

State of health prediction of lithium-ion batteries based on the HHO-BiLSTM-Attention model

Shuangxi He¹, Xiaomin Wang¹, Kun Li¹, Wenjun Du¹, Yidan Wang², Weili Wu^{2,}*

¹International Company, CCCC Second Highway Engineering Co., Ltd., Xi'an, China

²School of Electrical and Control Engineering, Xi'an University of Science and Technology, Xi'an, China

*Corresponding Author. Email: wllxm@163.com

Abstract. Aiming at the problems in State of Health (SOH) prediction of lithium-ion batteries, such as insufficient extraction of indirect health features, insufficient utilization of temporal degradation information, and model hyperparameters relying on manual tuning, a prediction method based on the Harris Hawks Optimization (HHO) algorithm, the Bidirectional Long Short-Term Memory Network (BiLSTM) and the attention mechanism is proposed. First, multi-dimensional health factors are extracted from the constant-current constant-voltage charge-discharge curves and preprocessed; second, an HHO-BiLSTM-Attention prediction model is constructed, which uses BiLSTM to extract the temporal dependence features of health factors bidirectionally, adaptively weights the hidden states of each time step through the attention layer, and uses the HHO algorithm to globally optimize the key hyperparameters of the model. The experimental results on the public NASA dataset show that, compared with the BiLSTM and BiLSTM-Attention models, the error of the proposed model is significantly reduced, the mean absolute percentage error is below 0.6%, and the coefficient of determination reaches more than 0.95, demonstrating higher prediction accuracy and generalization stability. The model can accurately adapt to SOH prediction tasks of batteries under different operating conditions, and can provide effective technical support for the health assessment and safe operation and maintenance of power batteries.

Keywords: lithium-ion battery, state of health assessment, bidirectional long short-term memory network, attention mechanism, Harris Hawks Optimization algorithm

1. Introduction

With the rapid development of the new energy industry and energy storage technology, lithium-ion batteries have been widely used in new energy vehicles, energy storage stations, portable electronic devices and other fields by virtue of their high energy density, long cycle life and excellent operational stability. As the core component of energy storage systems, the state of health of lithium-ion batteries directly affects the safety and reliability of the overall operation of equipment. Under long-term repeated charge-discharge conditions, batteries suffer from capacity fade, internal resistance growth and other aging and degradation problems, which are likely to induce equipment failures and pose great safety hazards. Therefore, achieving accurate prediction of the State of Health (SOH) of lithium-ion batteries has important engineering application value

and theoretical research significance for ensuring the stable operation of energy storage systems, extending battery service life, and reducing equipment operation and maintenance costs [1].

Existing SOH assessment methods for lithium-ion batteries are mainly divided into four categories: test-based, model-based, data-driven and fusion-based. Test-based methods evaluate battery health by directly measuring physical quantities such as capacity and internal resistance, but most of them need to be performed offline under static conditions and can hardly meet the demand for real-time dynamic monitoring; model-based methods describe battery aging behavior through equivalent circuit models or electrochemical mechanism models, but suffer from difficult parameter identification, large computation and poor real-time performance; data-driven methods build health state prediction models relying on a large amount of historical operation data, require no complex theoretical derivation, and have high computational efficiency, and have become a research hotspot. In recent years, deep learning models have made considerable progress in SOH prediction. For example, the SOH estimation method based on charging voltage segments and kernel ridge regression achieves high-precision estimation using indirect features of voltage curves [2]; the method based on the CNN-CBAM-BiLSTM fusion model combines convolutional neural networks with bidirectional long short-term memory networks for SOH estimation [3]; and the method based on the improved Harris Hawks optimization algorithm and support vector machine regression realizes SOH assessment [4]. However, existing data-driven deep learning models still have the following shortcomings: first, the hyperparameters of models mostly rely on manual empirical tuning, making it difficult to obtain the globally optimal configuration; second, unidirectional Long Short-Term Memory Networks (LSTM) cannot simultaneously use the forward and backward information of time-series data, and have limited ability to capture bidirectional temporal dependencies; third, most methods do not differentiate the importance of each time step of the health factors and cannot focus on key degradation information.

