A Predictive Approach for Lithium-Ion Battery SOH using LSTM Neural Networks Enhanced by Health Matrix Optimization

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Abstract

The State of Health (SOH) is a critical performance metric that characterizes the condition of lithium-ion batteries, directly influencing their lifespan and operational efficiency. In order to enhance the accuracy of SOH predictions for batteries and reduce operational risks, a novel approach has been introduced. This method, based on Health Matrix Optimization for Long Short Term Memory (LSTM) neural networks, aims to optimize the prediction process. Initially, the Spearman correlation coefficient method is employed to analyze the correlation of battery state data. Through the use of a heatmap, data points with strong correlations to SOH are identified, leading to the creation of a health feature matrix. This matrix is then utilized to fine-tune the hyperparameters of the LSTM neural network, resulting in refined approximations. Subsequently, by employing this optimized LSTM neural

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network, accurate predictions of the SOH for lithium-ion batteries are made. The results demonstrate a notable improvement in prediction accuracy by 35.71% and a significant increase in prediction speed by 35.5% when compared to traditional methods. This innovative approach proves to be effective in enhancing battery performance and longevity.

Keywords: SOH prediction, health matrix, neural network, prediction optimization.

1 Introduction

With the increasing utilization of renewable energy sources and the proliferation of electric vehicles, an efficient and reliable battery management system has become a pivotal technology in ensuring battery safety, enhancing efficiency, and extending battery lifespan. Lithium-ion batteries are widely employed in electric vehicles and energy storage systems due to their exceptional energy density and longevity [1]. However, the performance of lithium batteries gradually deteriorates over time, directly impacting the safety, reliability, and cost-effectiveness of the batteries. Therefore, enhancing the level of intelligence in Battery Management Systems (BMS) and accurately predicting the SOH of batteries are crucial for improving performance and prolonging lifespan.

Presently, the estimation methods for the SOH of lithium batteries can be broadly categorized into three groups: experimental methods, numerical model-based methods, and data-driven methods [2]. Experimental methods involve direct measurements [3] or the extraction of specific indicators under standardized charging and discharging conditions to estimate the battery's capacity [4]. However, these methods tend to be time-consuming, costly, and have limited practical applications. Numerical model-based methods encompass various approaches such as empirical models [5], electrochemical models [6], and equivalent circuit models [7]. In reference [5], an empirical model-based method was proposed for estimating the SOH. Yet, this model exhibits a limited ability to generalize as it fails to account for the intricacies of the battery's internal physical and chemical processes, thereby making it challenging to adapt to real-world variations. Reference [6] introduced an SOH prediction method based on an electrochemical model, but its implementation requires intricate data characterizations of complex chemical reactions and transport processes. Additionally, the accuracy of its predictions heavily relies on the precise determination of model parameters, which may demand sophisticated experimental procedures and fitting algorithms, thus resulting in higher costs. On the other hand, reference [7] employed an equivalent circuit model to estimate SOH. However, this model necessitates periodic adjustments of circuit parameters according to the battery's actual operating conditions, as well as recalibration, inevitably neglecting the impact of environmental temperature.

In recent years, data-driven methods have emerged as a research focus for SOH estimation due to their flexibility and universality [8]. Data-driven approaches exhibit excellent adaptability, flexibility, and remarkable nonlinear fitting capabilities, enabling real-time evaluation and prediction of SOH. For instance, Shaheer A [9] employed a data-driven method using sliding windows and system sampling for SOH prediction. Sudarshan M [10] employed a data-driven autoencoder neural network for degradation prediction in lithium batteries. Steffen B [11] utilized a time convolutional neural network with partial load profiles for SOH estimation. Ye Chen [12] used the particle filtration method to estimate the degradation state and then predict the remaining service life. Zheng Pan [13] used the state transition energy management algorithm to help the battery energy management system make decisions. Qing Chongyuan, Yin Chunjie, and others [14, 15] used neural networks to jointly estimate State of Charge (SOC) and SOH. Mao Baihai, Chang Wei, and others [16, 17] employed a multi-model fusion approach for predicting the SOH of lithium batteries. Li Suyang, Chu Ying, and others [18, 19] combined attention mechanisms with LSTM to estimate the SOH of lithium batteries. In the aforementioned studies, a significant amount of research has focused on optimizing neural network models, while fewer studies have explored enhancing feature extraction to improve their correlation with SOH. This limitation has resulted in unimproved SOH weighting and a lack of sufficient optimization of hyperparameters, which can affect both the predictive accuracy and speed of the models.

