKF to further improve the accuracy and robustness of the estimation results. Fig. 1-2 shows the research route and main content of this book.

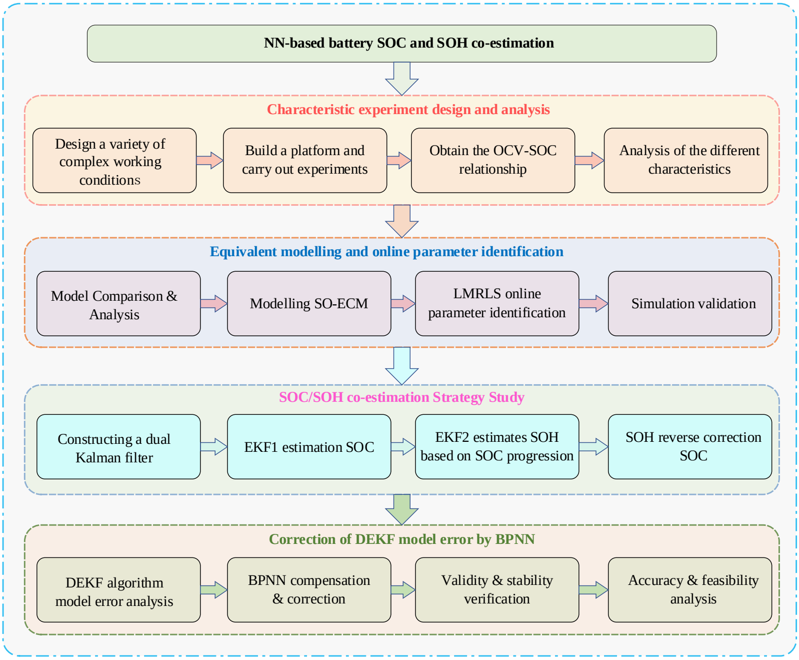

Fig. 1-2 Research route and main content

According to the route framework in Fig. 1-2, the content of each chapter of this book is arranged as follows.

Chapter 1 is the introduction, which analyzes and introduces the research background and significance of this topic. The current status of SOC estimation research, the current status of SOH estimation research, and the current status of SOC/SOH co-estimation research at home and abroad are thoroughly investigated and introduced, respectively. Finally, the shortcomings of the current study are summarized and analyzed, and the main research content and overall research framework of this topic are proposed.

Chapter 2 is the principle and characteristics analysis of power lithium batteries. Firstly, the internal structure and principle of lithium-ion batteries are analyzed in detail. Then, the data of voltage and current at different temperatures are obtained through experiments under various complex working conditions. After extraction and analysis, the effective data is obtained, and then the OCV-SOC function relationship is gained by curve fitting. In turn, the hybrid pulse test characteristics of lithium-ion battery, the variation law of OCV-SOC curve under different temperatures, the variation law of battery capacity under different temperatures, and the variation of terminal voltage under different discharge multipliers are studied and analyzed to provide a basis for battery modeling.

Chapter 3 is a study on the equivalent modeling and parameter identification of power lithium batteries. On the basis of Chapter 2, the second-order RC equivalent circuit model (SO-ECM)) is finally established by analyzing the input and output characteristics of the battery based on the experimental data, obtaining the internal parameters of the lithium-ion battery and its variation law, and taking into account the accuracy and complexity of the model at the same time. To address the problem that the recursive least squares (RLS) algorithm is poorly resistant to interference and prone to data saturation, the limited memory recursive least squares (LMRLS) algorithm is designed that removes the old data while inputting new data and use only the latest data of limited length for parameter estimation, which effectively improves the accuracy of online parameter identification.

Chapter 4 is a study on the cooperative estimation strategy of SOC and SOH based on BP neural network correction. This chapter first analyzes the principle of Kalman filter estimation SOC and its advantages and disadvantages, and discusses the strategy of BPNN optimization EKF estimation SOC, which lays the foundation for the next step of collaborative estimation of SOC and SOH. Then the SOC and SOH synergistic estimation strategy is realized by constructing a dual extended Kalman filter. Where the first EKF implements the estimation of SOC and takes the estimation result as the input of the second EKF for SOH estimation, and then the current moment SOH estimate obtained from the second EKF is used as the input of the next iteration loop to further correct the SOC estimate for the next moment. After the mutual correction feedback of the two forms a closed loop, and the collaborative estimation of the two is finally realized. Finally, the BPNN is introduced to compensate for the model error of DEKF to further improve the accuracy and robustness of the estimation results.

Chapter 5 shows the experimental validation analysis based on the LMRLS-BPNN-DEKF co-estimation model. To verify the effectiveness of the proposed LMRLS-BPNN-DEKF algorithm, detailed experimental validation and analysis of the co-estimation results of SOC and SOH are carried out by using data at different temperatures and complex test conditions, and the estimation results are compared with those of other algorithms. To further verify the robustness and correction capability of the LMRLS-BPNN-DEKF algorithm, experimental validation and analysis are conducted by selecting experimental data at 25°C and setting different initial values of SOC and SOH.

Chapter 6 provides a summary of the book's work and outlook This section summarizes the work and results of this study, analyzes the shortcomings of the current research methodology, and provides an outlook for the subsequent research work in this paper.

1.4. Chapter summary

This chapter first introduces the significance and necessity of this study by introducing global climate change, the shipment of lithium batteries, and the safety of lithium batteries in recent years. Then, the current status of SOC estimation, SOH estimation, and SOC and SOH co-estimation is investigated in detail. Finally, based on the shortcomings of the current SOC and SOH estimation research, the LMRLS-BPNN-DEKF synergistic estimation model is proposed, and the main chapters and contents of this book are briefly introduced.

CHAPTER 2

CHARACTERISTIC ANALYSIS OF POWER LITHIUM-ION BATTERIES

Understanding the internal operating mechanism of power lithium-ion batteries and conducting its characteristic analysis and research has important guiding significance for the subsequent research on battery modeling and synergistic estimation strategies of SOC and SOH. This chapter first briefly introduces the working mechanism of the lithium-ion battery and its internal main structural components, then builds the experimental platform and conducts experiments under complex working conditions, and then performs feature extraction and analysis of relevant data such as current and voltage during charging and discharging, which provides a sufficient scientific basis for the research and discussion of various theories such as battery modeling and parameter identification in Chapter 3 and collaborative prediction system construction in Chapter 4.

2.1 Working mechanism analysis of lithium-ion batteries

Due to many characteristics such as high energy density, excellent temperature adaptability and small clean pollution, and long service life, lithium batteries have been increasingly favored by new energy electric vehicles and various energy storage power stations in recent years (Huang et al., 2022; Zhang et al., 2022e; Zhang et al., 2021c). In this subsection, we will discuss and analyze the internal mechanism and related characteristics of the ternary lithium-ion power battery commonly used in electric vehicles at present. The charging and discharging process of a ternary lithium-ion power battery is carried out through its internal related chemical reactions,