State-of-Health Estimation of Lithium-ion Battery Based on Data-driven

Jingyi Gao [1], Ping Li [2], Yisu Yan [3], Mengjie Guo [4], Kai Wang [1*]

[1]*wkwj888@163.com

[1]2454353641@qq.com

[2]412505820@qq.com

[3]yanyisu@126.com

[4]563170475@qq.com

[1*]School of Electrical Engineering, Qingdao University, Qingdao 266071, China

[1]School of Electrical Engineering, Qingdao University, Qingdao 266071, China

[2]Dongying District Science and Technology Bureau, Dongying 257000, China

[3]Qingdao Dagang Customs, Qingdao, Shandong 266011, China

[4]Shandong Wide Area Technology Co., Ltd, Dongying 257081, China

Abstract—With the increase of the output of electric vehicles, it is of great significance to predict the health status of lithium-ion batteries for the safe operation of electric vehicles. In this paper, some common data-driven methods for health state estimation of lithium-ion batteries are reviewed. First of all, this paper introduces the charge and discharge principle of lithium-ion battery. Then four common SOH prediction methods are introduced, and their advantages and disadvantages are summarized and reviewed. In the part of introducing the data-driven research on the health status of lithium-ion battery, it focuses on the application of machine learning and deep neural network. Finally, the research prospect of health state estimation of lithium-ion battery is explained.

Keywords: State-of-health; Lithium-ion batteries; machine learning; data-driven model

1 Introduction

With the shortage of fossil energy, the traditional fuel automobile industry began to carry out electrification revolution. At the same time, in order to alleviate global warming and reduce environmental pollution, electric vehicles (EV) have become a better choice. Lithium-ion batteries are often used to power electric vehicles because of their high energy density, low temperature requirements and low environmental pollution. However, with the continuous use of lithium-ion batteries, the lithium in the anode is gradually decomposed, and the output

ICIDC 2022, June 17-19, Qingdao, People's Republic of China

DOI 10.4108/eai.17-6-2022.2322708

capacity after charging is weakened. Therefore, during the use of lithium-ion battery, it is necessary to monitor its health status (SOH) in real time. The specific chapters of this paper are as follows: Section 2 describes the operating principle and makeup of lithium-ion batteries. The third part summarizes the data-based SOH estimation methods for lithium-ion batteries, and comments on the characteristics and accuracy of different types of lithium-ion battery SOH estimation methods. The fourth section summarizes this paper.

2 The operating principle and makeup of lithium-ion batteries

Lithium-ion batteries include all batteries that use lithium-ion compounds as cathode materials and graphite as anode materials. There is a polymer film inside the battery, which has a microporous structure that allows lithium ions to pass freely, preventing electrons from passing through. The organic electrolyte of lithium-ion battery is carbonate solvent, which is dissolved with lithium hexafluorophosphate. As shown in Fig. 1, Lithium is stored in the electrodes, Li ion batteries rely on the movement of Li ions between the positive and negative electrodes to operate. When charging, electrons from the positive electrode travel through an external circuit to the negative electrode, where lithium ions enter the electrolyte and then travel through the membrane to the negative electrode. At the negative electrode, electrons reduce lithium ions to lithium, which is embedded in the carbon material of the negative electrode. During the discharge, electrons from the negative electrode pass through an external circuit to the positive electrode, from which lithium ions enter the electrolyte and then travel through the membrane to the positive electrode. At the positive electrode, electrons combine with lithium ions to power an external load.

