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Comparison and Evaluation of State-of-charge and Health Monitoring Methods for Lithium-sulfur Batteries

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Abstract: State-of-charge (SOC) estimation and state-of-health (SOH) prediction of lithium-sulfur batteries is an extremely important technology for battery management systems (BMS), which is affected by factors such as internal chemical reactions and external temperature changes of lithium-sulfur batteries, which makes it difficult to predict the state of charge and state of health of lithium-sulfur batteries. Firstly, the retrieval status of battery SOC estimation and SOH prediction is introduced, then the main methods and advantages and disadvantages of various methods are introduced, and finally the challenges of battery SOC estimation and SOH prediction are summarized, and the development direction and innovative ideas are proposed. The results show that state-of-charge estimation and health prediction techniques are of great significance for improving the safety, reliability and lifetime of lithium-sulfur batteries.

Keywords: Lithium-sulfur Battery; State-of-charge (SOC) Estimation; State-of-health Prediction.

1. Introduction

As a battery technology with high energy density and environmental protection, lithium-sulfur batteries have been widely used in electric vehicles, drones, solar energy storage and other fields. However, there are challenges in state-of-charge estimation and health prediction in the process of using lithium-sulfur batteries. State-of-charge estimation refers to the process of making an accurate estimate of a battery's charge, while health prediction refers to the process of predicting and monitoring battery life and performance degradation. Accurate state-of-charge estimation and health prediction can improve the performance, safety, and longevity of lithium-sulfur batteries, so they have received a lot of attention.

Lithium-sulfur batteries are a high-energy-density battery technology that has been used for more than half a century since it was first proposed in the 1960s. However, due to inherent technical challenges, the commercial application of lithium-sulfur batteries still faces many challenges, such as the "shuttle effect" caused by intermediate lithium polysulfide in the electrolyte [1], the insulation of elemental sulfur and its discharge products, large volume variation, SEI instability, and safety concerns posed by lithium anodes. Among them, analyzing the current status of lithium-sulfur battery SOC and SOH is a complex and important issue, which is the key to realize the efficient operation of BMS.

Therefore, this paper aims to comprehensively review the research status and development trend of state-of-charge estimation and health prediction of lithium-sulfur batteries, analyze different methods and their advantages and disadvantages, summarize the challenges of battery SOC estimation and SOH prediction, and put forward development directions and innovative ideas, in order to provide reference for the performance optimization and safe and reliable operation of lithium-sulfur batteries.

1.1. SOC Estimates

Researchers have proposed and explored a variety of methods for estimating the SOC of lithium-sulfur batteries, each with its own characteristics and applicable scenarios. The integral method is a common method for SOC estimation [2]. The SOC value is calculated by the accumulation of the charge/discharge current of the lithium battery. This method is simple and intuitive, but in practice, it is easily affected by current measurement errors, battery aging and other factors, resulting in the decline of SOC estimation accuracy. Therefore, it is necessary to correct and calibrate the errors of the integration method to improve the accuracy of the SOC estimation. In addition, there are some model-based SOC estimation methods: for electrochemical models, some researchers have proposed second-order RC equivalent circuit models, using the forgotten recursive least squares (FFRLS) algorithm for parameter identification, and improving the variable window AUKF algorithm to estimate battery SOC [3]. The SOC estimation method based on electrochemical model focuses more on the in-depth understanding of the internal reaction mechanism of the battery. By establishing an accurate electrochemical model, the dynamic behavior of the battery during charging and discharging can be simulated, so as to achieve accurate estimation of SOC. However, this approach typically requires a lot of computational resources and model parameters are difficult to determine. For the neural network model, some researchers have proposed a joint estimation model of SOH-SOC for lithium-ion batteries based on autoregressive recurrent neural network [4], which is a supplement and improvement of the ampere-hour integration method, which can control the error within 5%. There is also a deep learning model based on bidirectional long short-term memory network, which improves the accuracy of SOC estimation from the perspective of data optimization and model optimization. At the same time, a battery SOC prediction model for SOC prediction was constructed by using long short-term memory recurrent neural network. The researchers also divided the models used for state-of-charge (SOC) estimation into internal and external feature models, and categorized the two models in more detail, as shown in the Table 1 below:

Table 1. Comparison of internal and external models of lithium-sulfur batteries and their advantages and disadvantages

classify			**merit**	**shortcoming**
External property model	Equivalent circuit model	Rint model	The model is simple and the parameters are easy to measure	It cannot reflect the dynamic characteristics of the battery and the accuracy is low
		Thevenin model	The larger the n, the higher the accuracy	The larger n, the greater the computational cost
		PNGV model	The amount of computation is low, and the model accuracy is high	It does not reflect the problem of battery self-discharge
		GNL model	The accuracy is higher and the applicability is wider	The computation is more complex and computationally intensive
	Open Circuit Voltage - SOC type		The calculation is simple	Some parameters of the model have no actual physical meaning and are less accurate
Internal property model	P2D model		High precision and wide applicability	It is too complex and computationally intensive to get its analytical solution
	SP model		The structure is simple and the amount of calculation is small	The calculation error is large, and the application range is small
	Simplify P2D models		It greatly reduces the amount of computation and is more accurate and applicable than SP models	It does not solve the inherent problems of P2D and is difficult to apply online

Since lithium-sulfur batteries work on the principle of multi-step redox reactions between sulfur and lithium, rather than a simple lithium-ion melting process, these reactions involve the formation and conversion of a variety of intermediates, such as lithium sulfide and lithium polysulfide, their formation and concentration changes directly affect the voltage and SOC of the battery. In addition, during cathodic discharge, the active substance sulfur undergoes a solid to liquid state and then becomes a solid state. This conversion process is limited by the transport of substances such as sulfur and the solubility and diffusion rate of sulfides. All of these factors affect the voltage of a lithium-sulfur battery, resulting in a nonlinear relationship between the voltage of the lithium-sulfur battery and the SOC, making it difficult to use traditional voltage-based SOC calculation methods such as the open-circuit voltage method. To address this issue, researchers are exploring data-driven, front-end machine learning algorithms and models, as well as advanced algorithms based on electrochemical models, to improve the accuracy and robustness of lithium-sulfur battery SOC estimates. It is worth mentioning that the researchers proposed an extended method of the basic Kalman filter [5-6], which uses the second-order Thevenin equivalent circuit model combined with dynamic component parameters to correct the results of the equation of state, and uses the trace Kalman filter (UKF) algorithm.