To address the above problems, this paper proposes an HHO-BiLSTM-Attention prediction method. The method extracts four easily measured indirect health factors from the charge-discharge curves, namely the constant-current charging time, the constant-voltage charging time, the initial discharge voltage and the discharge voltage plateau time; it extracts temporal dependence features bidirectionally through BiLSTM, adaptively weights the hidden states by means of the attention mechanism, and uses the Harris Hawks Optimization algorithm to globally search for the optimal hyperparameters, effectively solving the subjectivity and limitations of manual tuning. Experiments are carried out on batteries B0005 and B0007 based on the public NASA lithium-ion battery aging dataset, which verifies the effectiveness and robustness of the proposed method in SOH prediction. It can provide an effective technical reference for accurate assessment of the state of health of lithium-ion batteries and intelligent operation and maintenance of power batteries.

2. Dataset and health feature extraction

2.1. Dataset introduction

To study the aging and degradation characteristics of lithium-ion batteries under different depths of discharge, this paper uses the lithium battery accelerated aging dataset released by the NASA Prognostics Center of Excellence (NASA PCoE) to carry out model simulation and performance verification experiments. The dataset was collected on the NASA Ames Research Center lithium battery life testing platform, and the experimental objects are commercial 18650 lithium-ion batteries. The core parameters of the dataset are shown in Table 1.

Table 1. Main parameters of the NASA lithium-ion battery dataset

Parameter	Value
Battery model	18650
Dimensions	Diameter 18 mm, length 65 mm
Rated capacity	2 Ah
Rated voltage	3.7 V
Cathode material	$\text{LiNi}_{0.8}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$
Anode material	Graphite
Charge-discharge mode	Constant Current-Constant Voltage (CC-CV)

In this study, two battery samples B0005 and B0007 in the dataset are selected as the research objects; the two samples are widely used in the field of battery SOH prediction and have good representativeness of operating conditions. The whole aging experiment was carried out in a constant temperature environment of 24 °C with a consistent charging strategy, and different depths of discharge were simulated by setting different discharge cut-off voltages: the discharge cut-off voltage of B0005 is 2.7 V and that of B0007 is 2.2 V, and both batteries completed 168 standardized charge-discharge cycles. The differentiated battery aging characteristics induced by different depths of discharge can, on the one hand, be used to verify the adaptability of the model to complex operating conditions, and on the other hand, objectively reflect the limitations of the model, providing a performance evaluation basis for the engineering application of the method. The experiment simultaneously collected operating parameters such as charge-discharge voltage, charge-discharge current and battery surface temperature. After feature extraction of the raw sampled data, a health factor sample set for model training and testing was constructed.

2.2. Health factors and their correlation analysis

To quantitatively characterize the variation of the charge-discharge curves with the number of cycles, this paper extracts four indirect health factors from the constant-current constant-voltage charge-discharge curves. These characteristic parameters can reflect the health state and degradation trend of the battery to a certain extent, which are:

(1) Constant-current charging time HI1: the duration of the constant-current stage from the start of charging until the battery terminal voltage first reaches the charge cut-off voltage (4.2 V). As the battery ages, the rechargeable capacity decreases and the constant-current charging time monotonically shortens.

(2) Constant-voltage charging time HI2: the duration required from entering the constant-voltage charging stage until the charging current drops to the preset cut-off current (20 mA). As the internal resistance of the battery increases, the constant-voltage charging time monotonically lengthens.

(3) Initial discharge voltage HI3: the battery terminal voltage at the moment discharge begins, which decreases slowly as the battery ages.

(4) Discharge voltage plateau time HI4: the time required for the battery voltage to drop from the first preset voltage to the second preset voltage during discharge. This paper takes the core plateau region from 3.6 V to 3.5 V, which is the most stable and longest-lasting region of the discharge curve. The duration of this interval is highly positively correlated with the available capacity of the battery and can well reflect the degree of battery aging.

