

Review of Key Technologies for Remaining Useful Life Prediction of Power Batteries

Jinbo Zhang¹, Rui Yang^{1, *}, Hang Qin²

¹ Xinjiang Vocational University of Technology, Kashgar 844210, Xinjiang, China

² Zhejiang Geely Holding Group Co., Ltd., Hangzhou 310051, Zhejiang, China

*Corresponding author: Rui Yang (Email: 2417300396@qq.com)

Abstract

As the core power source of new energy equipment, the accurate prediction of the Remaining Useful Life (RUL) of power batteries is of great significance for ensuring the operational reliability of equipment, optimizing the full-life cycle management of batteries and reducing operation and maintenance costs, and has become a research hotspot in the field of energy and power engineering. This paper systematically sorts out and summarizes the existing battery RUL prediction methods: first, from the perspective of mechanism models, it reviews the principles and application scenarios of three types of methods, namely electrochemical models, equivalent circuit models and empirical models; second, it introduces data-driven prediction methods, covering mainstream algorithms such as filtering technology, Gaussian process regression and neural networks; third, it discusses fusion-based prediction strategies, including two core forms: the integration of mechanism models with data-driven methods, and the combination of multiple data-driven methods; finally, it summarizes the advantages and disadvantages of various methods, analyzes their application status and development trends in power battery management systems, and prospects the evolution path of future RUL prediction technology toward intellectualization, lightweight design and high precision, aiming to provide a reference for relevant research on power battery health management.

Keywords

Lithium-ion Battery; Remaining Useful Life Prediction; Power Battery; Data-driven; Battery Management System.

1. Introduction

Against the backdrop of the "dual carbon" strategy, the new energy industry is experiencing rapid development. As the core energy carrier for new energy vehicles, energy storage power stations, portable electronic devices and other equipment, power batteries directly determine the operational efficiency and safety of such equipment with their performance and service life. Lithium-ion batteries have become the mainstream choice for power batteries due to their advantages such as high energy density, long cycle life and no memory effect. However, power batteries undergo performance degradation due to electrochemical reactions, material aging and other factors during charge-discharge cycles and storage, which directly impairs their operational safety and economic efficiency.

The Remaining Useful Life (RUL) of a battery refers to the remaining number of available charge-discharge cycles or service time from its current state to the End of Life (EOL)[1]. It is closely correlated with the battery's State of Health (SOH), and the industry generally regards a drop in SOH to 70%–80% as the criterion for determining that a battery has reached its EOL. Therefore, the accurate prediction of RUL for power batteries holds significant engineering

value for realizing real-time monitoring of battery health status, optimizing charge-discharge strategies, ensuring the safe operation of equipment, and promoting the cascade utilization of batteries.

However, the aging process of lithium-ion batteries is a nonlinear time-varying system affected by multiple factors such as temperature, charge-discharge rate and operating conditions, resulting in the fact that an optimal prediction model applicable to all operating conditions has not yet been developed to date. At present, RUL prediction methods can be mainly divided into three categories: mechanism models, data-driven methods and fusion technologies[2-4]. The different RUL prediction methods for lithium-ion batteries are summarized in Figure 1.