1.2. SOH Estimates

In terms of SOH estimation of lithium-sulfur batteries, the researchers adopted a variety of methods and strategies, and proposed a long-space storage model to accurately estimate SOH and other SOCs according to the extended Kalman filter algorithm. For the improved Gaussian process regression algorithm, data-driven methods such as support vector regression and neural network are used to predict the state of health of lithium-ion batteries. Some researchers have proposed an SOH prediction method based on improved antlion optimization algorithm and support vector regression (IALO-SVR) [7]. In this method, the characteristic factors related to battery capacity are extracted from the battery charging data and the correlation analysis is carried out, and three highly correlated features are selected as the model feature input. There is also a dynamic battery SOH estimation method based on Luckerts' law. The dynamic Pickarts law correlates capacity loss with the Pickarts coefficient, eliminating degradation inconsistencies and applying to the same type of battery. Since the Pickarts coefficient can be calculated by multiple discharge tests, SOH can be estimated directly, overcoming the limitation of missing data. In addition, some researchers have introduced a new SOH evaluation method under the framework of probability density function (PDF), including the concepts of characteristic probability (CP) and residual area capacity (RAC), and experiments have shown that there is a strong linear positive correlation between RAC and SOH regardless of charge-discharge conditions [8], as shown in Fig.1.

From the perspective of improving the prediction accuracy of lithium-sulfur battery SOH, some researchers have proposed a lithium battery SOH prediction method based on wavelet denoising and chaotic particle swarm-correlation vector machine [9]. Wavelet denoising can reduce various types and sizes of noise and improve the accuracy of SOH prediction. The figure below shows the correlation between SOH and cycle before and after denoising of the two types of batteries. These methods have improved the accuracy and reliability of SOH prediction to a certain extent, but they still need to be further explored and improved.

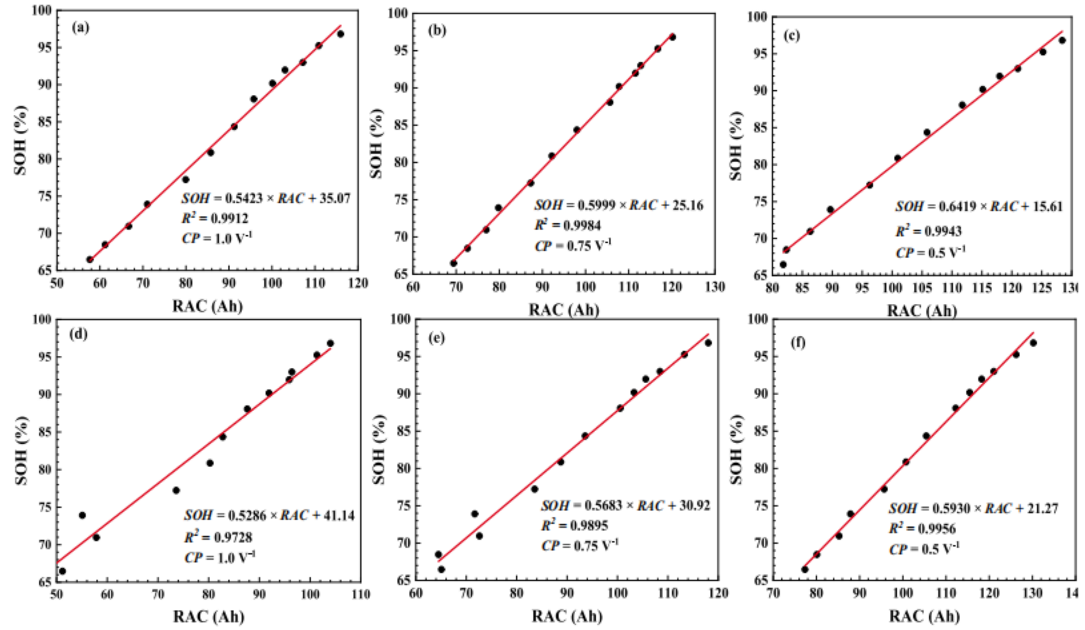


Fig 1. The module SOH dependence on RAC at different CP values. (a)–(c): RAC – SOH models during charging; (d)–(f): RAC – SOH models during discharging [8]

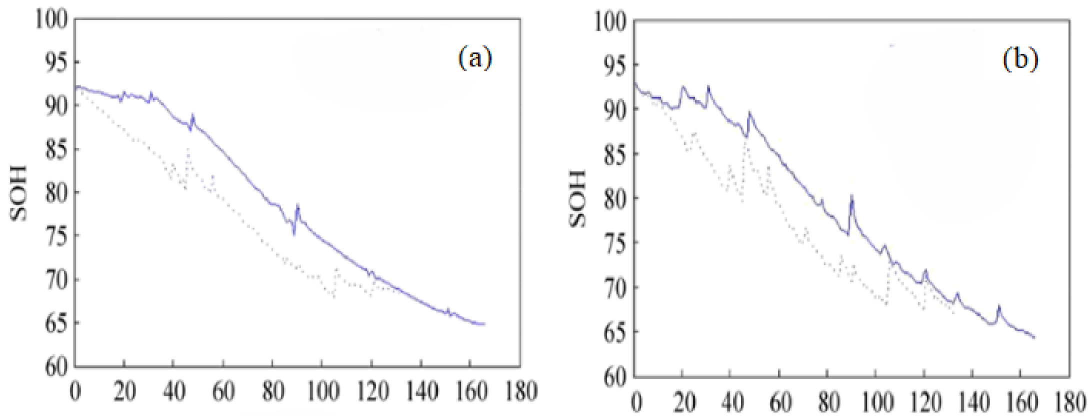


Fig 2. SOH data of two lithium batteries. (a): SOH measurement data for two types of lithium batteries; (b): SOH data of two lithium batteries after wavelet noise reduction [9]

Similar to estimating the SOC of lithium-sulfur batteries, a combined SOC-SOH estimation model can also be introduced when estimating the SOH of lithium-sulfur batteries [10]. In this method, the SOH estimation is completed by GWO-BP neural network, and the SOH is introduced into the ampere-hour integration method to correct the battery capacity and improve the accuracy of SOC estimation. This further accurately predicts the SOH of the battery.

