SOC Prediction of power lithium battery using BP neural network theory based on keras

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Abstract

The estimation of state of charge(SOC) is among the key technologies in battery management system. Compared with many estimation methods, neural network has obvious advantages in the estimation accuracy. But requiring great amount of data is its main limitation. In order to solve the above problems, a method for SOC estimation based on the cross validation of artificial neural network and k-fold was proposed. An 18650 power lithium-ion battery is used as the experimental object, and the data are obtained by collecting the battery voltage, current and temperature data. High SOC estimation accuracy on different verification sets is pursued under circumstance of low data amount. The BP artificial neural network model is established based on the Keras platform with tensorflow, and K-fold cross validation method is added to the network. After training, the model is used to predict the experimental data. The estimation of SOC is realized by function fitting. Compared with the traditional BP neural network prediction, the prediction accuracy is 99%. Finally, it is proved that the method combining BP neural network and K-flow cross validation is effective and the validity of the neural network model for SOC estimation is verified.

Keywords

State of charge; power lithium-ion battery; BP neural network; K-flod cross validation.

1. Introduction

With the development of science and technology in the world, energy shortage and environmental pollution have become the two major challenges. In order to achieve energy conservation, emission reduction and resource utilization, new energy vehicles represented by electric vehicles have gradually become the mainstream means of transportation. Power lithium-ion batteries are widely used in electric vehicles because of their high energy density, long service life and low self-discharge rate. With the recycling of power lithium-ion battery, the performance of the battery will be deteriorated, the safety will not be guaranteed, and the mismatch issues between driving mileage and remaining battery power will exist. The accurate state of charge is the premise of the reasonable use of battery power. Users determine the travelling distance and ways by referring to the SOC value. Meanwhile, the estimation of SOC is the core part of Battery Management System (BMS).

The estimation methods of SOC for Li-ion battery can be divided into five categories: (1) based on empirical equation and mathematical model, (2) estimation method based on Ah measurement, (3) estimation method based on Open circuit voltage[5], (4) estimation method based on internal resistance characteristics, (5) estimation method based on Kalman filter algorithm [2].

Researchers have also used third class of methods involving data analysis to estimate SOC, which rely on traditional machine learning techniques. In the literature [3], SVM technology is used to estimate SOC. And in the literature [4], researchers use the Extreme learning machine algorithm to estimate SOC. The main problem of traditional machine learning techniques is the dependence on the amount of data. Comparatively small amount of data will lead to inadequate training and poor prediction effect, while large amount of data will easily lead to over fitting, which makes the model work effectively on the training data set, but defectively on the prediction data set.

In view of the shortcomings of the above methods, the BP neural network method combined with K-fold cross validation is a very effective solution. The advantages of this method are as follows: (1) the method does not need a certain formula relationship between input and output, only needs proper selecting of input parameters and output parameters, and the multi-dimensional nonlinear relationship between them can be determined by self-learning in network training. (2) the neural network method has the characteristics of self-learning and self-adaptive. The new data can be retrained and new model parameters can be obtained to adapt to the characteristics of SOC value decreasing with time after lithium battery performance aging. (3) Only a small amount of training data is needed to achieve better prediction results. BP neural network based on K-fold cross validation is used in this paper to reduce the absolute error of SOC estimation to less than 1%.

2. BP neural network and K-fold cross-validation design

2.1 BP neural network introduction

The artificial neural network organizes the neurons with simple function through a certain structure to realize the parallel processing of the data population. According to different connecting methods, neural networks can be divided into hierarchical neural networks and interconnected neural networks. According to the characteristics of power lithium-ion battery acquisition and SOC estimation, this paper uses a four-layer BP neural network, which is a multi-layer forward neural network and its structure is as shown:

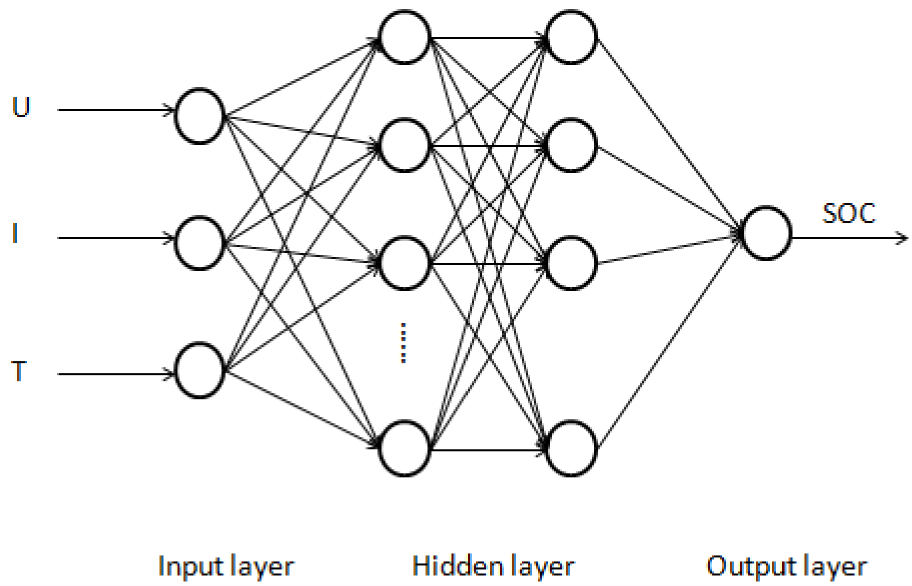

Fig.1 BP neural network

Generally speaking, the structure of multilayer feedforward neural network can be divided into three layers: input layer, hidden layer and output layer in which there can be multiple hidden layers. The external signal is connected to the input layer, and the input layer transmits the input signal to each unit of the hidden layer. As the inner processing unit of neural network structure, the hidden layer has different amount of layers according to different network requirements. The output signal transmits through the output layer.

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2.2 BP network design

When establishing a BP neural network, network structure is the prior thing. The network structure directly affects the estimation effect. According to theory and research, if other various conditions are properly selected in circumstance of two sets of nonlinear correlation data, the 4-layer BP neural network can generally achieve the required accuracy. The selecting of input and output parameters determines the number of neural network input and output layer nodes. Proper input models can achieve better network performance and improve network training speed and accuracy. The basic principles of neural network input parameter selection are:

(1) Select parameters as input of the network that have great influence on the network output and are easy to measure or extract.

(2) The selected input variables should be irrelevant with each other or have little correlation.

Voltage, current and temperature of the power lithium-ion battery are closely related to the SOC of battery, and the correlation between them is very small. Choose the voltage, current and temperature of the battery as the input variables of the neural network, the SOC value of the battery as the output variable of BP network. The training samples can be expressed in vector form [V I T SOC], where V is voltage, I is current, T is temperature, and SOC is the remaining battery power.

Voltage, current and temperature are selected as input parameters. That's why the number of network input layer nodes is 3, and the number of network output layer nodes is 1, which is the battery SOC value. The number of hidden layer nodes of the network is selected through experience, and a better result is obtained through experiment. Before conducting the test, the empirical formulas for determining the approximate number of hidden layer nodes based on some empirical formulas are:

$$m = \sqrt{n+1} + \alpha \tag{1}$$

$$m = \mathrm{lb}n \tag{2}$$

$$m = \sqrt{nk} \tag{3}$$

Where: α is a constant between 1 and 10; n is the number of input layer nodes; k is the number of output layer nodes. According to the empirical formula, the number of nodes in the hidden layer is about 10, which is suitable in actual operation. In actual operation, it is found that when the number of hidden layer nodes is less than 10, the prediction accuracy of the network is very low. As the number of nodes in the hidden layer increases, the accuracy of network training will become higher and higher. As the number of nodes increases, the training speed will also increase. However, as the number of nodes continues to increase, the training accuracy will hardly increase, and the network training time will become longer. Therefore, the number of nodes in the network hidden layer is 16.