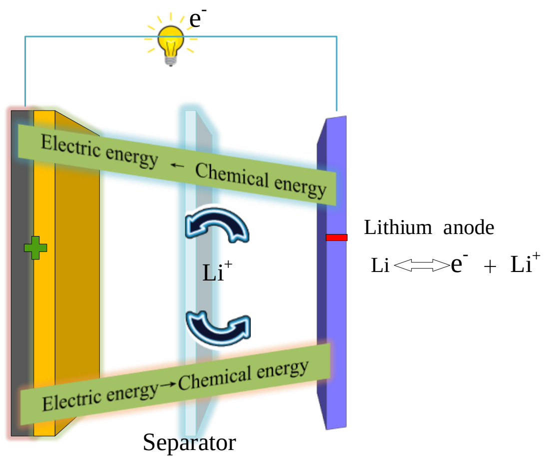

Fig.1 Charge and discharge process

3 SOH estimation of lithium-ion batteries based on data-driven

3.1 Definition of SOH

As an important index to judge the battery life, SOH can reflect the discharge ability of lithium-ion battery relative to the initial state. The life decay of lithium-ion battery needs to go through a complex process, which is affected by many factors, such as discharge depth, working temperature, charging voltage and so on. Therefore, the degradation process is nonlinear, which makes the prediction very complicated.

The SOH is defined as (1) or (2):

$$\text{SOH}=\frac{C_{now}}{C_0}\times 100\% \tag{1}$$

$$\text{SOH}=\frac{R_{EOL-R_{now}}}{R_{EOL}-R_{new}}\times 100\% \tag{2}$$

where C_{now} represents the maximum allowable discharge capacity, C_0 represents the nominal capacity of the battery, R_{now} represents the internal resistance at current time, R_{new} represents the internal resistance at current time from new cell, R_{EOL} represents the internal resistance at the battery's end-of-life.

3.2 SOH estimation method

The common SOH estimation methods can be summarized into three categories:

(1) Direct measurement: For example, the charge quantity can be obtained by integrating the time-current discharge curve, which can be used in battery management system (BMS) because of its simple calculation. However, affected by the noise of various sensors, this method has a large error and is difficult to eliminate.

(2) Model-based: Although the model-based method can avoid the error of the direct method itself. However, the accuracy of this method largely depends on the structure of the model. It is very difficult to build a model that can adapt to the aging process of lithium-ion batteries in different environments.

(3) The data-driven methods: When using the data-based method, there is no need to analyze the internal reaction of the battery, as long as the health characteristics corresponding to the non-linear change process of SOH can be found, it can be widely used in different scenarios. Battery capacity is usually regarded as a long-term time series, so SOH prediction becomes a nonlinear regression problem.

3.3 Data-driven method

Gaussian process regression: Machine learning methods such as support vector machine, Gaussian process regression and random forest have been widely used to predict battery SOH.

The charge-discharge curve is obtained from the battery charge-discharge experiment, and the required health features are extracted to estimate the battery SOH. However, if we can give the corresponding uncertainty measurement, rather than a single prediction result, it can help the system to make a more accurate judgment. In [1] the battery health status (SOH) was estimated by Gaussian process regression (GPR). The structure of the model is relatively simple and can give the probability of a series of SOH values in the future. However, when the data set is large or the input feature dimension is high, the time complexity and space complexity are higher. In addition, based on the nature of the problem and the data, more consideration should be given to the selection of kernel functions.

A variant of LSTM: With the development of deep learning technology, the advantage of recurrent neural network is reflected. At present, recurrent neural network (RNN) technology is widely used in the fields of language translation, time series prediction and picture recognition. Compared with the previous machine learning methods, the deep learning technique can extract more abundant features from the input by increasing the number of layers of the neural network. In order to solve the problems of gradient disappearance caused by weight parameter less than 1 and gradient explosion caused by weight parameter greater than 1 in traditional RNN network, a long-term memory (LSTM) neural network is proposed. This method uses gated structure to control the transmission of state variables, so as to ensure the normal change of gradient. As shown in figure 2, LSTM usually consists of amnesia gate, update gate, input gate and output gate, which can be used to determine which memories need to be transferred. Firstly, the correlation of the extracted features is analyzed, and the features with high correlation are used as the input of the network. As a variant of LSTM, Bi-LSTM usually has better performance because of its ability to capture information that may be ignored by unidirectional networks, which can reduce the time order sensitivity of LSTM when extracting features from sequences.