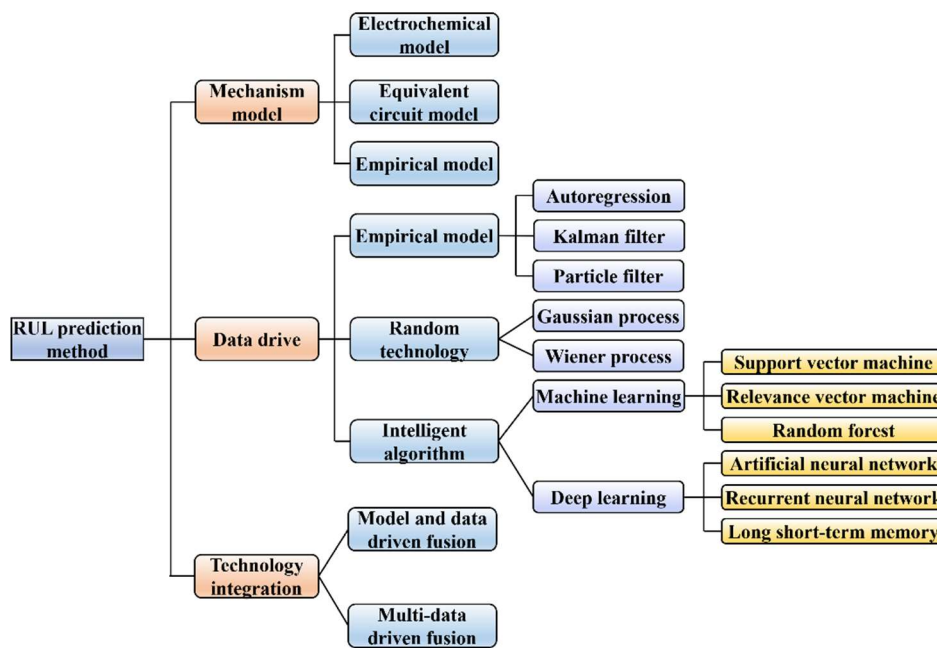


Figure 1. Lithium-ion Battery RUL Prediction Methods

2. RUL Prediction Methods

2.1. Mechanism-Model-Based Methods

Mechanism-model-based methods usually rely on the physical and chemical characteristics of batteries. By constructing mathematical models of internal battery behaviors to simulate battery degradation processes, these methods predict battery aging trajectories and estimate the remaining useful life of batteries. According to the differences in modeling methods and theoretical foundations adopted, they can be generally divided into three categories: electrochemical models, equivalent circuit models, and empirical models[5].

2.1.1. Electrochemical Models

Electrochemical modeling is a method that builds models based on the principles of electrochemical reactions inside batteries. By simulating factors such as battery charge-discharge processes, ion migration in electrolytes, and electrode reaction kinetics, it deduces the internal mechanisms of batteries and further reveals the mechanisms of battery performance degradation. This method achieves high accuracy under specific conditions; however, it involves numerous factors to be considered and a complex model construction process, which requires substantial experimental data and computing resources for support, making it difficult to implement for online applications[6]. Sadabadi et al.[7] developed a lithium-ion battery RUL prediction algorithm based on parameter estimation of the enhanced single particle model, and established an enhanced single particle model capable of predicting

the evolution of battery aging-related parameters. They took the molar amount of cyclable lithium and ohmic resistance as state of health indicators, verified the correlation between these parameters and battery state of health through experimental data, and finally designed an RUL predictor based on particle filtering. Huang et al.[8]integrated more than 15 internal battery mechanism parameters to establish an electro-thermal coupled model. This method can evaluate the battery state of health with relatively high accuracy, yet it still suffers from the problem of difficult online parameter identification due to its high model complexity and numerous parameters.

2.1.2. Equivalent Circuit Models

Equivalent circuit modeling refers to constructing circuit models that can reproduce the same electrical behavior of batteries by using various circuit components (e.g., independent power supplies, diodes, resistors, etc.). Such models are usually simple with low computational complexity, but they have high requirements for parameter accuracy and yield low prediction accuracy when dealing with complex problems such as lithium-ion battery life degradation[9]. Xia et al.[10]proposed a framework for lithium-ion battery state of health and RUL prediction combining disturbance-free incremental capacity and differential voltage analysis. This method reconstructs voltage through a second-order RC model to obtain incremental capacity and differential voltage curves, extracts new battery aging features, and adopts an improved bidirectional gated recurrent unit for prediction, which achieves high accuracy and robustness. Guha et al.[11]used a series-parallel circuit model to estimate the electrochemical impedance of batteries and established a battery RUL prediction model based on this impedance. The results show that this model has high accuracy, but it is difficult to measure under actual operating conditions, leading to poor practicality.

2.1.3. Empirical Models

Empirical modeling is a method for modeling battery degradation behavior based on a large amount of experimental data combined with statistical analysis or data fitting techniques[12]. Common types of empirical models include single exponential, double exponential, polynomial, Verhulst, and hybrid models[13]. This method features simple calculation and can quickly obtain prediction results with sufficient data, but it is prone to overfitting and has weak generalization ability. Xiong et al.[14]proposed an RUL prediction method based on improved Box-Cox transformation technology. By optimizing the update method of transformation coefficients, this method linearizes the nonlinear capacity degradation trajectory of power batteries and then fits the linearized trajectory. Experimental results show that this method improves the prediction accuracy in the early and middle stages of battery aging; however, it has a high dependence on data quality, and large noise in the data may exert a significant impact on the prediction results. Ma et al.[15]built a battery RUL prediction model based on the double exponential model with the introduction of Gauss-Hermite filtering technology. This method can update parameters in real time, but it also has a high dependence on data and is sensitive to initial parameters.