The training process consists of two processes: forward propagation of the signal and backpropagation of the error. The weight adjustment is performed according to the following algorithm. When the actual calculated value of the network is different from the expected value of the network, an output error E will be generated, which is defined as follows:

$$E = \frac{1}{2}\sum_{K=1}^{L}(d_k - o_k)^2 \tag{4}$$

Extend the above definition to the hidden layer:

$$E = \frac{1}{2}\sum_{k=1}^{l}[d_k - f(\sum_{j=0}^{m}\omega_{jk} y_j)]^2 \tag{5}$$

Further extending to the input layer:

$$E = \frac{1}{2}\sum_{k=1}^{l}\{[d_k - f[(\sum_{j=0}^{m}\omega_{jk} f(\sum_{i=0}^{n}\upsilon_{ij} x_i)]\}^2 \tag{6}$$

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The criterion for adjusting the weight is to continuously reduce the error, so that the adjustment amount is proportional to the gradient of the error:

$$\Delta\omega_{jk} = -\eta \frac{\partial E}{\partial \omega_{jk}} \tag{7}$$

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} \tag{8}$$

2.3 K-fold cross-validation

The main focus of machine learning has always been model performance, which requires accurate prediction of the model's performance in practice and applications. The ability of the model to be generalized from its training set. Accurate estimation of model performance is critical to the selection between models and the selection of optimal model parameters. It is unwise to estimate the prediction error for the same data used to train the model, which will lead to a serious underestimation of the prediction error. A simple alternative is to randomly divide the data into training and test sets, and use the trained model to tune the performance on the validation set.

A more complex method is based on resampling and a more efficient use of data; including bootstrapping and K-fold cross-validation(CV). Since bootstrapping has high computational cost and is easy to underestimate prediction error, CV is often used as the default method for estimating prediction error.

K-fold cross-validation(CV) is a common method for estimating the true performance of machine learning models. The operation of CV requires random division of data, so performance evaluation is random and changeable. This feature is very important for the training process. So it is recommended to use J-Kfold CV, where J independent K-fold cross-validation is used to evaluate performance. Experimental results show that using repeated J-K-fold cross-validation can reduce variance.

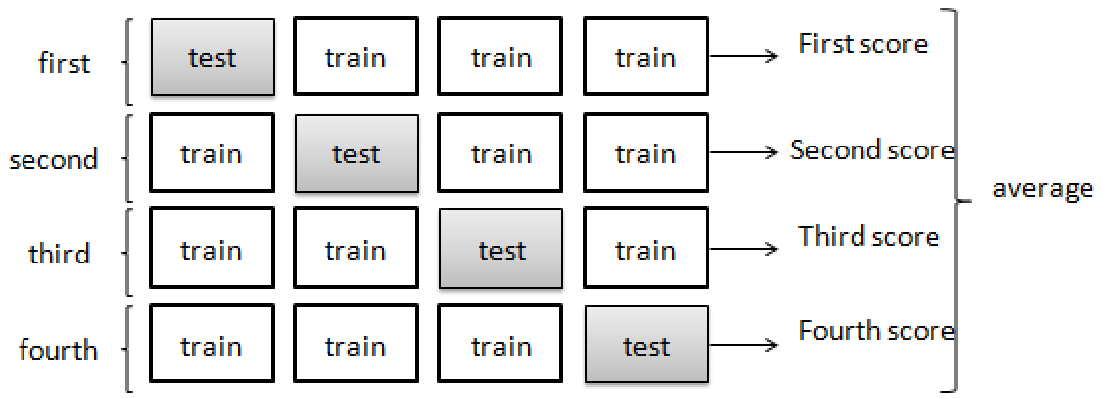

Fig. 2 K-fold cross-validation(CV)

3. Analysis of results

3.1 Experimental data collection

In this paper, a battery unit which is similar to Tesla Electric Vehicle is used. The NCR18650PF lithium-ion battery produced by Panasonic Corporation is used as the experimental object. The rated capacity of the battery is 2.9Ah and the rated internal resistance is 35mΩ. Refer to Table 1 for more info.

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Table 1 Panasonic NCR18650PF lithium battery unit parameters

Numble	Scheme 1
Rated voltage	3.6V
Rated battery capacity	2.9Ah
Maximum charging voltage / discharge Cutoff voltage	4.2V/2.5V
Internal resistance	35 $m\Omega$
Weight	47.5g
Discharge temperature	-20~+60℃

Single-cell battery test unit is shown in Fig.3. It consists of a single-section Panasonic 18650 lithium-ion battery, a Chroma charger, a WT1600 power meter, an electronic load, and a unit for temperature acquisition. The Chroma charger can charge the lithium-ion battery according to the set voltage and current. The WT1600 power meter can realize the voltage, current and power of battery. All experiments were performed at room temperature.