This study proposes a method that incorporates a feature selection process to identify highly correlated features with battery SOH. By constructing a health feature matrix and optimizing an LSTM neural network, the method achieves improved accuracy and prediction speed for battery SOH estimation. Importantly, this approach also provides more accurate data support for BMS, enabling optimized battery usage strategies.

2 State Estimation

2.1 State of Health

For battery management systems, a lithium battery's SOH is an essential parameter, as it measures the battery's aging level and remaining lifespan. SOH is typically expressed in terms of capacity or internal resistance. In this paper, we represent SOH using capacity and define it as follows [20]:

$$SOH = \frac{Q_C}{Q_r} \times 100\% \tag{1}$$

where Q_c represents the current capacity of the battery (Ah), and Q_r represents the nominal capacity of the battery (Ah).

This paper refers to the research on international standards related to testing and evaluation of lithium battery energy storage described by Zhou Yuan [21]. To validate the proposed method, the battery dataset from the Center for Advanced Life Cycle Engineering (CALCE) in the United States is employed [22]. Test data from batteries with serial numbers CS2 35 to CS2 38 are selected. All batteries are charged using a constant current (CC) mode with a rate of 0.5C until the battery voltage reaches the cut-off voltage of 4.2V. Then, the voltage is held constant at 4.2V in a constant voltage (CV) mode until the charging current decreases to 20mA. Finally, the batteries are discharged at a CC of 1C until the battery voltage drops to the cut-off discharge voltage of 2.7V. The test is terminated when the battery reaches the End of Life (EOL) criterion, which is defined as a decrease in the rated capacity to 30%.

In the testing process, strict charging and discharging requirements are followed to simulate the battery behavior in practical usage. Table 1 summarizes the battery parameters.

Table 1 Battery parameter characteristics

Parameters	Specification
Rated capacity	1100 mAh
Chemical composition	$LiCoO_2$ (with trace amounts of manganese)
Weight	28g
Dimensions	5.4 × 33.6 × 50.6 mm
Charging cut-off voltage	4.2V
Discharging cut-off voltage	2.7V

2.2 Health Assessment

The health assessment, proposed by Lars Landberg in 2011 [23], includes turning the complex two-dimensional multivariate probability density function into a health matrix by extracting strong association features from the statistical probability distribution characteristics of the model outputs.

(1) Data preprocessing: To improve data reliability, data cleaning is performed to address missing values, outliers, and noise [24]. To reduce the error caused by different data scales, the maximum-minimum normalization algorithm can be used:

$$\dot{x}_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where the values x_i, x_{min}, and x_{max} stand for the current, minimum, and maximum values of the data, respectively.

(2) Correlation analysis: In this study, the Spearman correlation coefficient is used to analyze the correlation of battery data. The correlation between two statistical variables, X and Y, is assessed through the application of a monotonic function. When the two variables are perfectly monotonically related and have no repeated values, the SCC is $+1$ or -1, negative values indicate negative correlation, and 0 indicates no correlation [25]. The correlation coefficient rs is calculated using Equation (3) to obtain the feature correlation heatmap shown in Figure 1.

$$r_s = 1 - \frac{6 \cdot \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \tag{3}$$

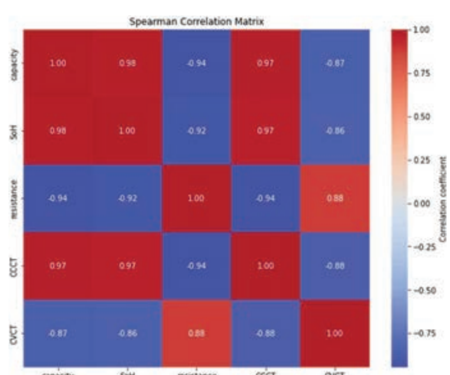

Figure 1 Feature correlation heatmap.