2. Research Methodology

SOC estimation and SOH prediction of a battery are two very important aspects of a battery management system that have a significant impact on the performance and longevity of the battery. Here are some common methods and their pros and cons:

2.1. The Main Methods for Battery SOC Estimation

Sedation filters. The state-of-charge state is predicted and corrected by using the time-domain state-space theory and combined with the voltage and current measurements of the battery [11]. The advantage is that the system noise and observation noise are considered, the robustness of the estimation is improved, and it has the characteristics of unbiased, stable and optimal. High-precision estimation can be carried out, and the Kalman filter method is based on the equation of state of the linear system and the observation data, and the estimation of the minimum mean square deviation value is realized through a recursive algorithm. Theoretically, this method has a good correction ability for the initial value of SOC, and can maintain a high accuracy, which provides a reliable basis for the SOC prediction of lithium-sulfur batteries. Updating and processing in real time, the Kalman filter is a recursive filter that estimates the state of a system from a series of measurements in real time. This means that it can continuously update and adjust the predicted value of the SOC based on the real-time charge and discharge data of the lithium-sulfur battery to more accurately reflect the actual state of the battery. It can also be applied to a variety of scenarios, and the Kalman filter method is not only suitable for SOC prediction of lithium-sulfur batteries, but also widely used in SOC prediction of other types of batteries. In addition, it can also be combined with other forecasting methods, such as neural network models, to improve the accuracy and robustness of predictions. It can effectively reduce the impact of noise and interference on the SOC estimation and provide relatively accurate prediction results, but its calculation is complex and requires accurate battery models and parameters. At the same time, its algorithm is relatively complex and requires high computing power and storage space. This may bring challenges to some resource-limited systems, so more methods based on the Kalman filter method are proposed. For example, based on the estimation method of the strong tracking extended Kalman filter [12], from the perspective of the algorithm, the extended algorithm of the Kalman filter [13]. It looks like this:

Table 2. Unscented Kalman filtering algorithm

UKF Algorithm

Input: $U_{oc}, U(t), I(t), R_{\Omega}, R_p, R_e, C_p, C_e$

Output: X

1. Initialize $X(0)$;

2. $X'(0)=E[X(0)], P_0 = E\{[X(0) - X'(0)][X(0) - X'(0)]^{\tau}$;

3. $for(k = 1; j \leq n; k++)do$;

4. $X_{k-1}^0 = x'(k-1); X_{k-1}^i = x'(k-1) + \sqrt{(n+\lambda)P_{k-1}} \quad i = 1.2 \cdots, n;$

$X_{k-1}^i = x'(k-1) - \sqrt{(n+\lambda)P_{k-1}} \quad i = n+1, \cdots, 2n;$

5. $X_{k/(k-1)}^i = f\left(X_{k-1}^i, u_{k-1}\right); x'_{k/(k-1)} = \sum_{i=0}^{2n} W_m^i X_{(k/k-1)}^i;$

$P_{k/(k-1)} = [X_{k/(k-1)}^i - x'_{k/(k-1)}]^T \times \sum_{i=0}^{2n} W_c^i \left[X_{k/(k-1)}^i - X'_{k/(k-1)}\right] + Q_k;$

6. $y_{k/(k-1)}^i = g(X_{k-1}^i, u_{k-1}); \ y_{k/(k-1)}^i = \sum_{i=0}^{2n} W_m^i y_{(k/k-1)}^i \ ;$

7. $P_{x_k, y_k} = [y_{k/(k-1)}^i - y'_{k/(k-1)}]^T \times \sum_{i=0}^{2n} W_c^i [X_{k/(k-1)}^i - X'_{k/(k-1)}];$

$P_{y_k, y_k} = \left[y_{k/(k-1)}^i - y'_{k/(k-1)}\right]^T \times \sum_{i=0}^{2n} W_c^i \left[y_{k/(k-1)}^i - y'_{k/(k-1)}\right] + R_k;$

8. $K = P_{x_k, y_k} P_{y_k, y_k}^{-1};$

9. $X'_k = y^i_{\frac{k}{k-1}} + K\left(y_k - y'_{\frac{k}{k-1}}\right); \ P_k = P_{\frac{k}{k-1}} - K P_{y_k, y_k} K^{-1};$

10. end for.

Electrochemical modeling. Based on the electrochemical properties and reaction mechanism of the battery, a SOC estimation model was established [14]. It has the advantage of better consideration of the electrochemical process inside the battery and high precision [15], and can be applied to different types of lithium-sulfur batteries, including different electrode materials, electrolytes, and battery structures. This makes the model have a wide applicability and can provide strong support for the SOC prediction of various lithium-sulfur batteries. Its physical significance is clear, and based on the electrochemical reaction mechanism inside the battery, it can accurately describe the state change process inside the battery. This model has a clear physical meaning and enables an in-depth understanding and analysis of battery performance and aging mechanisms. But the electrochemical model is complex and has many parameters, which needs to be accurately calibrated, and the accuracy depends largely on the accuracy of the parameters. If the parameters are set incorrectly or there are errors, the predictions of the model may deviate significantly from the actual situation. At the same time, it is computationally intensive, and because electrochemical models need to describe multiple complex processes inside the battery, they often require significant computational resources when making SOC predictions. Researchers can use different methods to build different electrochemical models from different perspectives, such as establishing an electrochemical model based on the Nernst equation [16], which uses the expression of the Nernst equation as:

$$E = E_0 - \frac{RT_k}{nF} ln \frac{\alpha_{red}}{\alpha_{ox}} \quad (1)$$

Among them: TK represents the thermodynamic temperature at which a chemical reaction occurs; E represents the electrode potential at this temperature, i.e., the open-circuit voltage of the battery; E0 represents the standard electrode potential, that is, the open-circuit voltage R and F in the fully charged state of the battery are the gas constant and Faraday constant, respectively, which are fixed values. n denotes the number of electrons gained or lost in the electrode reaction; αox and αred represent the activity of all ions and molecules at the end of the electrode reaction with high and low oxidation numbers, respectively.