2.2. Data-Driven Methods

Data-driven prediction methods usually do not require consideration of the complex internal aging mechanisms of batteries. Instead, they establish RUL prediction models by analyzing historical battery data, extracting health indicators closely related to battery aging, and mining the inherent variation laws of these indicators. Since such methods rely solely on data interaction, they are also referred to as black-box models[16]. Common data-driven RUL prediction methods for batteries include filtering techniques, Gaussian process regression, support vector machines, relevance vector machines, and neural networks[17-19].

2.2.1. Filtering Techniques

In the field of battery RUL prediction, the commonly used filtering techniques include the Kalman Filter (KF) and Particle Filter (PF). KF is a filtering method based on linear dynamic systems, whose core idea is to combine the prior estimated values of the system with the current observed data through recursive calculation to obtain the optimal estimation of the system state, and it is suitable for linear systems with low noise. Yan et al.[20]proposed a Lebesgue-sampled Extended Kalman Filter (LS-EKF) method, which reduces the computation time without sacrificing performance and achieves good prediction accuracy. PF is a filtering technique based on the Monte Carlo method; it represents the system state with multiple particles and approximates the probability distribution of the battery state through random sampling. Zhang et al.[21]combined the F-distribution Particle Filter (FPF) with the Kernel Smoothing (KS) algorithm to construct the FPFKS prediction model for battery RUL prediction. Experimental results show that this method can effectively solve the problems of particle degeneracy and unupdatable model parameters in the prediction stage, thus improving its long-term prediction capability.

2.2.2. Gaussian Process Regression

Gaussian Process Regression (GPR) is a Bayesian nonparametric regression method based on Gaussian processes. It defines the covariance through kernel functions to realize the uncertain prediction of nonlinear systems. Kang et al.[22]proposed an RUL prediction method combining fuzzy evaluation and GPR, which first preprocesses the data via the fuzzy evaluation method and then uses GPR to build the RUL prediction model. Wu et al.[23]proposed an RUL prediction method combining the improved grey wolf optimizer (GWO) with the GPR model. This method extracts five different indirect health factors and proposes a modified grey wolf optimizer based on the differential algorithm to solve the problem of premature convergence to local optima in traditional models. Finally, the GPR model is used to predict the RUL of power batteries, and experimental results show that the RUL prediction accuracy of this method is within 2%.

2.2.3. SVM and RVM

Support Vector Machines (SVM) are supervised learning algorithms applicable to both classification and regression problems. Their core idea is to construct an optimal hyperplane that maximizes the distance between the two types of data points and the hyperplane, thereby realizing data classification or regression. This method has strong generalization ability but is sensitive to data noise and outliers, and its operation efficiency is low when dealing with large-scale datasets. Zhao et al.[24]proposed a method combining feature vector selection and Support Vector Regression (SVR), which establishes a relational model between two health indicators (i.e., the charging voltage difference and discharging voltage difference at equal time intervals) and battery capacity to realize the online prediction of lithium-ion battery RUL. Wang et al.[25]processed the raw data through discrete wavelet decomposition, reconstructed the subsequences using the K-means clustering method, and finally combined SVR to predict battery RUL. Experimental results show that this method can effectively predict the variation trend of the battery capacity trajectory and achieve relatively accurate battery RUL prediction. Relevance Vector Machines (RVM) are an improved version of SVMs. By introducing Bayesian theory, RVMs enable probabilistic estimation of prediction results. Compared with SVMs, RVMs can output uncertain prediction results and yield sparser models with higher computational efficiency. Tian et al.[26]proposed a multi-kernel RVM-based RUL prediction method, which adopts the particle swarm optimization (PSO) algorithm to realize the automatic parameter optimization of each kernel function and achieves favorable prediction results. Wang et al.[27]extracted a directly online-measurable health indicator from the battery current curve, optimized this indicator through the Box-Cox transformation, and finally used RVM for probabilistic prediction to realize the RUL prediction of lithium-ion batteries.