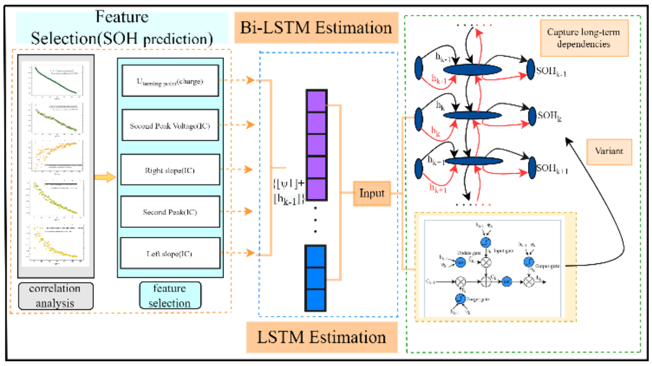

Fig.2 The variant structure of LSTM

A novel deep learning framework: [2] proposed a hybrid network based on a kind of gate recurrent unit and convolutional neural network. Convolutional neural networks can make use of the shared weights structure to reduce the number of weights. As shown in figure 3, the reset gate and update gate of GRU are connected with the nonlinear activation function, and the output is connected with the linear activation function. The mapping relationship between input and output is obtained by training to change the size of the weight. This structure can make full use of the advantages of CNN and GRU-RNN networks.

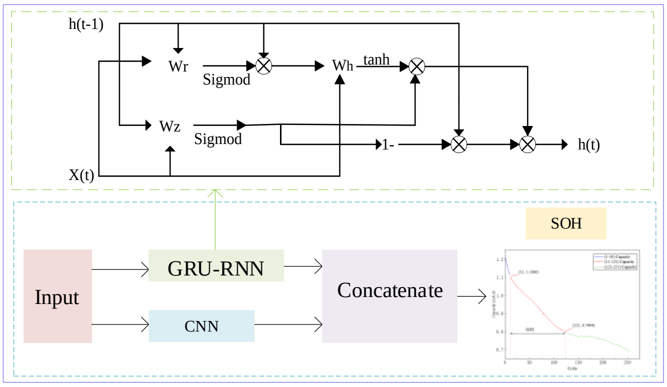

Fig.3 The structure of GRU-CNN

CNN and transfer learning method: Common CNN structures are shown in Figure 4 [3] . It mainly contains convolutional layer, pooling layer and full connected layer. The inputs are three-dimensional vectors constructed of charge current, voltage, and cell capacity and finally transformed into a single output that is used to represent the cell's SOH [4]. For migration learning, first by pretraining to get an initial network model, and then adjusting the parameters of the weights in the network according to the specific training data, we can greatly reduce the training time and the requirement for the number of data in the training set [5].

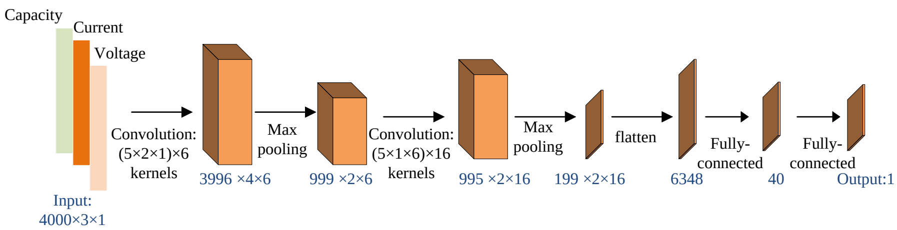

Fig.4 The overall structure of CNN

As shown in figure 5, the pre-training of the initial model uses accelerated aging data, while the target model is trained and tested using aging data at normal speed. When using different data, there are some similarities in the network parameters between input and output. Although the prediction results show different SOH decline curves, the prediction error is less than 0.4%, indicating that transfer learning is very practical [6]. When pretraining is performed, the battery capacity in the input vector is not directly measured. And the capacity can be calculated from the discharge curve, integrating the discharge current with time [7]. Since it takes a long time to carry out the aging experiments of batteries, resulting in limited training data, a large amount of time and money will be consumed if each model is to be retrained. Pretraining is aimed at saving experimental time and reducing experimental cost by reducing battery life, while ensuring a certain degree of accuracy.