The electrochemical model was then established, and the following results were obtained:

$$U = E_0 - I_c R_{in} + k_1 \ln SOC + k_2 \ln(1 - SOC) \quad (2)$$

Among them: I_c is the battery charge and discharge current; R_{in} is the equivalent internal resistance of the battery; k_1 and k_2 are constants related to Tk. Improved, the model is improved:

$$U(SOC, T) = E_0(T) - I_c R_{in}(SOC, T) + k_1(T) \ln SOC + k_2(T) \ln(1 - SOC) \quad (3)$$

Where: T is the ambient temperature

Discharge Test Methods. The battery is continuously discharged at a constant current, and the discharge amount is calculated when the cut-off voltage is reached. The advantage is that the method is simple, intuitive, and easy to understand, does not require complex modeling or calculation processes, and has relatively high estimation accuracy [17]. Under laboratory conditions, by controlling the discharge current and discharge time, the discharge amount of the battery can be measured more accurately, so as to obtain a more accurate SOC prediction value. This approach avoids the errors and uncertainties that may exist with other forecasting methods. It has strong versatility and is suitable for various types of batteries, including lithium-sulfur batteries, and can be easily applied to different types of battery SOC prediction. However, it cannot be measured with load, and needs to be carried out when the battery is not loaded, which means that in practical applications, if you need to perform SOC measurements on the battery in use, you need to take the battery off the system first and stop its operation, which may be inconvenient in practice. It also takes a lot of measurement time, often discharging the battery to a specific SOC level and then measuring its voltage or other parameters to estimate the SOC. This process can take a long time, especially when the battery capacity is large. It also interrupts the battery's previous work, requiring the battery to be offline during the measurement, which means that the battery cannot perform other tasks at the same time, such as driving an electric vehicle. This can lead to the battery not being able to perform SOC measurements in real-time, online in some applications. In addition, there is a problem that the discharge current is not constant, and for batteries in use (such as those in electric vehicles), the discharge current may change depending on the conditions of use. However, the discharge test method usually assumes that the battery is carried out in a constant current discharge state, so it may not accurately reflect the SOC of the battery under actual use conditions. Finally, there will be errors and uncertainties, which can be affected by a variety of factors, such as ambient temperature, battery aging, etc., which can lead to errors and uncertainties in the SOC measurement results. The graph below shows the parameter changes of a lithium-ion battery during charging and discharging [18].

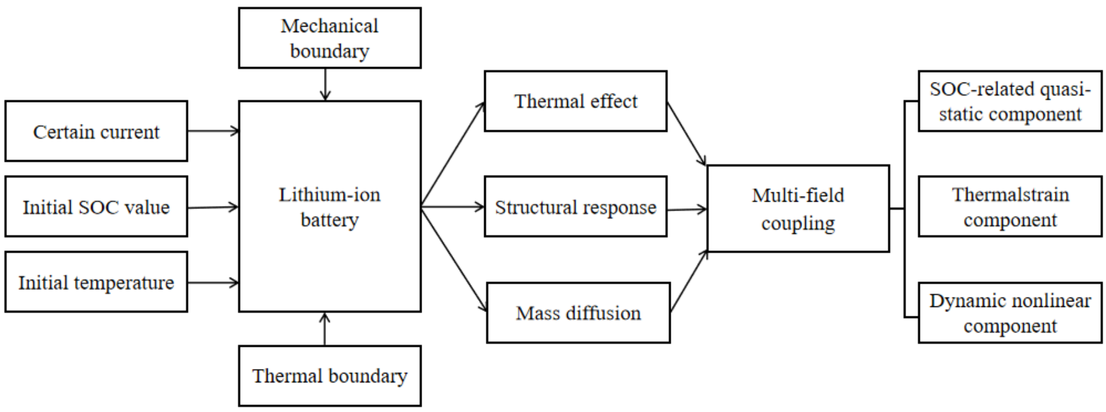


Fig 3. Deformation of lithium-ion batteries during charging and discharging

2.2. The Main Methods of Battery SOH Prediction

Electrochemical impedance spectroscopy. A method of assessing the state of a battery by measuring the change in impedance of the battery at different frequencies. By analyzing the EIS data, information such as the internal resistance of the battery, the resistance of the electrode interface, and the electrochemical reaction of the electrode can be obtained to predict the SOH of the battery [19]. It has the advantage of being able to directly reflect the electrochemical processes inside the battery, providing health information [20], and is a non-destructive testing method that does not cause any physical damage to the battery. And with a wide frequency range, electrochemical impedance spectroscopy can be measured over a wide range of frequencies to cover a wide range of electrochemical reactions within the battery. At the same time, EIS is very sensitive to small changes inside the battery, and can detect early signs such as battery aging and capacity decay. However, the cost of the equipment is high, the testing process is cumbersome, and the results are greatly affected by the test conditions such as temperature, electrode material, electrolyte, etc. Therefore, in order to obtain accurate results, experiments need to be carried out under strict test conditions, and precise control of the experimental conditions is required. The test time is long and requires a long test time, especially when measuring over a wide frequency range. This may limit its use in applications where a rapid assessment of battery SOH is required. Data interpretation is difficult, data is often complex, and professional knowledge and experience are required to interpret and analyze. Different cell systems and test conditions may produce different impedance spectra, so analysis needs to be tailored to the specific situation.