2.2.4. Neural Networks

Although the above three methods are widely applied in the field of lithium-ion battery RUL prediction, they still have certain limitations when dealing with big data, which restricts their performance in practical applications. In contrast, neural network methods can effectively overcome this shortcoming due to their advantages in big data processing. A neural network[28] is a computational model inspired by biological neural systems, which is mainly composed of neuron nodes and connection weights. It learns the mapping relationship between inputs and outputs by organizing multiple nodes (i.e., neurons) in the form of weighted connections, thus mining the potential laws of data. Recurrent Neural Networks (RNN) are widely used in battery RUL prediction due to their unique advantages in processing time-series data. Eddahech et al.[29] proposed an RUL prediction method combining electrochemical impedance spectroscopy (EIS) and RNN and applied it to power battery RUL prediction. However, RNNs tend to suffer from the problems of gradient vanishing and gradient exploding when processing long data sequences, which has prompted numerous researchers to improve its variant, the Long Short-Term Memory (LSTM) network[30]. Li et al.[31] designed an improved LSTM neural network, which adds fixed connection coupling to the input gate and forget gate of the LSTM respectively, performs a multiplication operation on the information of the current and past moments, and introduces a direct connection of Constant Error Carousel (CEC) to the output gate of the LSTM. Ardeshiri et al.[32] proposed a capacity-oriented RUL predictor combining RNN and Gated Recurrent Unit (GRU), and adopted a random forest-based feature selection method to improve the prediction accuracy.

2.3. Fusion-Technology-Based Methods

Fusion-technology-based methods for lithium-ion battery RUL prediction conduct RUL prediction by combining two or more approaches. Aiming to complement the advantages of different methods and overcome the limitations of single models, these methods can improve the RUL prediction accuracy and the generalization ability of the model. They are mainly divided into two categories: the fusion of mechanism models and data-driven methods, and the fusion of multiple data-driven methods.

2.3.1. Fusion of Mechanism Models and Data-Driven Methods

The fusion technology of mechanism models and data-driven methods combines the two types of approaches to better adapt to the requirements under different battery states. Chang et al.[33] proposed an RUL prediction method based on the idea of error correction, which integrates the Unscented Kalman Filter (UKF), Complete Ensemble Empirical Mode Decomposition (CEEMD) and Relevance Vector Machine (RVM), and introduces an error correction mechanism that can effectively reduce the prediction deviation of the model. Yi et al.[34] proposed a VF-DW-DFN fusion RUL prediction method by combining variational filtering, data warping and deep fusion network, which can effectively improve the reliability and robustness of the model.

2.3.2. Fusion of Multiple Data-Driven Methods

There are also many fusion technologies for multiple data-driven methods, which mainly focus on combining several machine learning or deep learning models to improve the accuracy and robustness of the model. Hu et al.[35] analyzed the key factors affecting RUL (e.g., battery capacity, internal resistance, ambient temperature, etc.), then used random forest for feature selection, and finally constructed a Stacking fusion model combining the grey prediction model with Long Short-Term Memory (LSTM) network. Zhu et al.[36] proposed a prediction method that integrates the Whale Optimization Algorithm (WOA), Variational Mode Decomposition (VMD), Sparrow Search Algorithm (SSA) and LSTM model. This method optimizes the two parameters of VMD via WOA and tunes the hyperparameters of LSTM by SSA, thus improving

the prediction performance of the LSTM model. However, this method needs to be re-optimized when migrated to new battery datasets, resulting in poor practicality in engineering applications. Wu et al.[37]proposed an EEMD-DBN-LSTM method combining Ensemble Empirical Mode Decomposition (EEMD) with neural networks. First, the capacity degradation curve is decomposed by EEMD, then the Intrinsic Mode Function (IMF) components and residuals are predicted by LSTM and Deep Belief Network (DBN) respectively, so as to realize the RUL prediction. This method achieves high accuracy and strong robustness, but it is sensitive to data and has high computational complexity.

Each of the above methods has its own advantages and disadvantages, which are summarized in Table 1.