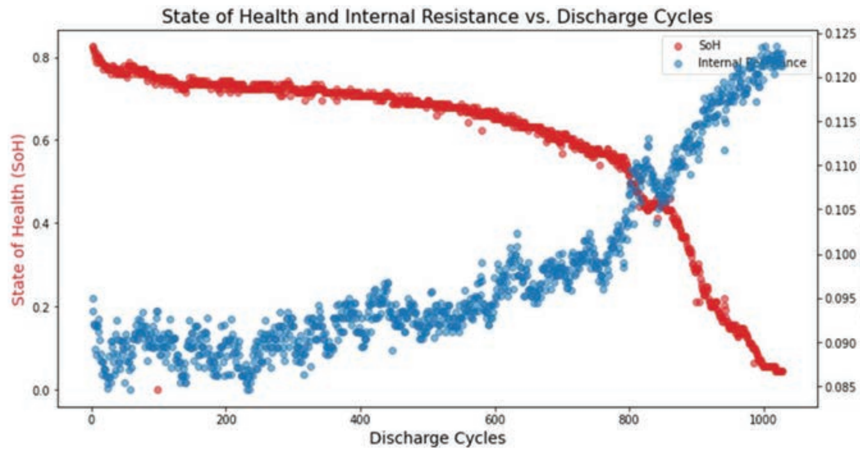

Figure 2 CS2-35 battery SOH and internal resistance variation.

where n denotes the sample size and d_i is the rank difference between X_i and Y_i.

(3) Feature selection: Based on the correlation analysis, strongly correlated feature data are selected to obtain the matrix elements and dimensions of the health matrix [26], as well as the neural network's approximate hyperparameters.

Changes in internal resistance can serve as an early warning signal for battery aging and degradation. Studying the dynamic changes in internal resistance helps develop more accurate battery health prediction models. The variation of internal resistance for the CS2-35 battery during charge-discharge cycles is shown in Figure 2.

The capacity loss rate of a battery throughout its lifecycle is an important indicator for assessing SOH. It indirectly reflects the battery's degradation performance and the consistency and variability of its performance under the same cycle count. The relationship is illustrated in Figure 3.

Constant Current Charging Time (CCCT) and Constant Voltage Charging Time (CVCT) are widely used in battery management systems as important indicators for monitoring and evaluating battery health status. Long-term tracking of CCCT and CVCT provides insights into battery life degradation rate and performance changes during the charging process. The relationship is depicted in Figure 4.

(4) Matrix Generation: The selected features are arranged in a matrix according to their numerical values, with each matrix element representing

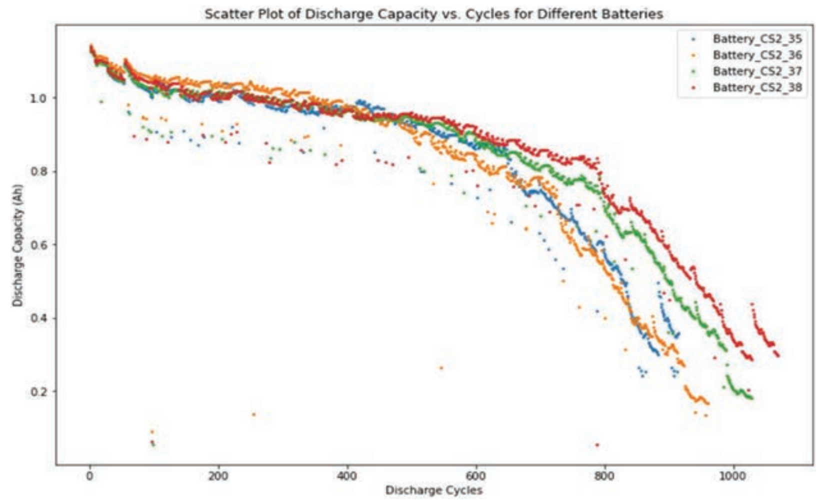

Figure 3 Capacity decay over unit lifecycle.