To verify the degree of association between the four extracted indirect health factors and the battery health state, this paper uses the Pearson correlation coefficient to carry out correlation analysis between HI1~HI4 and

SOH, and its expression is shown in Equation (1).

$$r = \frac{\sum_{k=1}^n (F_k - \bar{F})(SOH_k - \overline{SOH})}{\sqrt{\sum_{k=1}^n (F_k - \bar{F})^2 \sum_{k=1}^n (SOH_k - \overline{SOH})^2}} \quad (1)$$

where F_k is the health factor value of the k th cycle (HI1, HI2, HI3 and HI4 respectively), SOH_k is the SOH value of the k th cycle, $\bar{F}$ and $\overline{SOH}$ are their respective means, and n is the number of cycles.

The Pearson correlation coefficient measures the degree of linear correlation between two random variables; the closer its absolute value is to 1, the stronger the linear correlation [5]. Table 2 gives the Pearson correlation coefficients and correlation strength between the four health factors and SOH on batteries B0005 and B0007. The results show that the constant-current charging time HI1 and the discharge voltage plateau time HI4 decrease monotonically with the number of cycles, and their correlation coefficients with SOH are close to 1.00, showing a strong positive correlation; the constant-voltage charging time HI2 rises monotonically with the number of cycles and is strongly negatively correlated with SOH; the initial discharge voltage HI3 is moderately correlated with SOH. The selected health factors have significant linear correlations with SOH and can serve as effective input features of the prediction model.

Table 2. Pearson correlation coefficients between each health factor and SOH

Health factor	Physical meaning	Degradation trend	Pearson correlation coefficient (B0005/B0007)	Correlation strength
	Constant-current charging time	Monotonically decreases with cycles		Strong positive correlation
	Constant-voltage charging time	Monotonically increases with cycles		Strong negative correlation
	Initial discharge voltage	Slowly decreases with cycles		Moderate correlation
	Discharge voltage plateau time	Monotonically decreases with cycles		Strong positive correlation

Affected by sensor acquisition noise, the extracted HI1 sequence of constant-current charging time contains some abnormal jumps. According to the physical characteristics of lithium battery aging, the HI1 fluctuation between adjacent normal cycles generally does not exceed 300 s. This paper sets this value as the difference threshold; when the absolute difference of HI1 between adjacent cycles exceeds the threshold, the abnormal point is corrected with the mean of the preceding and following valid cycles. No obvious outliers were observed in the other health factors, so no correction is needed. To eliminate the dimensional differences between features, MinMax normalization is performed on the health factors, mapping all features to the interval [0, 1], and the samples are divided into the training set and the test set by charge-discharge time series at a ratio of 7:3.

3. Construction of the HHO-BiLSTM-Attention model

3.1. Bidirectional Long Short-Term Memory network (BiLSTM)

BiLSTM is a bidirectional recurrent neural network derived from the Long Short-Term Memory Network (LSTM). Through the gating mechanisms of the forget gate, input gate and output gate, LSTM alleviates the gradient vanishing problem that occurs when traditional recurrent neural networks train long sequences, relies

on the cell state to selectively retain and update historical information, and realizes the mining of long-term dependencies of time-series data [6].

BiLSTM consists of two parallel LSTM sub-networks, forward and backward: the forward LSTM processes the input sequence in the original time order, while the backward LSTM operates on the time-reversed sequence; the hidden states output by the two networks at the same time step are concatenated to obtain the comprehensive feature output at that moment. The forward and backward hidden state updates of BiLSTM are shown in Equation (2).

$$\vec{h}_t = LSTM([x_t, \vec{h}_{t-1}]), \overleftarrow{h}_t = LSTM([x_t, \overleftarrow{h}_{t+1}]) \quad (2)$$

The forward and backward hidden states of each time step are weighted and merged to obtain the final output state of the network, as calculated in Equation (3).

$$h_t = w_t \cdot \vec{h}_t + v_t \cdot \overleftarrow{h}_t + b_t \quad (3)$$

Through the above bidirectional information transfer mechanism, BiLSTM can simultaneously use the forward and backward context information of the sequence. Compared with unidirectional LSTM, it has stronger temporal feature extraction ability and is more suitable for modeling the degradation dynamics of lithium-ion battery charge-discharge cycles.

3.2. Attention mechanism

The attention mechanism (Attention) can improve the model's ability to parse time series, automatically mine the feature components that contribute more to the task, and assign differentiated weights according to feature importance, strengthening the role of key information while suppressing the interference of invalid information, thereby improving the accuracy and robustness of prediction [7].