Table 1. Strengths and Drawbacks of Different Prediction Strategies

Method	Category	Advantages	Disadvantages
Mechanism-Model-based	Electrochemical model	Reflects the internal mechanisms of batteries	Large number of parameters and high computational complexity
	Equivalent circuit model	Clear physical meaning, simple calculation	Poor adaptability under complex operating conditions
	Empirical model	Simple implementation, fast fitting	Low prediction accuracy, weak generalization ability
	Filtering technology	Model-independent, strong adaptability	Dependent on data quality and feature selection
Data-driven	Gaussian process regression	Provides uncertainty estimation	High computational complexity
	SVM/RVM	Strong generalization ability, good sparsity	Sensitive to noise, low efficiency for large-scale datasets
	Neural network	Strong nonlinear fitting ability, suitable for big data	Requires massive data, poor interpretability
Fusion-technology-based	---	High prediction accuracy; strong robustness	Complex model structure; difficult parameter optimization

Use American English when writing your paper. The serial comma should be used (“a, b, and c” not “a, b and c”). In American English, periods and commas are within quotation marks, like “this period.” Other punctuation is “outside”! The use of technical jargon, slang, and vague or informal English should be avoided. Generic technical terms should instead be used.

3. Conclusion and Prospects

This paper systematically reviews the main methods for predicting the remaining useful life (RUL) of power batteries, which are categorized into three types: mechanism models, data-driven methods, and fusion technologies. Mechanism-model-based methods offer strong physical interpretability but involve complex modeling processes; data-driven methods feature high flexibility and adaptability yet have a high dependence on data quality; fusion technologies, by complementing the advantages of different single methods, have improved prediction accuracy and robustness, thus becoming a current research hotspot.

With the rapid development of the new energy industry, the application scenarios of power batteries are continuously expanding, which puts forward higher engineering requirements for RUL prediction technologies in terms of intellectualization, lightweight design, high precision,

and full operating condition adaptability. Based on the current development status of related technologies, the future development directions of power battery RUL prediction technologies can be summarized as follows:

(1) Model Lightweight Design and Online Implementation

Aiming at the engineering characteristics of power battery management systems, such as limited hardware computing power and high real-time performance requirements, research on the lightweight design of prediction models should be carried out. Technologies including model pruning, quantization, and knowledge distillation are adopted to simplify the structure of complex fusion models and neural network models, thereby reducing computational complexity. Combined with edge computing and embedded technologies, the hardware deployment of prediction models is realized to meet the demand for real-time online prediction of power battery RUL.

(2) Multi-source Information Fusion and Feature Optimization

The aging state of power batteries is affected by multiple factors such as voltage, current, temperature, internal resistance, and vibration, and a single type of monitoring data cannot fully reflect the battery aging law. In the future, it is necessary to fuse multi-source sensing information to extract more robust battery health features. By combining technologies such as feature selection, feature fusion, and feature dimensionality reduction, redundant features are eliminated and noise interference is reduced, which can improve the model's ability to capture battery aging laws and achieve accurate prediction under full operating conditions.

(3) Research on Few-shot and Cross-domain Prediction Technologies

In practical engineering, it is difficult to fully collect the full-life cycle aging data of power batteries, and the aging laws of batteries from different models and manufacturers are quite different, which limits the generalization ability of the models. Future research should focus on few-shot learning, transfer learning, federated learning and other related technologies, which can realize effective model training with a small amount of labeled data and achieve RUL prediction of power batteries of different models and under different operating conditions through cross-domain knowledge transfer, thus improving the generalization ability of the models.

(4) Construction of a Full-life Cycle Data Platform for Batteries

Data is the foundation of data-driven and fusion-based RUL prediction methods. In the future, relying on application scenarios such as new energy vehicles and energy storage power stations, a full-life cycle operation data platform for power batteries should be constructed to realize the collection, storage and sharing of data in all stages including battery production, transportation, usage, and cascade utilization. Combined with big data and cloud computing technologies, the aging laws of batteries throughout their full life cycle are explored to provide data support for the research, development and optimization of RUL prediction models, and promote the in-depth integration of prediction technologies with engineering applications.