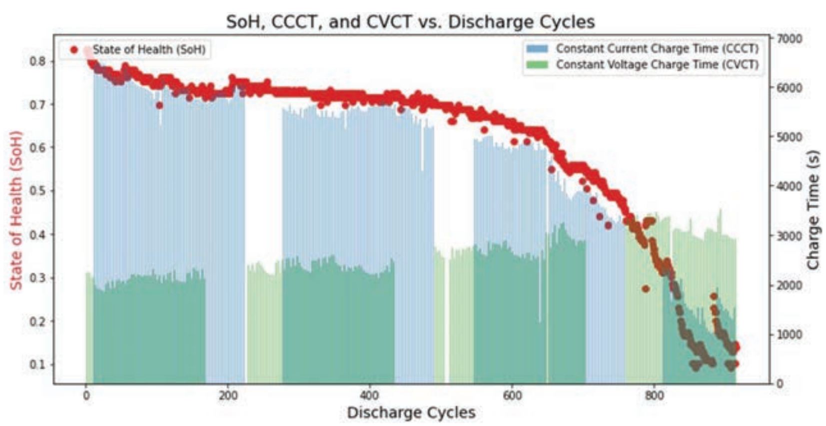

Figure 4 SOH variation under different charging modes for CS2-35 battery.

a health factor of the battery's SOH. The calculated SOH values are arranged in the state matrix $S_{n\times 1}$ in the order of the features.

Factor analysis is applied to the battery data, resulting in the feature correlation matrix $R_{1\times n}$ of SOH. Rearranging S using transposition S^T and multiplying it with R yields the health matrix H, as shown in Equation (4):

$$H_{n\times n} = S_{n\times 1}R_{1\times n} \tag{4}$$

where n, which typically ranges from 6 to 12, is the health matrix's dimension. When n exceeds 12, factor analysis method is usually used for dimensionality reduction, which can effectively capture the potential relationship between battery performance data and reduce the data dimension while retaining important information.

3 Optimization Approach

To improve the accuracy of SOH prediction and reduce prediction errors, an optimization approach is proposed, involving the selection of health factors, health assessment, calculation of improved SOH weights, and utilizing a neural network for predicting SOH.

(1) Health Assessment: Based on the health factors, a health assessment is conducted to obtain the health matrix and approximate hyperparameters for the neural network.

(2) SOH Prediction: Accelerating the optimization process using the approximate hyperparameters, a neural network is employed for power prediction, resulting in the initial SOH prediction.

Equation (4) indicates that n health factors correspond to the dimension of the health matrix $H_{n\times n}$. The current feature data of the lithium battery is arranged in the order of the state matrix S, forming the feature matrix $C_{n\times 1}$.

First, multiplying the matrices H and S gives the weight matrix $W_{n\times 1}$ as follows:

$$W_{n\times 1} = H_{n\times n}C_{n\times 1} \tag{5}$$

Next, expanding the original predicted battery health state (SOH_i) into the SOH prediction matrix $A_{1\times n}$, where all elements in A are the same as the original predicted SOH_i.

Then, multiplying the matrix A with W, followed by multiplying the result with a correction factor λ and adding it to the original SOH_i, yields the reconstructed prediction $\overline{SOH}_{\mathrm{i}}$, as shown in the equation:

$$\overline{SOH_i} = \lambda \cdot |A \times W| + SOH_i \tag{6}$$

where λ is determined based on the constructed Lasso regression model and can effectively reflect the impact of battery health factor and working state. This coefficient is set between 0.01 and 0.1 to optimize model performance and ensure accuracy.

