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Reliable Life Prediction and Evaluation Analysis of Lithium-ion Battery Based on Long-short Term Memory Model

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***Abstract*—Lithium-ion batteries are widely used in portable electronic equipment, vehicles, and aerospace. The life and reliability of lithium-ion batteries are directly related to the performance and safety of electric drive products. It is of great practical significance to study lithium-ion batteries. Deep learning technology has strong data structure mining ability. Long-short Term Memory (LSTM) neural network is more suitable for solving serialized data problems. Therefore, in this paper, based on the capacity degradation data of lithium-ion battery, the fault prediction model based on LSTM neural network is designed to obtain the pseudo-failure life when the failure threshold is reached. Through statistical analysis of pseudo-failure life data, predicting and evaluating reliable life, and finally obtaining reliability indicators such as reliability function, it is of great significance to ensure the good performance and state safety of lithium-ion batteries.**

Keywords—Lithium-ion batteries, Reliability, LSTM, Life prediction

I. INTRODUCTION

In recent years, lithium-ion batteries have been widely used in portable electronic equipment, transportation, aerospace and other fields due to their unique advantages of high operating voltage, light weight, long life and low discharge rate. The life and reliability of lithium-ion batteries are directly related to the performance and safety of electric drive products.

At present, the methods for predicting the life of lithium-ion batteries fall into two categories: one is based on model-based prediction methods [1,2]; the other is based on data-driven prediction methods [3,4]. The model-based method is difficult to use mathematical models to clearly express the capacity degradation process due to its complex internal electrochemical reaction and is easily interfered by external factors. Therefore, the data-driven method has attracted the attention of most scholars[5,6,7]. Compared with traditional shallow learning methods such as support vector machine and Back-Propagation neural network, deep learning can better characterize complex functional relationships with good learning performance and generalization ability. Therefore, the Long-short Term Memory neural network model with powerful modeling capabilities for time series data learning is used to process lithium-ion battery data. And most of the existing researches predict the cycle life of lithium-ion batteries at a given threshold, and have not evaluated their reliability, nor have they clearly given reliable life analysis results.

In this paper, based on the performance degradation data of lithium-ion battery, a fault prediction model based on Long-short Term Memory (LSTM) neural network is designed. A pseudo-failure lifetime corresponding to the failure threshold is obtained. Through statistical analysis of pseudo-failure life samples, predicting and evaluating reliable life, and combining with the reliable life under specified reliability to determine the actual service life, this is of great significance to ensure the good performance and state safety of lithium-ion batteries.

II. EXPERIMENTAL

The 18650 model lithium battery is selected as the test battery due to its wide application, representativeness and high safety. The data used in this paper is the capacity degradation of the battery during the charge and discharge test. The specific flow of the charge and discharge test for each cycle is described in the literature [8]. The capacity degradation curves of the four groups of batteries tested are shown in Figure 1. Considering the insufficient number of samples, use the Bootstrap Method to expand four groups data into 100 groups.

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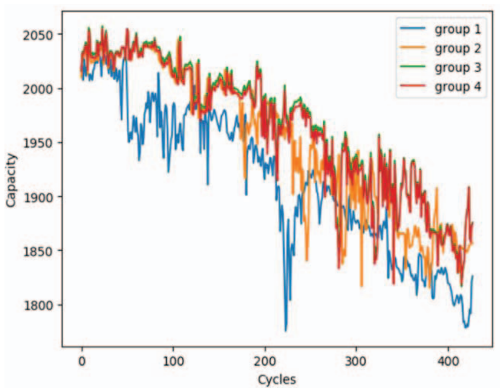

Fig. 1. Four sets of lithium-ion battery capacity degradation curves

III. DEGRADATION PREDICTION MODEL BASED ON LATM MODEL.

As shown in Figure 2, an LSTM network prediction model consisting of six LSTM layers and one fully connected layer is constructed. The input to the model is the lithium ion battery capacity degradation time series and temperature sequence, and the output of the model is the remaining capacity of the lithium ion battery.

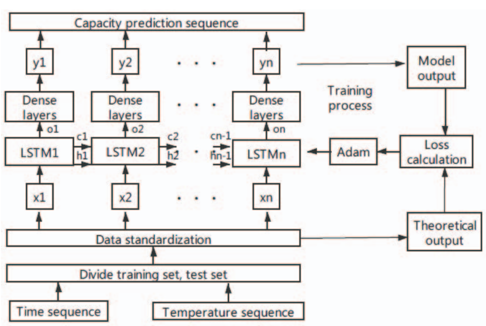

Fig. 2. Battery capacity prediction framework

Bring each group of data into the designed LSTM model, By predicting the battery capacity, when the remaining capacity of the battery reaches 80% of the rated capacity, the corresponding number of cycles is recorded as pseudo-life data.