(5) Multi-objective Collaborative Optimization

Power battery RUL prediction is not an independent link and needs to be optimized collaboratively with battery charge-discharge control, thermal management, cascade utilization and other links. In the future, an integrated battery health management system featuring "RUL prediction - state monitoring - strategy optimization" should be constructed. Based on the RUL prediction results, the charge-discharge strategies and thermal management strategies are optimized in real time to realize the refined management of power batteries and improve the operational safety, economic efficiency and full-life cycle value of batteries..

References

- [1] Chen D Q, Hong W C, Zhou X Z. Transformer network for remaining useful life prediction of lithium-ion batteries[J]. *IEEE Access*, 2022, 10: 19621-19628.
- [2] Zhai X, Liu G, Lu T, et al. Transforming waste to value: Enhancing battery lifetime prediction using incomplete data samples[J]. *Journal of Energy Chemistry*, 2025, 106: 642-649.
- [3] Liu Y F. Research on fusion prediction method of lithium-ion battery remaining useful life based on data-driven approach[D]. Harbin: Harbin Institute of Technology, 2020.
- [4] Zhao J H, Tian L T, Cheng L. A review of state estimation and remaining useful life prediction methods for lithium-ion batteries[J]. *Power Generation Technology*, 2023, 44(1): 1-17.
- [5] Zhai X, Liu G, Lu T, et al. Transforming waste to value: Enhancing battery lifetime prediction using incomplete data samples[J]. *Journal of Energy Chemistry*, 2025, 106: 642-649.
- [6] Deng Z, Hu X, Lin X, Xu L, Li J, Guo W. A reduced-order electrochemical model for all-solid-state batteries[J]. *IEEE Transactions on Transportation Electrification*, 2021, 7(2): 464-473.
- [7] Sadabadi K, Jin X, Rizzoni G. Prediction of remaining useful life for a composite electrode lithium-ion battery cell using an electrochemical model to estimate the state of health[J]. *Journal of Power Sources*, 2021, 481: 228861.
- [8] Huang H Q. Estimation of lithium-ion battery aging state based on electro-thermal coupled model[D]. Harbin: Harbin Institute of Technology, 2021.
- [9] Li B J, Han X X, Zhang W J, et al. A review of remaining useful life prediction methods for lithium-ion batteries[J]. *Energy Storage Science and Technology*, 2024, 13(4): 1266-1276.
- [10] Xia F, Wang K, Chen J J. State of health and remaining useful life prediction of lithium-ion batteries based on a disturbance-free incremental capacity and differential voltage analysis method[J]. *Journal of Energy Storage*, 2023, 64: 1-14.
- [11] Guha A, Patra A. Online estimation of the electrochemical impedance spectrum and remaining useful life of lithium-ion batteries[J]. *IEEE Transactions on Instrumentation and Measurement*, 2018, 67(8): 1836-1849.
- [12] Li C L. Research on remaining useful life prediction method of vehicle lithium-ion batteries[D]. Changchun: Jilin University, 2023.
- [13] Zhang R K, Guo Y F, Yu X Y, et al. A review of data-driven remaining useful life prediction for lithium-ion batteries[J]. *Journal of Power Sources*, 2023, 21(5): 182-190.
- [14] Xiong R, Lu J H. A remaining useful life prediction method for power batteries based on improved Box-Cox transformation technology[C]//China Society of Automotive Engineers. Proceedings of the 2019 Annual Conference of the China Society of Automotive Engineers (Volume 2)[C]. Beijing: Beijing Institute of Technology Press, 2019: 5.
- [15] Ma Y, Chen Y, Zhou X W, et al. Remaining useful life prediction of lithium-ion battery based on Gauss-Hermite particle filter[J]. *IEEE Transactions on Control Systems Technology*, 2019, 27(4): 1788-1795.
- [16] Wang S L, Jin S Y, Bai D K, Fan Y C, Shi H T, Fernandez C. A critical review of improved deep learning methods for the remaining useful life prediction of lithium-ion batteries[J]. *Energy Reports*, 2021, 7: 5562-5574.
- [17] Chen H Y, Tao Z J, Zhu Y L, et al. Research on state of health and remaining useful life prediction technology for retired power lithium-ion batteries[J]. *Power System Protection and Control*, 2025, 53(7): 174-187.
- [18] Chatterjee S, Gatla R, Sinha P, et al. Fault detection of a Li-ion battery using SVM based machine learning and unscented Kalman filter[J]. *Materials Today: Proceedings*, 2023, 74(4): 703-707.
- [19] Xing J, Zhang H, Zhang J. Remaining useful life prediction of lithium batteries based on principal component analysis and improved Gaussian process regression[J]. *International Journal of Electrochemical Science*, 2023, 18(4): 100048.
- [20] Yan W Z, Zhang B, Wang X F, et al. Lebesgue-sampling-based diagnosis and prognosis for lithium-ion batteries[J]. *IEEE Transactions on Industrial Electronics*, 2016, 63(3): 1804-1812.