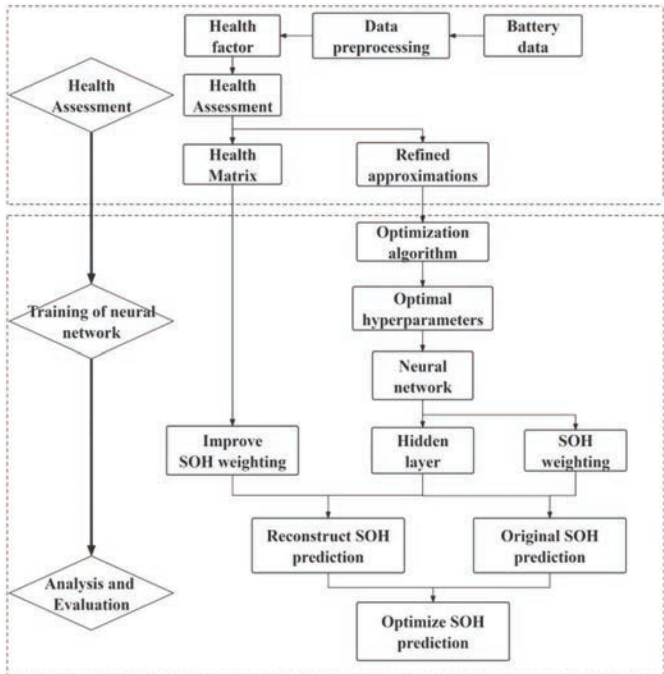

Figure 5 Neural network optimization approach based on the health matrix.

Finally, the accuracy and reliability of the reconstructed predictions are assessed through analysis and comparison. Continuously optimizing and adjusting the hyperparameters is performed to improve prediction accuracy and efficiency. In practical applications, flexible adjustments and improvements should be made based on specific circumstances to adapt to different battery states and application scenarios.

Figure 5 is an illustration of the neural network optimization method based on the health matrix.

The optimization process for the LSTM model is as follows:

During the training process of the LSTM network for SOH prediction, the Mean Squared Error (MSE) loss function is utilized:

$$L(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

where y_i represents the true value and $\widehat{y_i}$ represents the predicted value.

To further enhance prediction accuracy, the health matrix H is integrated into the loss function, defining a new loss function L_{new}:

$$L_{new}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} (1 - H(y_i, \hat{y}_i))(y_i - \hat{y}_i)^2 \tag{8}$$

where the health matrix H is a function based on the prediction errors.

$$H(y_i, \hat{y}_i) = \exp\left(-\frac{(y_i - \hat{y}_i)^2}{2\sigma^2}\right) \tag{9}$$

During the training process, the update formula for the hidden layer weights W is adjusted according to the new loss function using gradient descent. The update rule for the weights is as follows:

$$W_{t+1} = W_t - \eta \frac{\partial L_{new}}{\partial W_t} \tag{10}$$

where W_t represents the weights at time step t and η is the learning rate.

The partial derivative of L_{new} with respect to the weight W is given by Equation (11):

$$\frac{\partial L_{new}}{\partial W} = \frac{\partial L_{new}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial W} \tag{11}$$

Specifically, the calculation of gradients depends on the influence of the health matrix on the error of each sample.

$$\frac{\partial L_{new}}{\partial \hat{y}_i} = 2(1 - H(y_i, \hat{y}_i))(y_i - \hat{y}_i) - \frac{(y_i - \hat{y}_i)^2}{\sigma^2} H(y_i, \hat{y}_i) \tag{12}$$

Finally, the weight update equation is derived as follows:

$$W_{t+1} = W_t - \eta \sum_{i=1}^{n} \left(2 \left(1 - H(y_i, \hat{y}_i)(y_i - \hat{y}_i) - \frac{(y_i - \hat{y}_i)^2}{\sigma^2} H(y_i, \hat{y}_i) \right) \right) \frac{\partial \hat{y}_i}{\partial W_t} \tag{13}$$

After the optimization with the health matrix, each weight update takes into account the prediction errors, enabling the model to learn effectively while reducing errors and improving prediction accuracy and speed.