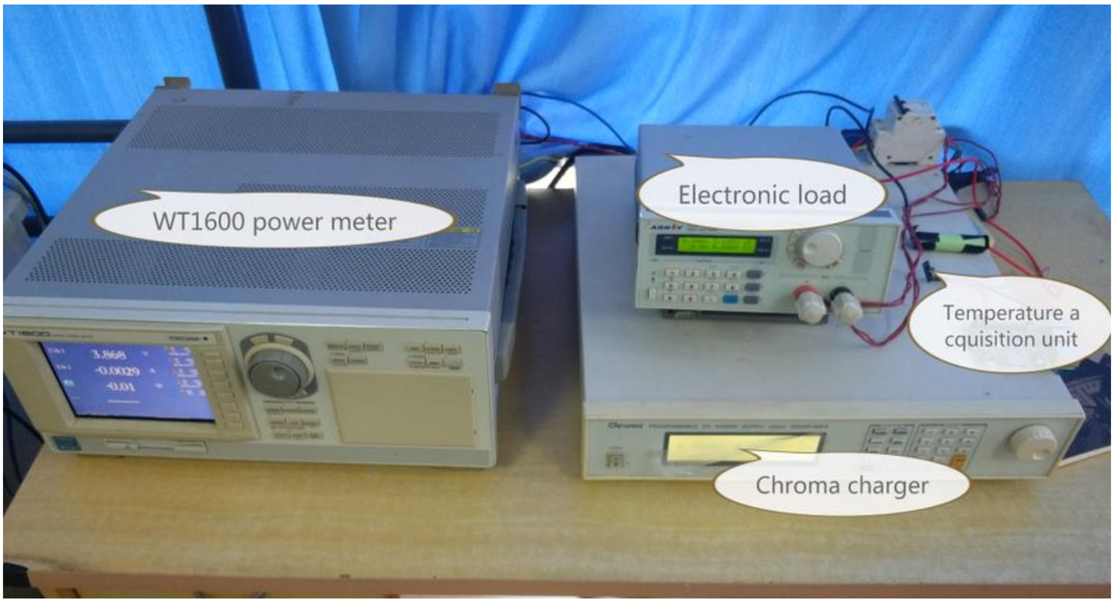

Fig. 3 Single-cell battery test unit

In order to obtain data of battery discharge for training and verifying the BP neural network, the battery is charged in the 4.2V/2.9A-charging mode. When the voltage of battery is maintained at 4.2V and the charging current decreases to 50mA, the battery is fully charged. After the charging is completed, the battery will be kept at room temperature for 1 hour, and a 0.5 Ω resistor is used to discharge the battery, which is a constant resistance discharging test. Related discharging data will be recorded. When the battery voltage drops to 2.5 V, the battery has been completely discharged. The battery will be kept still for another hour again, the charge and discharge test is repeated, and the data is repeatedly recorded. Voltage, current and the surface temperature of the battery collected during a single discharge test are shown in Fig.4, Fig.5, Fig.6.

In the room temperature environment, the battery is charged and discharged 9 times in total. Four groups of data are used as the training set of BP neural network for training neural network, and the remaining five groups are used as the test set of neural network for testing the accuracy of neural network after training. The results of SOC estimation are compared with the real values. Statistical error term is used to evaluate the performance of SOC prediction model based on BP recurrent neural network including mean square error MAE, mean absolute error MAE and maximum absolute error MAX. The mathematical equation of statistical error is as follows:

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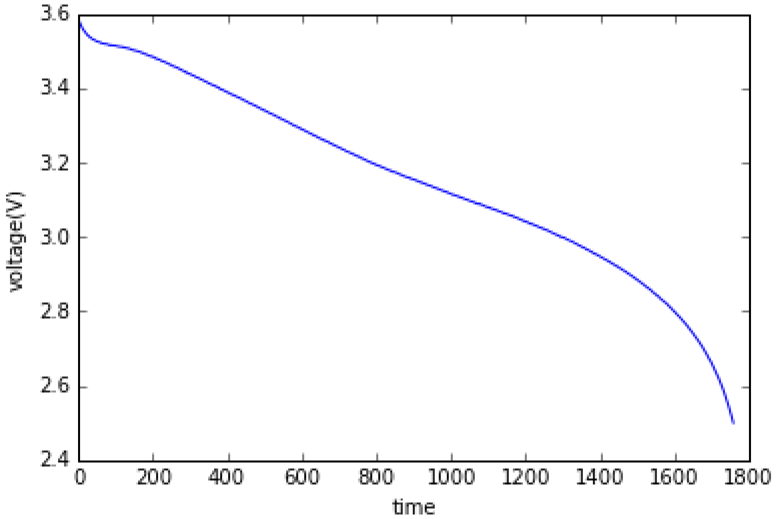

Fig. 4 Voltage(V)

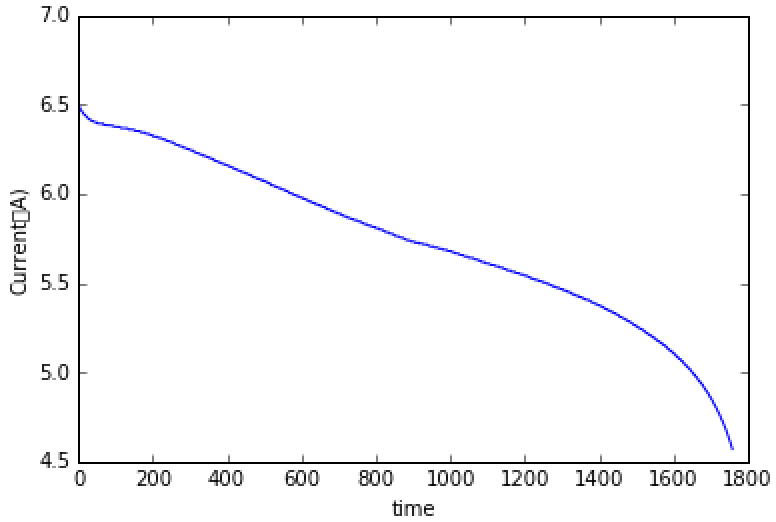

Fig. 5 Current(A)

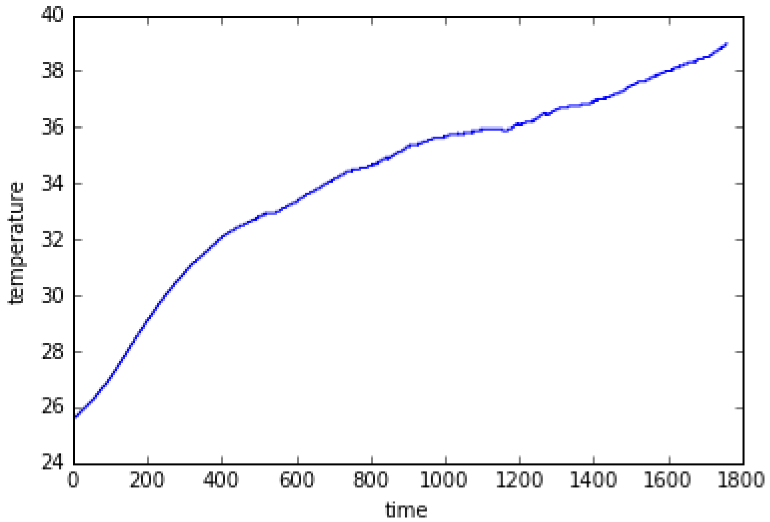

Fig. 6 Temperature(℃)

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$$MAE = \frac{1}{m}\sum_{l=1}^{m}\left|y - y^{'}\right| \tag{9}$$

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y - y^{'})^{2} \tag{10}$$

$$MAX = \max\left\{\left|\frac{y_i - y_i^{'}}{y_i}\right|, i = 1...m\right\} \tag{11}$$

Where y is the true value, $y^{'}$ is the predicted value, and m is the number of observations.