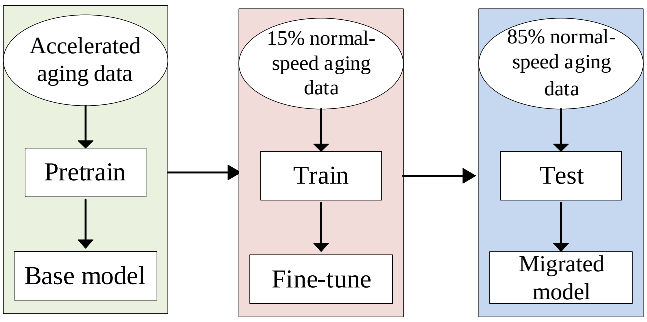

Fig.5 The overall strategy of transfer learning

4 Conclusion

This chapter summarizes the state-of-health estimation of lithium-ion battery from data-based aspects:

(1) In this paper, a Gaussian regression method is introduced, which can be used to measure the range of SOH prediction. According to the shortcomings of RNN network structure, a Bi-LSTM structure is proposed for SOH on-line prediction.

(2) In this paper, a hybrid network structure composed of two types of neural networks is introduced, and its advantages in SOH prediction are explained.

(3) In this paper, the application of convolution neural network structure in battery SOH prediction is illustrated. This paper introduces the principle of transfer learning and gives an example to illustrate the application of transfer learning.

In recent years, data-driven SOH prediction technology has made great progress, but with the continuous development of artificial intelligence and machine learning, the widespread use of electric vehicles, lithium-ion battery health assessment will still be the focus of research. Therefore, this subject still has scientific research significance and broad research space.

Acknowledgment. This work was supported by the Youth Fund of Shandong Natural Science Foundation (No. ZR2020QE212), Key Projects of Shandong Natural Science Foundation (No. ZR2020KF020).

References

[1] K. Liu, X. Hu, Z. Wei, Y. Li, and Y. Jiang. Modified Gaussian Process Regression Models for Cyclic Capacity Prediction of Lithium-Ion Batteries [J]. IEEE Transactions on Transportation Electrification, 2019, 5(4): 1225-1236.

[2] Y. X. Fan, F. Xiao, C. R. Li, G. R. Yang, and X. Tang. A novel deep learning framework for state of health estimation of lithium-ion battery [J]. Journal of Energy Storage, 2020, 32.

[3] Y. Li, J. Tao, and Ieee. CNN and transfer learning based online SOH estimation for lithium-ion battery. Chinese Control and Decision Conference (CCDC), 2020, pp: 5489-5494.

[4] Wang C, Xu M, Zhang Q, *et al.* Parameters identification of Thevenin model for lithium-ion batteries using self-adaptive Particle Swarm Optimization Differential Evolution algorithm to estimate state of charge [J]. Journal of Energy Storage, 2021, 44.
[5] Sui X, He S, Vilsen S B, *et al.* A review of non-probabilistic machine learning-based state of health estimation techniques for Lithium-ion battery [J]. Applied Energy, 2021, 300.
[6] Wang Z, Feng G, Zhen D, *et al.* A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles [J]. Energy Reports, 2021, 7: 5141-5161.
[7] Z. Chen, H. Zhao, Y. Zhang, S. Shen, J. Shen, and Y. Liu. State of health estimation for lithium-ion batteries based on temperature prediction and gated recurrent unit neural network [J]. Journal of Power Sources, 2022, 521.c.