Health State Prediction of Lithium Ion Battery Based On Deep Learning Method

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Abstract. To predict the health status of lithium-ion batteries, long and short-term memory (LSTM) recurrent neural networks are used to build two types of battery SOH evaluation models. The discharge capacity is as input to a single feature model. While, the charge capacity, the charge time, the average charge temperature, the charge average voltage, the discharge temperature, and the discharge average voltage are as input to a multiple feature input model. The data samples are separated to training and test dataset. The test results show that the maximum absolute error of the LSTM-based model is less than 2%, which satisfies the industry standard (less than 5%). Meanwhile, this study transfers the NASA-based lithium-ion battery model to the University of Maryland lithium-ion battery data, which can reduce model training iterations and get good performance as well. The experimental results validate the effectiveness of transfer learning in the field of lithium-ion battery SOH prediction and provide a reference for future work in this field.

1. Introduction
Recently, the 2019 Nobel Prize in Chemistry was announced. The Royal Academy of Sciences in Stockholm, Sweden, awarded this honor to three scientists to reward them for their outstanding contributions to the development of lithium-ion batteries. Due to its light weight, high energy density, low self-discharge rate, and long cycle life, lithium batteries are currently widely used in the military and aviation fields, especially in the field of electric vehicles. However, due to the by-products of the battery reaction, the battery capacity is gradually attenuated and the internal resistance is gradually increased, which reduces the mileage and power capability of the electric vehicle. Therefore, battery state of health (SOH) detection and prediction, and battery remaining life prediction (RUL) are necessary means for determining battery system maintenance and replacement. Battery health status refers to the health status of the battery, including capacity, power, internal resistance and other performance, and more often is a prediction of battery life. Usually refers to the ratio of the measured capacity to the rated capacity. The measured capacity is the discharge capacity of a fully charged battery under standard discharge conditions and is a visual reflection of battery life. The remaining
useful life is used to describe the number of cycle cycles that can continue when the lithium ion battery’s discharge capacity reaches a certain value. How to accurately reflect the health status of the battery and accurately predict the remaining battery life has been a subject that researchers have paid much attention to and invested.

There are many types of SOH estimation and RUL prediction methods. Currently, there are two main types of methods: (1) model-based methods; (2) data-driven methods.

Model-based methods rely on battery load conditions, material properties, and degradation mechanisms combined with battery failure mechanisms to achieve battery health predictions. Research on battery models has become more mature, such as the first-principles model of electrochemical, electrochemical impedance spectroscopy model, equivalent circuit model, and empirical degradation model. ZHANG Jin [1] compared and analyzed 12 common lithium-ion battery equivalent circuit models, and based on particle swarm algorithm to realize model parameter identification and battery state estimation. In addition, PNGV models, CPE models, Tanh models, and nonlinear equivalent battery circuit models [2, 3, 4, 5] are also widely used, and the identification of model parameters covers multiple methods in the time-frequency domain.

For complex electrochemical dynamic systems such as lithium-ion batteries, model-based methods are often complex and difficult to implement, making data-driven prediction methods a research hotspot. The data-driven method regards the battery as a "black box", and does not consider the electrochemical reaction and failure mechanism inside the lithium-ion battery. It contains the battery health status information and its evolution law to achieve battery health prediction. Reference [6] analyzed the battery terminal voltage curve under different number of cycles in the charging process, and adopted a feedforward neural network (FFNN) to simulate the relationship between RUL and the charging curve. Importance Sampling (Importance Sampling, IS) uses the FFNN method, and estimates the RUL of the battery by using the online method of FFNN and IS to improve the prediction accuracy. In Reference [7], incremental feature analysis (ICA) was used to identify feature vectors related to battery aging, and SVM was used for modeling. The experimental results show that the model has lower prediction error.

Considering the time series and non-linear characteristics of characteristic data such as battery capacity, this paper uses a stack LSTM Neural Network to build a lithium-ion battery health assessment model and predict the remaining life. In addition, the method of model transfer learning was also used to migrate the lithium ion SOH evaluation model to different lithium ion batteries, and good results were achieved.

2. SOH Evaluation Model Based on Stacked LSTM

2.1. Overview of recurrent neural networks

Recurrent neural networks (RNNs) are significantly different from conventional BP neural networks. The input of a general neural network is a feature of the current moment, and it cannot transfer information from a previous period to the current moment. Recurrent neural networks not only consider the input of the previous moment, but also give the network the ability to remember the information of the previous moment. The RNN model is shown in Figure 1.