Machine Learning Methods. A method to predict the state of health (SOH) of a battery by using algorithms and models to learn and analyze large amounts of data [21]. The advantage is the ability to understand the health of the battery from large amounts of data, learn rules from historical data, predict future trends, and adapt as the battery ages, changes in the environment, or changes in operating conditions. By continuously learning and updating the model, you can better adapt to various practical application scenarios and improve the accuracy and stability of SOC predictions. However, it is highly data-dependent, and the prediction accuracy is highly dependent on the quantity and quality of training data. If the training data is insufficient or biased, the machine learning model's predictions can be greatly reduced. It is not easy to obtain large and representative battery aging data for lithium-sulfur battery SOH prediction, which may limit the application of machine learning methods. And the models are not interpretable, and many machine learning models, especially deep learning models, are considered "black box" models, that is, their predictions are difficult to interpret in a human-understandable way. In the SOH prediction of lithium-sulfur batteries, this may make it difficult for people to understand and trust the prediction results of the model, and it is also difficult to optimize and adjust the prediction results accordingly.

Data-Driven Approach. Using the historical data of the battery, the change in battery performance over time is mined through machine learning algorithms [22]. The advantage is that it is highly flexible and can be adapted to a variety of complex scenarios and battery types, without the need for an in-depth understanding of the electrochemical mechanisms inside the battery. Prediction accuracy is high, and if the model is designed properly and there is enough training data, the data-driven approach can provide fairly accurate SOH predictions. In addition, the data-driven approach based on online learning can update the model in real time to reflect the latest changes in battery performance over time. Easy to integrate, can be easily integrated into the BMS for real-time SOH monitoring and prediction. Scalability, as more data is collected, the model can be further optimized to improve prediction performance. However, it is data-dependent, and its performance is highly dependent on the quantity and quality of data. If there is insufficient training data or noise, the predictive performance of the model can be severely impacted. And with model complexity, for complex battery performance degradation patterns, complex models may need to be designed to accurately capture these patterns. This can increase the complexity and computational cost of the model. At the same time, the interpretability is poor, and the prediction results of the data-driven method usually lack interpretability compared with the prediction methods based on physical models. This can make it difficult for people to understand and trust the model's predictions. And there is a risk of overfitting, which can occur when the model is too complex and the training data is insufficient, where the model performs well on the training data but performs poorly on unseen test data. Finally, there is the issue of data privacy, which may involve user privacy and security issues when collecting and analyzing battery data. This requires appropriate safeguards during data collection, storage, and use.

3. Challenges and Innovations

3.1. Challenges

Nonlinearity and Uncertainty. For SOC, its nonlinearity is mainly reflected in the change of battery performance with the change of discharge depth, and this change is not a simple linear relationship. In addition, the internal reaction mechanism of lithium-sulfur batteries is complex, and factors such as voltage, current, and temperature during charging and discharging may affect the accurate estimation of SOC. Uncertainty comes from a variety of factors, such as battery aging, changes in ambient temperature, fluctuations in charge/discharge rates, etc., which can affect the capacity and performance of the battery, making SOC estimation more difficult. In the case of SOH, the nonlinearity is reflected in the fact that the decline in battery performance over time is not uniform or linear. During the charging and discharging process of lithium-sulfur batteries, the sulfur of the cathode material will gradually react, resulting in a decrease in capacity, and the lithium metal of the negative electrode may also have problems such as dendrite growth, thereby gradually reducing the performance of the battery. The uncertainty mainly comes from factors such as small differences in the battery manufacturing process, the complexity of the use environment, and the diversity of battery maintenance, which can lead to unpredictable changes in the state of health of the battery.

Aging effects. The aging of the battery can lead to degradation in its performance and failure, resulting in a decrease in the accuracy of SOC estimates and SOH predictions. The aging process of a battery is complex and involves a variety of physical and chemical changes, which makes it difficult to accurately predict the remaining life and performance of the battery. How to accurately predict and evaluate the impact of aging effects on battery state is an important challenge [23]. The aging effect can lead to a gradual decline in battery capacity, which in turn affects the accurate calculation of SOC. With the use of lithium-sulfur batteries, their internal chemical structure and physical properties may change, such as the loss of active materials, the decomposition of electrolytes, and the degradation of electrode materials. These changes result in a decrease in the usable capacity of the battery, which distorts the SOC value calculated from the initial capacity. At the same time, during the charge-discharge cycle of lithium-sulfur batteries, the sulfur of the positive electrode and the lithium of the negative electrode will undergo certain structural changes and losses. For example, a sulfur cathode may expand and contract in volume during charging and discharging, leading to a destruction of the electrode structure, while a lithium anode may experience the growth of lithium dendrites, which can puncture the separator and cause a short circuit in the battery. In addition, factors such as the aging decomposition of the electrolyte and the increase of interface resistance will also accelerate the aging process of the battery. These aging phenomena will gradually reduce the performance of the battery, which is manifested by a decrease in SOH.

Temperature and Environmental Factors. The operating environment of the battery is variable, including temperature, humidity, vibration, etc., which can affect the SOC and SOH of the battery [24]. How to accurately estimate the SOC and predict the SOH under different scenarios is a challenge. How to achieve accurate estimation and prediction under different conditions is a difficult problem [14]. The high temperature accelerates the chemical reactions inside the battery, improving the efficiency and performance of the battery. But at the same time, high temperatures can also trigger some irreversible chemical reactions, resulting in a decrease in active substances, which in turn leads to battery aging and reduced capacity. On the other hand, low temperature has a great impact on the discharge ability of lithium-sulfur batteries. At low temperatures, the discharge performance of the battery decreases significantly, mainly due to the decrease in the conductivity of the electrolyte and the slowing down of the rate of chemical reaction inside the battery.

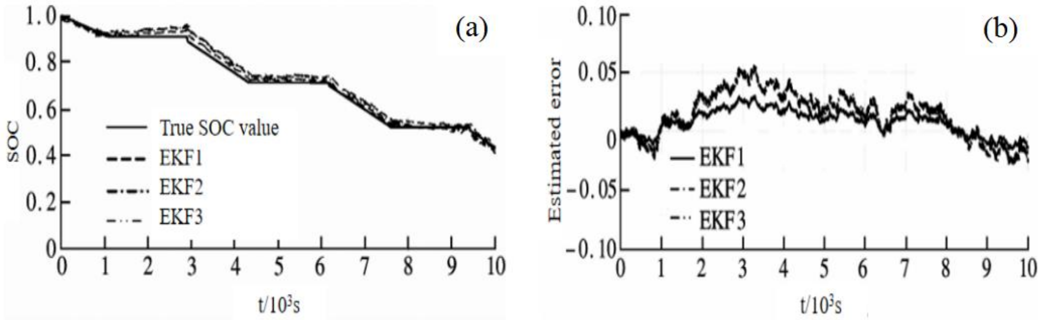


Fig 4. 30°C SOC estimation curve and error curve. (a): SOC estimation curve versus actual SOC curve; (b): SOC estimation error curve [24].