- [21] Zhang K, Zhao P, Sun C, Wang Y, Chen Z. Remaining useful life prediction of aircraft lithium-ion batteries based on F-distribution particle filter and kernel smoothing algorithm[J]. Chinese Journal of Aeronautics, 2020, 33(5): 1517-1531.
- [22] Kang W, Xiao J, Xiao M, et al. Research on remaining useful life prognostics based on fuzzy evaluation Gaussian process regression method[J]. IEEE Access, 2020, 8: 71965-71973.
- [23] Wu X Z, Guo J. A power battery RUL prediction method based on improved grey wolf optimizer optimized GPR model[J]. Energy Storage Science and Technology, 2025, 14(2): 728-736.
- [24] Zhao Q, Qin X L, Zhao H B, et al. A novel prediction method based on the support vector regression for the remaining useful life of lithium-ion batteries[J]. Microelectronics Reliability, 2018, 85: 99-108.
- [25] Wang X M, He Y, Wang L L, et al. Remaining useful life prediction of lithium-ion batteries based on DWD-SVR model[J]. Acta Energetica Solaris Sinica, 2025, 46(2): 52-59.
- [26] Tian Q, Chen H, Ding S, Wang L, Huang J, Yang Z. Remaining useful life prediction method of lithium-ion batteries based on relevance vector machine[A]//Dong X, Yang Q, Ma W, Eds. Proceedings of the 10th Frontier Academic Forum of Electrical Engineering (FAFEE2022)[C]. Singapore: Springer, 2023: 1303-1313.
- [27] Wang R, Feng H. Remaining useful life prediction of lithium-ion battery using a novel health indicator[J]. Quality and Reliability Engineering International, 2021, 37(3): 1232-1243.
- [28] He T Z. Research on self-learning neural network algorithm[D]. Wuhan: Central China Normal University, 2011.
- [29] Eddahech A, Briat O, Bertrand N, et al. Behavior and state-of-health monitoring of Li-ion batteries using impedance spectroscopy and recurrent neural networks[J]. International Journal of Electrical Power and Energy Systems, 2012, 42(1): 487-494.
- [30] Hochreiter S, Schmidhuber J. Long short-term memory[J]. Neural Computation, 1997, 9(8): 1735-1780.
- [31] Li P, Zhang Z, Xiong Q, et al. State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network[J]. Journal of Power Sources, 2020, 459: 228069.
- [32] Rouhi Ardeshiri R, Chengbin M. Multivariate gated recurrent unit for battery remaining useful life prediction: A deep learning approach[J]. International Journal of Energy Research, 2021, 45: 1212-1224.
- [33] Chang Y, Fang H J, Zhang Y. A new hybrid method for the prediction of the remaining useful life of a lithium-ion battery[J]. Applied Energy, 2017, 206: 1564-1578.
- [34] Yi S M, Xie L B, Peng L. Remaining useful life prediction of lithium-ion batteries based on VF-DW-DFN[J]. Energy Storage Science and Technology, 2022, 11(7): 2305-2315.
- [35] Hu J, He C, Zhu X L, et al. Remaining useful life prediction of electric vehicle batteries based on real vehicle data[J]. Journal of Transportation Systems Engineering and Information Technology, 2022, 22(1): 292-300.
- [36] Zhu Z J, Gu F H. Lithium-ion battery RUL prediction based on optimized VMD-SSA-LSTM algorithm[J]. Journal of Anhui University of Science and Technology (Natural Science Edition), 2024, 44(2): 11-19.
- [37] Wu T Z, Cheng K J, Kang J, et al. Remaining useful life prediction of lithium-ion batteries based on a combination of ensemble empirical mode decomposition and deep belief network-long short-term memory[J]. Energy Technology, 2024, 12(5): 2301033.