![Figure 1. Basic RNN model.](image-url)
In Figure 1, we can see that an RNN layer can be regarded as a basic layer that is continuously expanded in multiple times. The input end inputs a time series \( X = (x_1, x_2, \cdots, x_t) \), and gradually calculates a hidden layer sequence \( H = (h_1, h_2, \cdots, h_t) \) through Equation (1), and then outputs the result \( Y = (y_1, y_2, \cdots, y_t) \) at time \( t \).

\[
h_t = f(W_x x_t + W_h h_{t-1} + b)
\]

In the formula: \( f \) is the activation function; the subscript \( t \) represents the time; \( W \) is the weight between different layers (such as \( w \) represents the weight from the input layer to the hidden layer); \( b \) is the offset vector of a certain layer.

Although theoretically, the recurrent neural network can effectively deal with time series, as the length of the time series increases, it will lead to gradient descent or gradient explosion, losing the previous effective information, which will reduce the prediction accuracy. Therefore, a series of algorithms for improving RNN have appeared. Long-short-term memory recurrent (LSTM) neural network is one of the better ones. Figure 2 shows the structure of the LSTM unit.

![LSTM network structure](image)

Figure 2. LSTM network structure.

Different from the basic RNN, the LSTM implements the function of filtering redundant information through a "gate" structure. The input gate is called "input gate", the gate used for forgetting is called "forgotten gate", and the control output is called "output gate". Through the logic control unit of these three gates, the LSTM can effectively decide whether to update or discard certain information, thereby overcoming the disadvantages of gradient disappearance and explosion. The formula for the antecedent propagation of LSTM recurrent neural network is as follows:

\[
f_t = \sigma(W_f [h_{t-1}, X_t] + b_f)
\]

\[
i_t = \sigma(W_i [h_{t-1}, X_t] + b_i)
\]

\[
c_t = \tanh(W_c [h_{t-1}, X_t] + b_c)
\]

\[
h_t = f_t \cdot c_t + i_t \cdot c_{t-1} + \frac{1}{f_t} \cdot (h_{t-1} - i_t \cdot c_{t-1})
\]

\[
y_t = \sigma(W_o h_t + b_o)
\]
\[ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \]  

(5)

\[ o_t = \sigma(W_o[h_{t-1}, X_t] + b_o) \]  

(6)

\[ h_t = o_t \cdot \tanh(C_t) \]  

(7)

In the formula: \( \sigma \) and \( \tanh \) are sigmoid activation function and double tangent activation function, respectively; \( i_t, f_t, o_t, c_t \) represent input gate, forget gate, output gate and cell state at time \( t \), respectively.

2.2. SOH Evaluation Model Based on Stacked LSTM

Stacked LSTMs stack multiple LSTMs to deepen the network and predict more complex problems. The LSTM structure of the previous layer will output a three-dimensional time series instead of a single value to the LSTM network of the next layer. The hierarchical stacking of LSTMs will play a better role in predicting the health status of lithium-ion batteries in this paper.

This paper designs a health assessment model for lithium-ion batteries based on stacked LSTMs. The model structure is shown in Figure 3.

![Figure 3. Lithium-ion battery health assessment model.](image)

3. Analysis of battery capacity decline data

This section uses actual lithium-ion battery test data to verify the health evaluation model of lithium-ion batteries based on Stack LSTM. The data used are from the lithium-ion battery datasets published by NASA and the University of Maryland.

3.1. Analysis of experimental data

NASA battery data comes from a lithium-ion battery test platform built by the NASA PCoE Research Center. This article selects Lithium-ion batteries 5,6,7,18 with a rated capacity of 2Ah. The cycle test experiment is performed at room temperature: charge in the 1.5A constant current (CC) mode until the battery voltage reaches 4.2V, and then continue charging in the constant voltage (CV) mode until the charging current drops to 20mA; Discharge in CC mode until the battery drops to 2.7V, 2.5V, 2.2V, 2.5V, respectively. Repeated charge and discharge cycles lead to accelerated battery aging, and impedance measurements provide insight into the aging process of battery parameter changes. In the battery aging test of NASA laboratory, when the battery reached the end-of-life (EOL) standard, the experiment was stopped, and the rated capacity decreased by 30% (from 2Ahr to 1.4Ahr).

Figure 4 shows the capacity degradation process of NASA lithium-ion battery data sets for batteries 5, 6, 7, 18.
3.2. Data preprocessing
Using appropriate data preprocessing methods can make the network training more effective and robust. Use the filtering method to smooth the data, and then use the max-min normalization method to shrink the data between 0 and 1:

\[ X = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

Where: \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum values of the model input data.