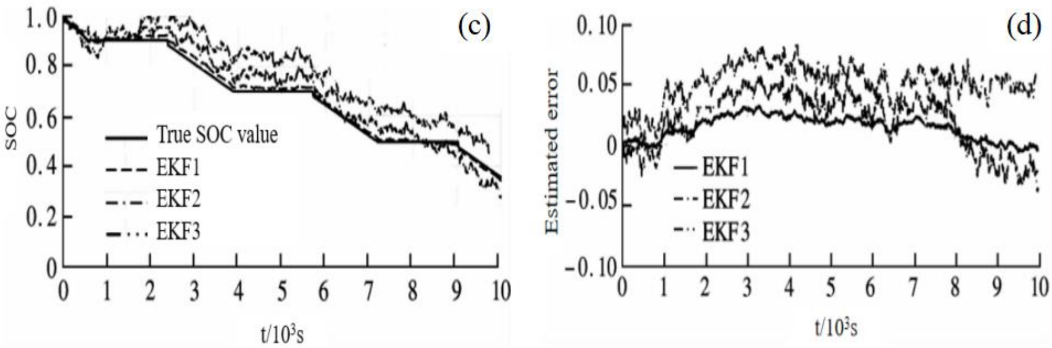


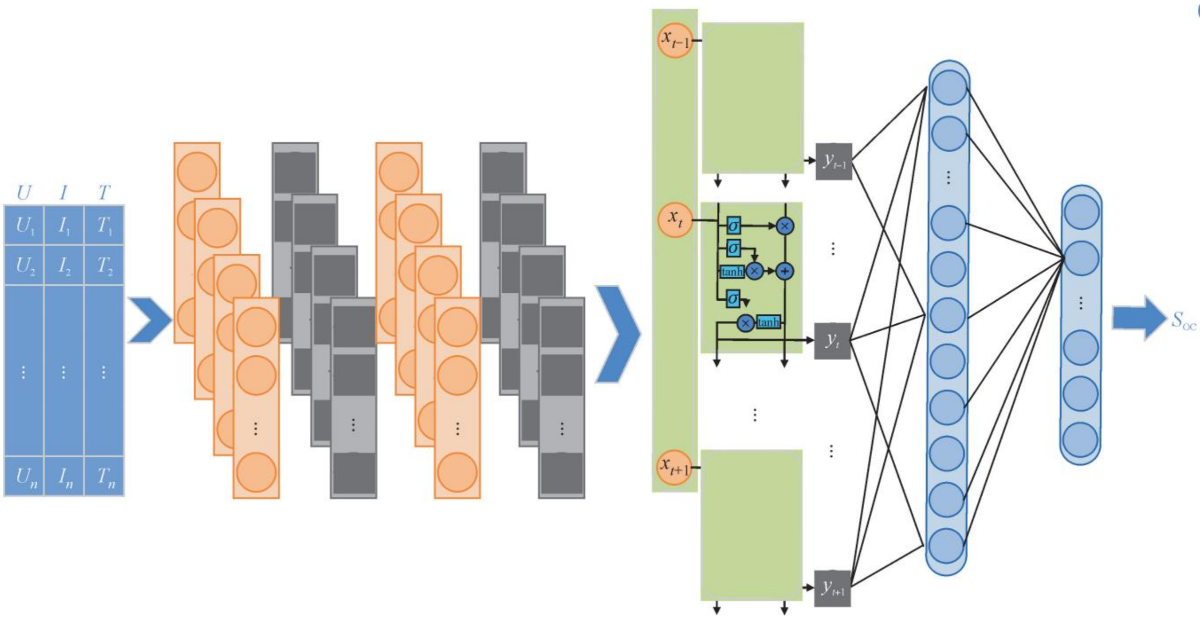
Fig 5. -14°C SOC estimation curve and error curve. (c): SOC estimation curve versus actual SOC curve;(d): SOC estimation error curve [24]

In addition to temperature factors, environmental factors can also affect the SOC and SOH of lithium-sulfur batteries. For example, humidity may affect the charge/discharge characteristics of a battery, especially in a high humidity environment, where the electrochemical reactions inside the battery may be affected, resulting in degraded performance. In addition, other factors in the environment, such as vibration, shock, electromagnetic interference, etc., may also have an impact on the operating state of the battery, which in turn affects the accurate measurement of SOC and SOH.

3.2. The Direction of Development

Advanced sensor technology. Develop sensors that can more accurately monitor the internal state of the battery to improve the accuracy of estimation and prediction. For example, high-precision voltage and current sensors: Voltage and current are the basic parameters for battery SOC prediction. With the advancement of sensor technology, high-precision, high-stability voltage and current sensors can provide more accurate data, thereby optimizing SOC prediction algorithms and improving prediction accuracy Optimization of temperature sensors: The performance of lithium-sulfur batteries is greatly affected by temperature, so accurate measurement of battery temperature is essential for SOC prediction. Advanced temperature sensors can not only monitor battery temperature in real time, but also provide higher measurement accuracy and faster response speed, which is of great significance to improve the accuracy of SOC prediction Internal Resistance Measurement Sensor: The internal resistance of a battery is an important parameter that reflects the health and performance of the battery. As sensor technology evolves, sensors that can accurately measure battery internal resistance in real-time will provide more valuable information for SOC predictions. By monitoring the change of internal resistance, the attenuation of the battery can be predicted, so as to adjust the SOC prediction algorithm and improve the prediction accuracy.