4 Optimization Analysis

4.1 Error Metrics

In this study, three error metrics, namely R^2 (Coefficient of Determination), *MSE* (Mean Squared Error), and *MAE* (Mean Absolute Error), are used to evaluate the performance of the model. The formulas for these evaluation metrics are as follows:

$$\begin{cases} R^2 = 1 - \dfrac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - y_i)^2} \\ MSE = \dfrac{1}{n}\displaystyle\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \\ MAE = \dfrac{1}{n}\displaystyle\sum_{i=1}^{n}|\bar{y}_i - y_i| \end{cases} \tag{14}$$

where y_i represents the true value, $\widehat{y_i}$ represents the predicted value, $\overline{y_i}$ represents the mean value of the true values, and n represents the number of samples.

4.2 Results Analysis

Under the same dataset, a comparison is made between the prediction error metrics and prediction time of the LSTM model before and after optimizing with the health matrix. The results are presented in Table 2.

From Table 2, it can be observed that after incorporating the health matrix, the prediction accuracy improves by 35.71%, and the prediction time reduces by 35.5%. The optimized LSTM neural network model exhibits improved prediction accuracy and generalization capability. Furthermore, the health matrix enhances the quality of features, enabling real-time monitoring of battery characteristics by the BMS. With continuous assessment of the battery's SOH and adjustment of operational parameters based on actual conditions, the performance and lifespan of the battery can be maximized.

Table 2 Comparison of neural network prediction errors

	R^2	*MSE*	*MAE*	Time
LSTM	0.993	0.00028	0.01135	27.6s
Optimized LSTM	0.995	0.00018	0.00574	17.8s

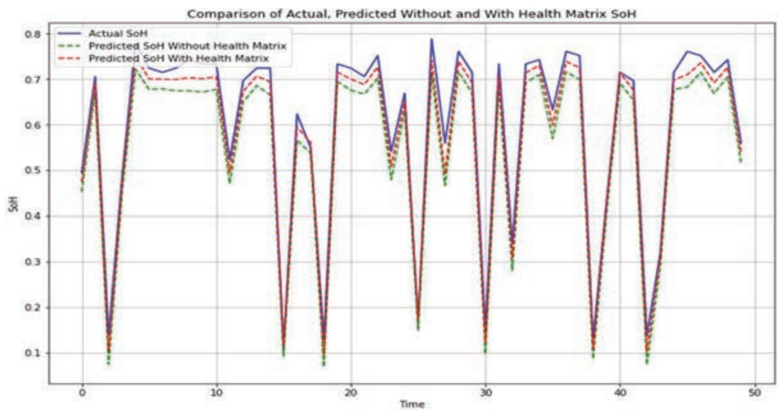

Figure 6 Comparison of prediction results before and after using the health matrix for CS2-35.

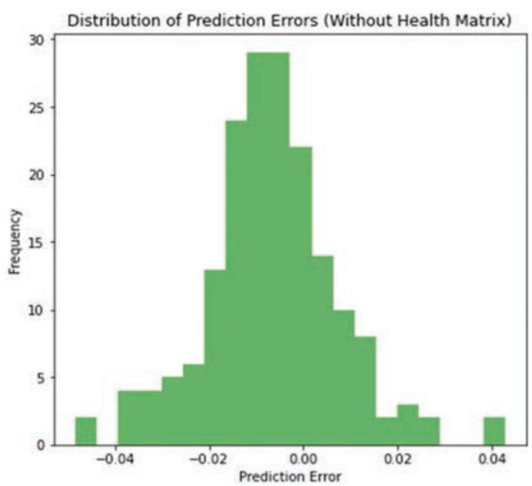

Figure 7 Distribution of prediction errors without using the health matrix.

Taking the CS2-35 battery as an example, the comparison of prediction results before and after using the health matrix in the LSTM network is illustrated in Figure 6.

The distribution of prediction errors before and after using the health matrix in the LSTM network is shown in Figures 7 and 8, respectively.