For the temporal features output by BiLSTM, the attention score of each time step is first calculated, and the formula is shown in Equation (4):

$$e_t = f(s_{t-1}, h_t) \quad (4)$$

where s_{t-1} is the hidden state of the previous time step, h_t is the input feature of the current time step, and f is the trainable scoring function.

The Softmax function is used to normalize the attention scores to obtain the attention weights, and the formula is shown in Equation (5):

$$a_t = \frac{\exp(e_t)}{\sum_{t=1}^T \exp(e_t)} \quad (5)$$

The obtained weights are used to weight and aggregate the input features to generate the output feature of the attention layer, and the formula is shown in Equation (6).

$$c = \sum_{t=1}^T a_t h_t \quad (6)$$

After the attention mechanism is integrated into the BiLSTM network, the weights of temporal features can be allocated dynamically, and the aging and degradation characteristics of lithium-ion batteries during charge-discharge can be captured adaptively.

3.3. Harris Hawks Optimization (HHO)

The Harris Hawks Optimization (HHO) algorithm is a metaheuristic swarm intelligence optimization algorithm [8]. The prediction effect of the BiLSTM-Attention model is sensitive to hyperparameters; manual

experience-based tuning is not only inefficient but also prone to falling into local optima. This paper introduces the HHO algorithm to realize automatic optimization of the key hyperparameters of the model.

The HHO algorithm is mainly divided into two stages, global exploration and local development, and switches dynamically between the two search modes depending on the prey escape energy coefficient. This paper selects the number of neurons in the BiLSTM hidden layer, the initial learning rate and the L2 regularization coefficient as the variables to be optimized, and sets the search range of the L2 regularization coefficient λ to $[1 \times 10^{-6}, 1 \times 10^{-2}]$, the search range of the initial learning rate η to $[0.001, 0.1]$, and the search range of the number of hidden layer neurons h to $[100, 300]$. This paper takes minimizing the model prediction deviation as the core objective of hyperparameter optimization and uses the Root Mean Square Error (RMSE) as the performance metric in the iterative optimization process of HHO, and its specific calculation formula is shown in Equation (7).

$$f(\theta) = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i(\theta))^2} \quad (7)$$

where n is the number of training samples, y_i is the true SOH value of the i th sample, and $\hat{y}_i(\theta)$ is the predicted value of the model under the hyperparameter combination θ .

The algorithm iteratively searches within the preset intervals, and the finally obtained optimal hyperparameter combination is shown in Table 3. The parameter configuration of the BiLSTM-Attention model is completed with this set of optimal parameters, avoiding the subjectivity brought by manual tuning and improving the comprehensive performance of the lithium-ion battery SOH assessment model.

Table 3. Parameter settings of the HHO algorithm

Parameter	Symbol	Value
Population size	N	
Maximum number of iterations	T_{max}	
Search dimension	D	
Initial escape energy range	E_0	$[-1, 1]$

3.4. HHO-BiLSTM-Attention model

BiLSTM has strong bidirectional temporal modeling ability and obvious advantages in capturing the dynamic changes of battery charge-discharge cycles. However, the contribution of health factors to SOH differs at different cycle stages, and the model can hardly complete targeted weight allocation on its own. The attention mechanism can dynamically identify key feature information and strengthen the model's focus on the core degradation stages of the battery. Therefore, this paper introduces the attention module into the BiLSTM network to build a BiLSTM-Attention feature prediction structure. To further improve the prediction accuracy and generalization performance of the model, the Harris Hawks Optimization algorithm is used to automatically optimize the key hyperparameters of the model, and the HHO-BiLSTM-Attention prediction framework is built.

4. Experimental procedure, results and analysis

4.1. Experimental setup

Based on the above model architecture, the overall procedure of the HHO-BiLSTM-Attention lithium-ion battery SOH prediction experiment constructed in this paper is shown in Figure 1.