Taking a set of data as an example to observe the accuracy of model training. It can be seen from the training data comparison chart (Fig. 3) that the prediction results have obtained good results, indicating the effectiveness and practicability of using the LSTM network model to predict the capacity of lithium ion batteries.

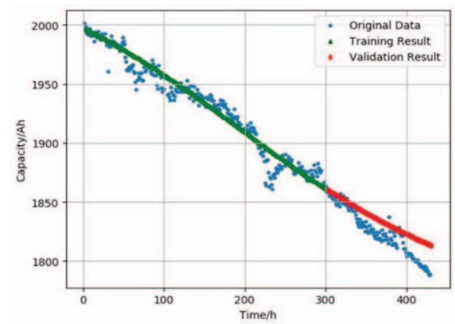

Fig. 3. Training data comparison

IV. RELIABILITY ASSESSMENT

The Kolmogorov-Smirnov test is performed on the pseudo-failure life samples, and the goodness of fit of the sample data to the Weibull distribution and the normal distribution are obtained respectively. The relevant parameters are shown in Table I.

TABLE I. DISTRIBUTION HYPOTHESIS TEST RESULT

	h	D	p
Weibull	0	0.13726	0. 9394
Normal	0	0.13836	0.8791

In the table, h=0 means accept the hypothesis, h=1 means reject the hypothesis, D denotes the difference from the hypothesis, and p denotes the probability of the distribution function obeying the hypothesis.

It can be seen from the test results that the optimal distribution function of the pseudo-failure life sample is Weibull distribution, the shape parameter m are 8.8189 and the true scale parameter η are 573.6534.

The lithium ion battery failure distribution function F(t), the failure distribution density function f(t), and the reliability function R(t) are:

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^m} = 1 - e^{-\left(\frac{t}{573.6534}\right)^{8.8189}} \tag{13}$$

$$f(t) = \frac{m}{\eta}\frac{t^{m-1}}{\eta} e^{-\left(\frac{t}{\eta}\right)^m}$$

$$= 2.68 \times 10^{-5} \times t^{7.8189} \times e^{-\left(\frac{t}{573.6534}\right)^{8.8189}} \tag{14}$$

$$R(t) = 1 - F(t) = e^{-\left(\frac{t}{257.0091}\right)^{2.1428}} \tag{15}$$

The reliability curve of the lithium ion battery under normal stress is shown in Figure 4:

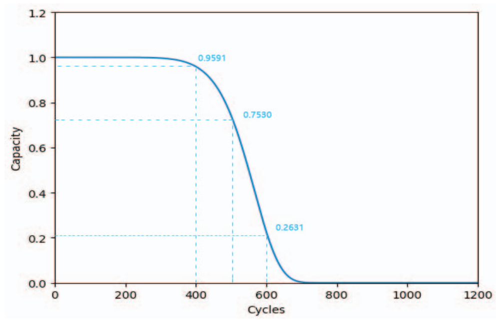

Fig. 4. Lithium-ion battery reliability curve

It can be seen from Fig. 4 that when the cycle life is less than 400 times, the battery can maintain a high reliability of 0.9591 or more. When the cycle life is between 400 and 500 times, the reliability reduction rate is 21.49%;500 times to 600 times. The reliability reduction rate was 60.06%.Therefore, the battery starts from 500 cycles and the reliability drops sharply from 0.7530. The 18650 lithium-ion battery specification shows that the cycle life under normal stress is about 600 times, but the reliability of 600 times is only R(t)=0.2631,this is far from meeting the requirements for battery reliability. In order to ensure the high reliability of lithium-ion batteries in actual use, only the indicators in the lithium-ion battery specification are used as a reference for lack of accuracy, and should be analyzed in combination with reliable life indicators. When the number of cycles is 500 to 600 times, This kind of lithium-ion battery has low reliability, so the final service life can be evaluated according to the actual demand for reliability indicators.

V. CONCLUSION

Based on the LSTM neural network model to predict the capacity degradation of lithium-ion batteries, the LSTM neural network has good performance in processing time series data, and has the ability to memorize historical data. The historical capacity data of lithium-ion batteries is input into the neural network. The capacity of lithium ion is predicted by the battery capacity degradation data, and the pseudo-failure life corresponding to the failure threshold is obtained. The pseudo-failure life sample is statistically analyzed to obtain the reliability function of the lithium ion battery under the normal stress, and combined with the specified reliability. The reliable life is used to determine the actual service life. This degradation model is also suitable for performance degradation analysis of other lithium-ion battery products, with a wide range and adaptability.

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