From Figures 7 and 8, it can be observed that the use of the health matrix results in a more concentrated error distribution, with a decrease in the frequency of prediction errors.

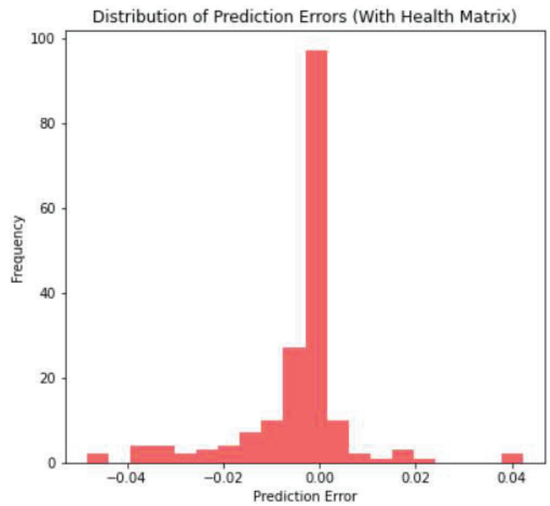

Figure 8 Distribution of prediction errors using the health matrix.

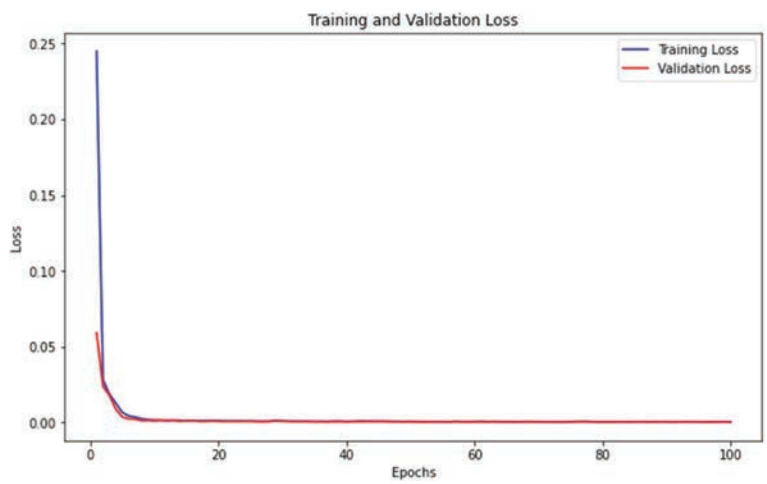

Figure 9 Training and validation loss curves.

Figure 6 clearly demonstrates that the health matrix significantly improves the lag effect in predictions and enhances the quality of LSTM network SOH weights. After optimization, the LSTM network shows a significant improvement in prediction accuracy.

The training and validation loss of the model is shown in Figure 9. The model exhibits good learning efficiency and rapid convergence. It performs consistently on the training and validation sets, indicating good generalization ability. The model reliably predicts the SOH of the battery by effectively learning from the training data, making it suitable for battery performance monitoring and management systems.

5 Conclusions

The LSTM neural network SOH prediction method optimized with the health matrix offers improvements in both prediction accuracy and speed. This method can be applied to various modules in BMS, such as real-time health monitoring, warning systems, charging control, performance optimization, and fault diagnosis. By dynamically adjusting operating parameters based on real-time data, the BMS can proactively identify potential failures and devise effective charging plans. Additionally, it supports data analysis and long-term trend evaluation, providing a scientific basis for charge and discharge strategies. Ultimately, this method contributes to extending battery life and reducing maintenance costs effectively.

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List of abbreviations

State of Health (SOH)
Long Short Term Memory (LSTM)
Battery Management Systems (BMS)
State of Charge (SOC)
The Center for Advanced Life Cycle Engineering (CALCE)

Constant Current (CC)
Constant Voltage (CV)
End of Life (EOL)
Constant Current Charging Time (CCCT)
Constant Voltage Charging Time (CVCT)
Mean Squared Error (MSE)
Coefficient of Determination (R^2)
Mean Absolute Error (MAE)

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