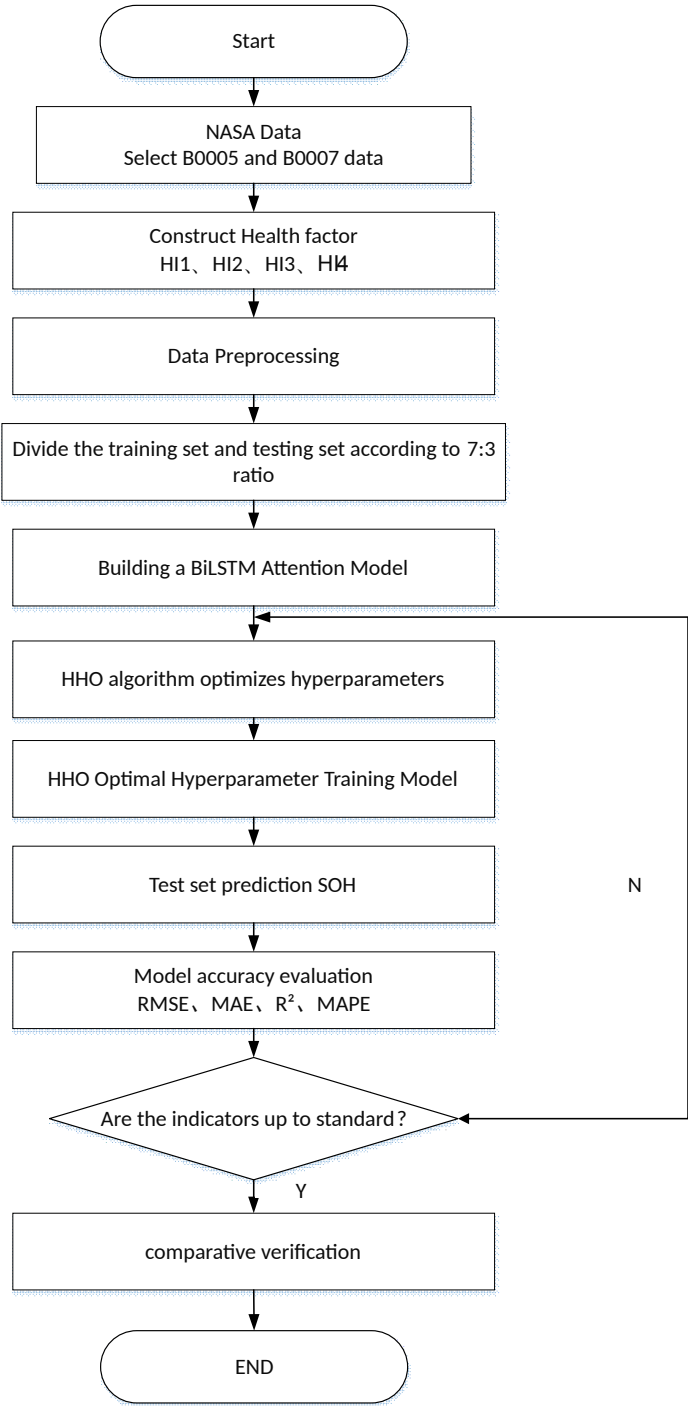


Figure 1. Flow chart of the HHO-BiLSTM-Attention prediction

The procedure shown in Figure 1 is mainly divided into several steps: feature screening and data processing, model construction, model training, prediction output and performance evaluation. The specific steps are as follows:

(1) Health factor extraction and screening

The constant-current charging time, constant-voltage charging time, initial discharge voltage and discharge voltage plateau time in the battery charge-discharge process are selected as health factors. Pearson correlation

analysis shows that the correlation between each health factor and battery SOH is significant, so they can be used as input features of the model.

(2) Data preprocessing

The four health factors are normalized by max-min normalization, mapping the data uniformly to the interval [0,1]. After preprocessing, the dataset is divided into the training set and the test set at a ratio of 7:3 in time order, and the hyperparameter optimization is completed with an internal subset of the training set.

(3) Prediction model construction

The preprocessed temporal health factors are input into the BiLSTM network to mine the temporal features of battery degradation, and then the attention mechanism adaptively allocates the weights of the output features, strengthens the key degradation features and optimizes the feature extraction effect of the model, thus completing the construction of the prediction model.

(4) Model training and parameter configuration

The model is trained with the training set data, with MSE as the loss function and Adam as the optimizer, completing the iterative training of the model and outputting the battery SOH prediction results.