Deep learning and machine learning. Deep learning and machine learning algorithms are used to process complex nonlinear problems, extract useful information from massive amounts of data, and improve the accuracy of estimates and predictions [25]. Deep learning has powerful feature extraction and pattern recognition capabilities, and can learn the complex relationship between battery state and SOC by training large amounts of battery data. In the future, the application of deep learning algorithms in SOC estimation can be further explored to improve the estimation accuracy and real-time performance. Unsupervised learning algorithms can automatically detect and correct for drift of these parameters without labeling the data, enabling real-time calibration of SOC estimates, and transfer learning can transfer what is learned in one domain or task to another. In battery SOH prediction, transfer learning algorithms can transfer aging rules learned in one battery model or working environment to other models or environments, so as to achieve fast SOH prediction of new batteries. Combining deep learning and transfer learning, some researchers have constructed a deep neural network structure based on convolutional-long short-term memory networks, and proposed a method for estimating the state of charge of smallsample lithium batteries [26]. The figure below shows the neuronal structure of its neural network.



Orange-convolution layer; gray-pool layer; green-LSTM layer; light blue-total connection layer.
Fig 6. CNN-LSTM neural network model [26]

Multiphysics Modeling. Considering the electrochemical, thermal, and mechanical effects of the battery, a more accurate model of the battery can be built. By building a more accurate physical model of battery aging, we can gain a deeper understanding of the underlying mechanisms of battery performance degradation. Combined with real-time monitoring data, accurate prediction of battery SOH can be achieved. At the same time, the physical model can also provide theoretical support for the formulation of battery management strategies. For the direction of electrochemical reaction modeling, the working process of lithium-sulfur batteries involves complex electrochemical reactions, including the intercalation and removal of lithium ions, the reduction and oxidation of sulfur, etc. [27]. by building a sophisticated electrochemical reaction model, it is possible to gain insight into the kinetic processes and influencing factors of these reactions, so as to more accurately predict the SOC of the battery. For the direction of thermal conduction modeling, lithium-sulfur batteries generate heat during operation, and temperature has a significant impact on battery performance and SOC. Through thermal conduction modeling, the temperature distribution and change inside the battery can be analyzed, and the influence of temperature on the internal resistance and chemical reaction rate of the battery can be considered, and then the SOC prediction model or stress deformation modeling direction can be optimized, so that the electrode materials of the lithium-sulfur battery expand and contract during charging and discharging, resulting in stress and deformation. These changes can affect the performance and SOC of the battery. By building stress and deformation models, the impact of these changes on battery performance can be analyzed, providing a more comprehensive consideration for SOC predictions.

3.3. Relevant Innovative Ideas

Estimation method based on multi-source information fusion. Combined with a variety of sensor data (such as temperature, pressure, current, voltage, etc.), multi-source information fusion technology is used for comprehensive analysis and processing to improve the accuracy and reliability of estimation [28]. To estimate SOC, we can combine several parameters such as voltage, current, and temperature for fusion. For example, voltage and current data can be used to calculate the immediate power of a battery, while temperature data can reflect how active the chemistry inside the battery is. By fusing this information, we can more accurately describe the state of charge of the battery and predict its remaining usable capacity. For the estimation of SOH, parameters such as battery impedance and capacity decay rate can be introduced. These parameters can reflect the physical and chemical changes inside the battery, giving a more direct indication of the battery's health. By fusing these parameters, it is possible to more fully assess the extent of degradation in battery performance and predict its future useful life.

Health prediction based on generative adversarial networks. The generative adversarial network (GAN) is used to generate simulated battery aging data, which is used to train the prediction model and improve the generalization ability of the model in the real environment. Generative adversarial networks can be used to learn the historical data distribution of battery health states and generate virtual samples similar to real data, thereby expanding the size of the dataset and enhancing the generalization ability of the model. With this approach, we can more effectively deal with the nonlinear changes and uncertainties that occur during the aging of lithium-sulfur batteries. Specifically, generative models can learn the distribution rules of existing battery state health data and generate a large number of virtual samples that resemble real data. These virtual samples can include battery data under different usage conditions and different aging stages, so as to enrich the training set and improve the prediction accuracy of the model. At the same time, the discriminant model is used to distinguish the generated virtual samples from the real battery state of the health data, which further guides the optimization of the generative model.

Collaborative processing based on cloud computing and edge computing. Cloud computing and edge computing technologies are used to realize real-time processing and analysis of data, and improve the real-time and accuracy of estimation and prediction. Edge computing can do the initial data acquisition and processing on the side close to the battery or data source. Since lithium-sulfur batteries generate a large amount of real-time data during operation, including voltage, current, temperature, etc., these data are crucial for the estimation of SOC and SOH. Edge computing devices collect and process this data in real time, which can effectively reduce the delay of data transmission to the cloud and improve response speed. Cloud computing can use its powerful computing power and storage resources to perform in-depth analysis and processing of data uploaded by edge computing devices. On cloud computing platforms, we can use advanced algorithms and models to analyze and predict battery data more accurately, including data-driven forecasting methods, physics-based forecasting methods, and more. At the same time, cloud computing can also provide powerful data storage and backup functions to ensure the reliability and security of battery data.

4. Conclusion

As a battery technology with high energy density and environmental protection, lithium-sulfur batteries have been widely researched and applied. However, there are still challenges and difficulties in state-of-charge estimation and state-of-health prediction of lithium-sulfur batteries. In this paper, the research status and development trend of state-of-charge estimation and health prediction of lithium-sulfur batteries are reviewed, and the advantages and disadvantages of different methods are discussed. By analyzing the shortcomings and problems of existing research, the direction and suggestions for future research are proposed.

The results show that the state-of-charge estimation and health prediction technology of lithium-sulfur batteries is of great significance to improve the performance, safety and life of lithium-sulfur batteries. Traditional current-voltage methods still play an important role, but the accuracy and stability need to be further improved. Data-driven methods have made significant progress in state-of-charge estimation and health prediction of lithium-sulfur batteries, but more battery operation data and reasonably designed neural network structure parameters are still needed.