4. Analysis of Model result

4.1. Analysis of univariate input model evaluation results
In this section, the discharge capacity in the NASA lithium-ion battery experimental data is used as the model input, that is, \( X_i = C_i \), where \( C_i \) is the discharge capacity per cycle. After training, the neural network can iteratively obtain network weights and bias specific parameters.

Set the LSTM recurrent neural network to 2 LSTM nuclei, the number of hidden layer neurons is 20 and 50, the time step is set to 6, the batch size is 4, the maximum number of iterations is 300, and the last two layers are densely connected layer neurons. The numbers are 10, 1. The penultimate layer uses ReLu as the activation function, and the last layer does not use the activation function. Using three sets of data to train the neural network, each round of training time is about 0.92s, and the total time is 276s. The obtained model is verified with the remaining 1 set of data. The root mean square error and the maximum absolute error of the prediction results are 0.26% and 1.47%, respectively. The degree of deviation between the predicted value and the true value is small, so it can be determined that the LSTM cycle can be used. The neural network predicts the battery capacity decay trend. The evaluation results of this prediction model are shown in Figure 5.

**Figure 4.** NASA lithium-ion battery capacity decay graph.
4.2. **Analysis of Multivariate Input Model Evaluation Results**

Different from the single feature quantity model input in Section 4.1, the input sequence $X_i = (C_i, T_i, T_i, V_i, T_i, V_i)$ in this section, where $C_i, T_i, V_i$ are the charging capacity and charging time obtained from the NASA lithium ion battery experimental data. Charge average temperature, charge average voltage, discharge temperature, discharge average voltage. The above characteristics are used to predict the discharge capacity decay trend of the last group of NASA during the entire life.

Set the LSTM recurrent neural network to 2 LSTM nuclei, the number of hidden layer neurons is 40 and 100, the batch size is 4, the maximum number of iterations is 500, and the number of the last two densely connected layer neurons is 10. The second to last layer uses ReLu as the activation function, and the last layer does not use the activation function. It takes 3 sets of data to train the neural network, and the total time is 528s. The obtained model is verified with the remaining 1 set of data. The root mean square error and the maximum absolute error of the prediction results are 0.2% and 1.36%, respectively. The degree of deviation between the predicted value and the true value is small, so it can be determined that the LSTM cycle can be used. The neural network does not directly predict its attenuation trend through the discharge capacity. The performance of this prediction model is shown in Figure 6.

![Figure 5. Diagram of single-feature input model evaluation results.](image)
4.3. Analysis of model migration results

Transfer learning method is a common way to solve the problem of insufficient samples, make full use of previous training data and knowledge, and not sacrifice model performance. Sections 4.1 and 4.2 are predictive evaluations of NASA data. In this section, the model will be transferred to the data of Caryland University through transfer learning method, so that the model can accurately evaluate the health status of Caryland University's lithium-ion batteries.

This paper uses the TensorFlow framework to build a neural network framework with the same structure as in section 4.1, and loads the weights of the first two LSTM network layers, and randomly initializes the last two dense layers. At the same time, the first two layers of the LSTM recurrent neural network are set to the frozen state, and the last two layers of the dense layer are set to the trainable state. The batch size is 4 and the maximum number of iterations is 100. Use this network to train CS2 # 33, CS2 # 35 and CS2 # 37 in the lithium ion battery data of Karyland University, and use CS2 # 36 as the test set. The prediction effect of this model is shown in Figure 8.

Figure 6. Multi-feature input model evaluation results graph.

Figure 7. CS2 # 36 single feature input model evaluation results.
It can be seen from FIG. 7 that compared to directly training the Caryland University battery data, the number of training rounds is reduced to 1/3, and the training time per round is only 0.46 seconds, and the prediction effect is still very good. RMSE and MAE were 0.32% and 1.84%, respectively, which verified the effectiveness of the migration model.

5. Conclusion
Aiming at the problem of lithium ion battery health state (SOH) assessment, this paper introduces a prediction model based on LSTM recurrent neural network, and has achieved good results, which has practical significance. This paper uses a neural network model to explore the prediction effect in the case of single feature quantities, multiple feature quantities, etc., and uses a deep learning migration method to transfer the model based on NASA lithium-ion battery data to the Lilan University battery data through transfer learning to reduce training. In the case of the number of times, a good prediction effect is also obtained. This article shows how deep learning algorithms can be used to predict battery SOH and generalize the model. Because the battery cycle experiment is a long-term process, its data acquisition process and cost also become difficult and expensive. In future work, it is feasible and meaningful to use deep learning prediction models to predict the SOH of one type of battery and use only a small amount of data to predict other types of batteries of a similar type.

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