(5) Model testing and performance evaluation

After model training, the test set is used to test the generalization performance of the trained model, and multiple evaluation metrics are used to quantitatively analyze the prediction accuracy and generalization ability of the model.

To quantitatively evaluate the SOH prediction performance of the proposed model, four evaluation metrics are introduced: the coefficient of determination R^2 , the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE).

$$R^2 = 1 - \frac{\text{residual sum of squares}}{\text{total sum of squares}} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (10)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (11)$$

where n is the number of samples in the test set, y_i is the true SOH value of the i th sample, and $\hat{y}_i$ is the corresponding predicted value of the model.

4.2. Experimental results and analysis

To verify the prediction performance and optimization advantages of the proposed HHO-BiLSTM-Attention model, this paper selects two groups of lithium-ion batteries B0005 and B0007 from the public NASA database as experimental objects. Under a unified experimental framework, three prediction models, BiLSTM, BiLSTM-Attention and HHO-BiLSTM-Attention, are designed for comparative experiments, and the effectiveness of the model improvement scheme is verified through comparison. To ensure the fairness of the comparative experiments, the experimental environment, data processing methods and training strategies of each group of models are kept completely consistent. This paper uses the time-series splitting method to divide the dataset: the first 70% of the cycle data of batteries B0005 and B0007 are used as the training set and the last 30% as the test set, and the prediction effects and error characteristics of each model are compared and analyzed on the test set. The SOH prediction results of the two batteries are shown in Figure 2 and 3.