Future research can improve the accuracy and stability of lithium-sulfur battery state-of-charge estimation and health prediction by establishing more accurate battery models, improving the robustness of algorithms, exploring new data collection methods, and considering changes and uncertainties in the battery's operating environment. Through unremitting efforts, it is believed that the state-of-charge estimation and health prediction technology of lithium-sulfur batteries will provide important support for the performance optimization and safe and reliable operation of lithium-sulfur batteries.

References

[1] Li LB, Shan YH. The use of graphene and its composites to suppress the shuttle effect in lithium-sulfur batteries. New Carbon Materials. 2021;36(2):336-47.

[2] Yang W, Zhu S, Chen Y, Zhu J, Xue L. SOC estimation of lithium-ion battery based on improved ampere-hour integral method. Chinese Journal of Power Sources. 2018;42(2):183.

[3] Huang LM, Guo YF, Zhao ZS, Ieee, editors. Study on Prediction Algorithm of AUKF for the Lithium-ion Battery SOC. IEEE International Conference on Communication Problem-Solving (ICCP); 2015 Oct 16-18; Guilin, PEOPLES R CHINA2015.

[4] Song ZY, Wang H, Hou J, Hofmann HF, Sun J. Combined State and Parameter Estimation of Lithium-Ion Battery With Active Current Injection. Ieee Transactions on Power Electronics. 2020;35(4):4439-47.

[5] Guo X, Hua X, Fu Z, Wang Y, Xie D. SOC estimation of Kalman filter based on the model data optimization. Journal of Electronic Measurement and Instrument. 2018;32(8):186-92.

[6] Deng K, Wang Y, Liu D. Kalman Filter for HEV's Battery SOC Estimation Based on Wavelet Transform. Control Engineering of China. 2015;22(3):398-403.

[7] Li QL, Li DZ, Zhao K, Wang LC, Wang K. State of health estimation of lithium-ion battery based on improved ant lion optimization and support vector regression. Journal of Energy Storage. 2022;50.

[8] Lin Zhicheng, Hou Penghu, Liu Wei, Zhang Zixia, Zhang Ya, Geng Nankun, Liao Qiangqiang. State of health estimation of lithium-ion batteries based on remaining area capacity

[9] Zhang C, He Y, Yuan L. Approach for Lithium-ion Battery RUL Prognostics Based on CPSO-RVM. Journal of System Simulation. 2018;30(5):1935-40.

[10] Zhang Xin, Hou Jiawei, Wang Zekun, Jiang Yueqiu. Joint estimation model of SOH-SOC for lithium-ion battery based on GWO-BP neural network

[11] Mao H, Wan G, Wang L, Zhang Q. Estimation of battery SOC based on Kalman filter correction algorithm. Chinese Journal of Power Sources. 2014;38(2):298-302.

[12] Tian S, Lu Q, Li Y. SOC Estimation of Li-Ion Power Battery Based on STEKF. Journal of South China University of Technology Natural Science Edition. 2020;48(2):69-75.

[13] Yang X, Liu X, Chen T, Mao X. Lithium Battery SOC Estimation Based on DTW-KiBaM Model. Journal of Hunan University Natural Sciences. 2023;50(12):203-12.

[14] Tan B, Du J, Ye X, Cao X, Qu C. Overview of SOC estimation methods for lithium-ion batteries based on model. Energy Storage Science and Technology. 2023;12(6):1995-2010.

[15] Wu L, Pang H, Jin J, Geng Y, Liu K. A Review of SOC Estimation Methods for Lithium-Ion Batteries Based on Electrochemical Model. Transactions of China Electrotechnical Society. 2022;37(7):1703-25.

[16] He Y, Cao C, Liu X, Zheng X, Zeng G. SOC estimation method for lithium battery based on variable temperature model. Electric Machines and Control. 2018;22(1):43-52.

[17] Gao H, Chen Y. A machine learning based method for lithium-ion battery state of health classification and prediction. Journal of Beijing University of Aeronautics and Astronautics. 2023;49(12):3467-75.

[18] Zhang L, Cheng H, Meng D. Experimental Study on ETSS Coupling Mechanism and Identification of Key Parameter for Lithium-Ion Batteries. Journal of Xi'an Jiaotong University. 2017;51(8):142-8.

[19] Li L, Zhang X. SOH estimation for lithium-ion batteries based on combination of frequency impedance characteristics. Energy Storage Science and Technology. 2023;12(5):1705-12.

[20] Xu X, Wang L, Shi H. Research on battery aging mechanisms based on electrochemical impedance spectroscopy. Chinese Journal of Power Sources. 2015;39(12):2579-83.

[21] Li H, Zhang X, Zhang W. SOC estimate method and application of high capacity lithium-ion battery. Chinese Journal of Power Sources. 2015;39(5):1100-2.

[22] Chen Y, Bai Y, He Y. Comparison of data-driven lithium battery state of health estimation methods. Energy Storage Science and Technology. 2019;8(6):1204-10.

[23] Fu S, Lyu T, Min F, Luo W, Luo C, Wu L, et al. Review of estimation methods on SOC of lithium-ion batteries in electric vehicles. Energy Storage Science and Technology. 2021;10 (3): 1127-36.

[24] Liu X, Sun Z, He Y, Zheng X, Zeng G. SOC estimation method based on lithium-ion cell model considering environmental factors. Journal of Southeast University Natural Science Edition. 2017;47(2):306-12.

[25] Gao J, Zhu Y, Liu Y. A new optimization algorithm for state of charge estimation of electric vehicle batteries. Chinese Journal of Power Sources. 2014;38(1):75-7.

[26] Li L, Yan X, Zhang Y, Feng Y, Hu H, Duan Y, et al. Lithium Battery State of Charge Estimation Method Based on Transfer Learning. Journal of Xi'an Jiaotong University. 2023;57(11): 142-50.

[27] Gao M, Xu H, Wu M. Review of SOC Estimation Methods for Power Battery Based on Equivalent Circuit Model. Journal of Electrical Engineering. 2021;16(1):90-102.

[28] Sun D, Xu S. State of Health Prediction of Second-Use Lithium-Ion Battery. Transactions of China Electrotechnical Society. 2018;33(9):2121-9. (1)