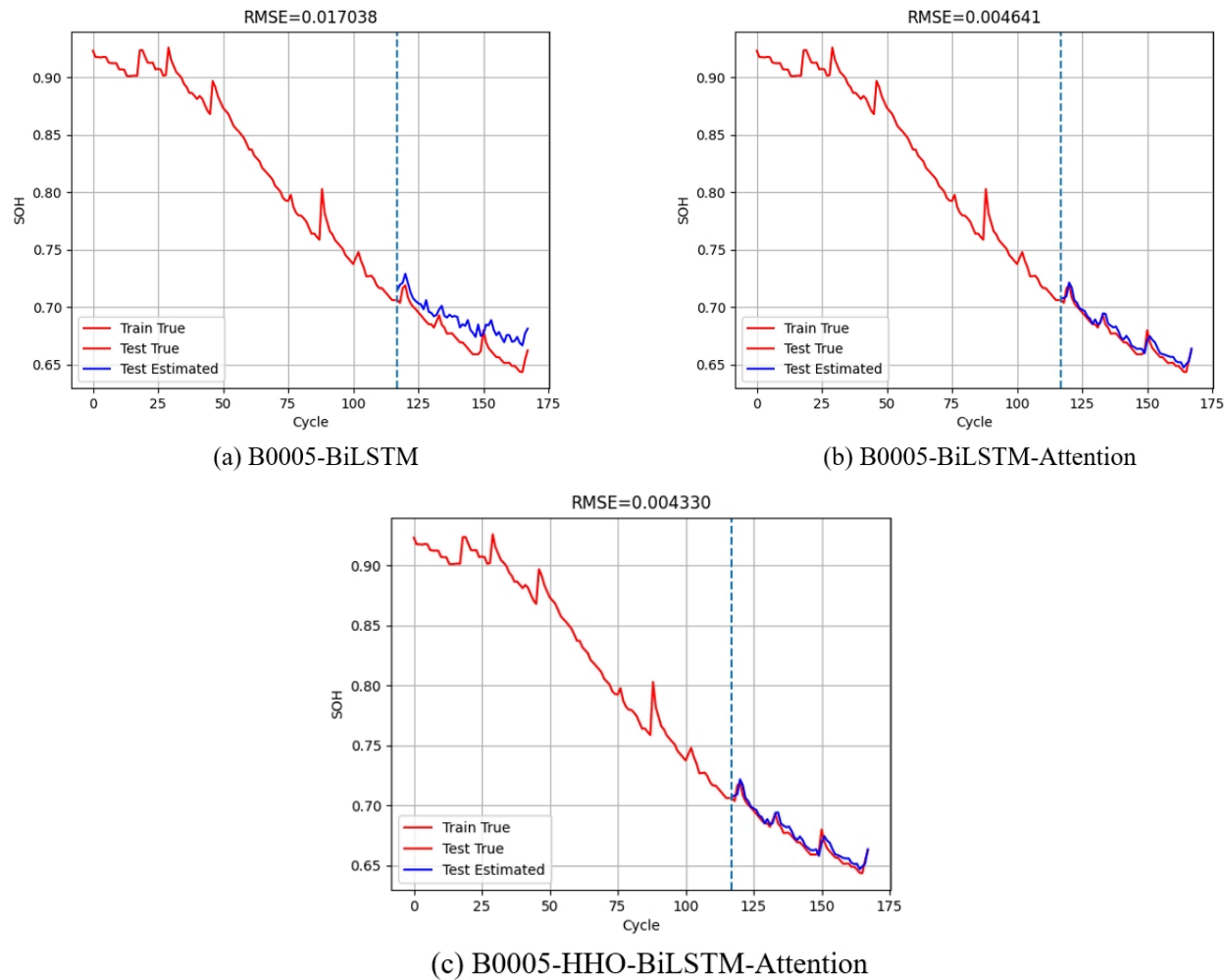
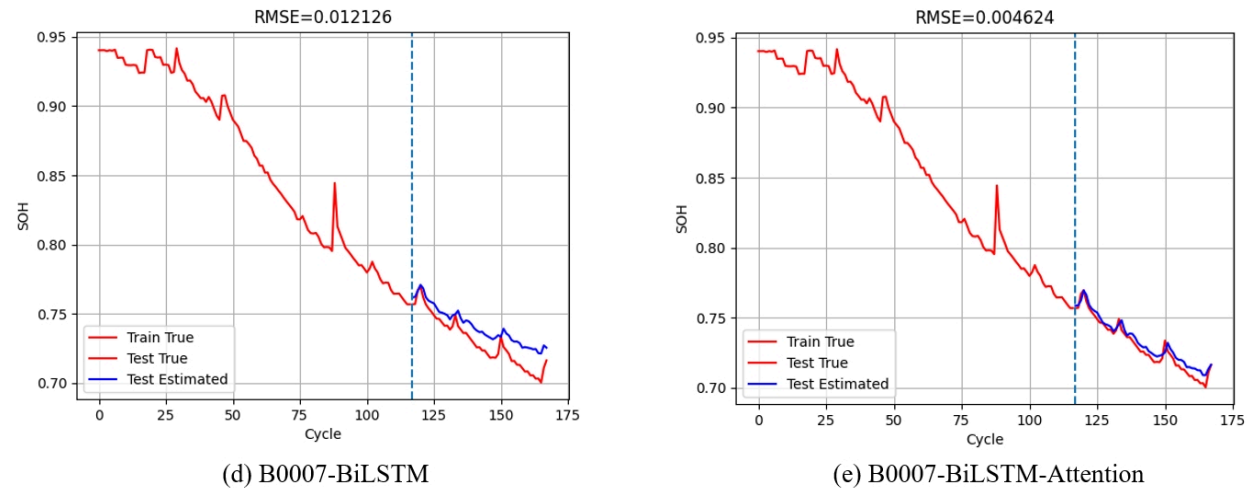
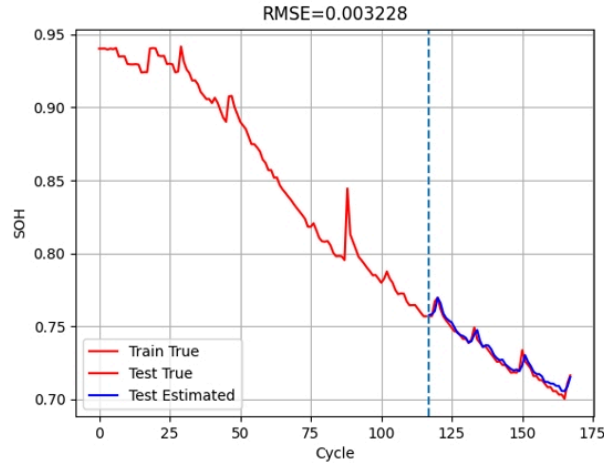


Figure 2. Experimental prediction results of battery B0005





(f) B0007-HHO-BiLSTM-Attention

Figure 3. Experimental prediction results of battery B0007

Table 4 gives the SOH prediction performance comparison of the three models on battery B0005, and Table 5 gives the SOH prediction performance comparison of the three models on battery B0007.

Table 4. Comparison of the prediction performance of the three models on battery B0005

Battery	Metric (%)	BiLSTM	BiLSTM-Attention	HHO-BiLSTM-Attention
B0005	RMSE	1.7037	0.4641	0.443
	MAE	1.5792	0.4119	0.3775
	R2	26.0687	94.5147	95.2241
	MAPE	2.3667	0.6129	0.5606

Table 5. Comparison of the prediction performance of the three models on battery B0007

Battery	Metric (%)	BiLSTM	BiLSTM-Attention	HHO-BiLSTM-Attention
B0007	RMSE	1.2126	0.4624	0.3228
	MAE	1.0935	0.408	0.2581
	R2	54.7312	93.4188	96.7923
	MAPE	1.5144	0.5631	0.3546

From the quantitative evaluation results of the different models in Table 4 and 5, it can be seen that, compared with the BiLSTM and BiLSTM-Attention models, the prediction performance improvement of the proposed HHO-BiLSTM-Attention model is significant. For the SOH estimation results of batteries B0005 and B0007, the MAPE of the proposed model is below 0.6%, the RMSE and MAE values are at a low level, and the goodness of fit R^2 reaches more than 0.95, showing excellent fitting effect and prediction accuracy.

5. Conclusion

Aiming at the problems of complex temporal degradation characteristics of lithium-ion batteries, insufficient feature mining ability of traditional prediction models, strong subjectivity of manual hyperparameter tuning

and limited prediction accuracy [9], this paper completes health factor screening and data preprocessing based on the public NASA B0005 and B0007 lithium-ion battery datasets, and builds the HHO-BiLSTM-Attention battery SOH prediction model. Through multiple groups of comparative experiments combined with visualization results and quantitative evaluation metrics, the model performance is comprehensively verified. The main research conclusions are as follows:

(1) This paper selects four features, the constant-current charging time, the constant-voltage charging time, the initial discharge voltage and the discharge voltage plateau time, as battery health factors. Pearson correlation analysis shows that each factor has a significant linear correlation with battery SOH and can effectively characterize the aging and degradation law of the battery. Through outlier correction, MinMax normalization and 7:3 time-series dataset division, the risk of data leakage is effectively avoided, the reliability of the experimental data and the authenticity of the experimental results are guaranteed, and high-quality feature support is provided for high-precision prediction of the model.

(2) The introduction of the attention mechanism can effectively optimize the prediction performance of the model. Compared with the basic BiLSTM model, the BiLSTM-Attention model can adaptively allocate the weights of temporal features, focus on the key degradation features of the battery and suppress the interference of redundant information, making up for the defects of the single BiLSTM model such as insufficient targeting of feature extraction and poor fitting effect, significantly reducing the SOH prediction error and improving the model's temporal feature mining ability and prediction accuracy.

(3) The Harris Hawks Optimization (HHO) algorithm is used to intelligently optimize key hyperparameters such as the model learning rate, the number of hidden layer neurons and the regularization coefficient, solving the drawbacks of low efficiency of manual tuning and the tendency to fall into local optima. The results of the comparative experiments on the two batteries show that the proposed HHO-BiLSTM-Attention model has the best performance, the MAPE of the model is below 0.6%, the RMSE and MAE error metrics are significantly better than the two comparison models, and the R^2 goodness of fit reaches more than 0.95, with outstanding advantages of small error and high fitting accuracy.

In summary, the HHO-BiLSTM-Attention model constructed in this paper can accurately capture the temporal degradation law of lithium-ion batteries and achieve high-precision and high-stability SOH prediction. The model shows good generalization ability and robustness in battery samples with different depths of discharge, with strong adaptability. This research can provide technical reference for the state of health assessment, remaining useful life prediction and safe operation and maintenance of energy storage systems of lithium-ion batteries, and has certain engineering application value for intelligent health management of power batteries [10].

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