3.2 Data preprocessing

For multi parameter analysis and calculation, the basic measurement units of parameters should be unified, which is also applicable to neural networks. The data of training neural network must be normalized, and then it can be used for network training. At the same time, the normalized data is also helpful to accelerate the convergence speed of the training network. The normalization method used in this paper is to convert the input and output to the range between 0 and 1, and the formula is as follows:

$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

Where x_{max} and x_{min} are the maximum and minimum values of the neural network input vector x.

3.3 Analysis of experimental results

The neural network is established by Keras, and the sequential model is adopted. After repeated cyclic experiments, the neural network level is set to four levels. It includes input layer, two hidden layers and output layer. The input layer has three values: voltage, current and temperature. Because the data amount is very small, so the built neural network shouldn't be too large. Basically two middle layers with 16 nodes each layer are enough. The smaller the training data amount, the more serious over fitting it will be. Only by reducing the structure of the network, can the over fitting be suppressed. The predicted value needed is SOC value, so the output layer is set as a neuron. The activation function is Relu function, the optimization method is launched by Rsmtop function, the maximum training times is set to 200, and the batch size is set to 10. After training, the neural network can learn the parameters of the whole network.

The comparison between the measured data and the predicted data is shown in the Fig.7:

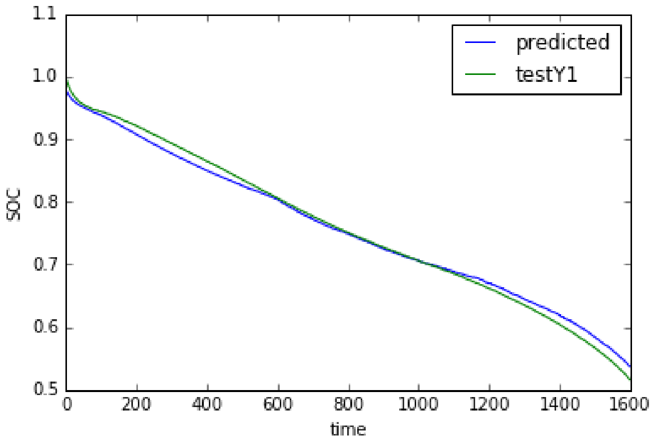

Fig. 7 The true and predicted value

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Table 2 Error values on five validation sets

Error function	First validation set	Second validation set	Third validation set	Fourth validation set	Fourth validation set
MSE(%)	7.56	5.22	7.83	10.3	6.96
MAE(%)	12.10	11.22	8.97	6.38	5.32
MAX(%)	7.64	6.53	7.76	7.21	9.46

As shown in Table 2 and Fig.7, BP neural network model can basically meet the needs of predicting SOC value of lithium-ion power battery. However, after training, the network prediction error is large and the maximum error is 12%. The average error is about 8%. And the situation is severe in some areas, which may mislead the user or control system in practice and application, make the battery over discharge, cause serious damage to the battery.

The reason for this is that the amount of data is too small. As a result, different ways of data division will have different effects on the verification results, so that the training situation of the network cannot be accurately mastered. Resorting to K-fold cross validation is an effective way to deal with this situation.

The selection of K is related to the prediction accuracy and network training time. The larger value of K, the longer training time it is. The smaller value of K, the less network prediction accuracy it is. Therefore, the selection of K value is a very important parameter for the prediction method in this paper. Take k = 4, k = 6, k = 10 respectively to train and verify on the data set.

Table 3 MSE values In the case of K values

K	4	6	10
MSE	1.32	5.96	4.29

It can be seen from the Table 3 that when K value is taken as 4, the value of MSE changes to minimum. Input the standardized experimental data into the neural network, and set the cycle number of every training process to 200. After each training process, the error of the verification data judgment is recorded, and the data is drawn into a graph to graphically view the changes of the model during the training process.

The outermost layer has 4 rounds of loops. When the network is trained internally, there are 200 rounds of loops, which is the value of num_epochs. A bias result will be attained after every single epoch training process, so 200 results will be gathered during the first loop in outermost layer. The deviation result is recorded as (x1[0], x1[1]...x1[199]), and the outermost second round also has 200 deviations, denoted as (x2[0], x2[1]...x2[199]), and so on. Calculating error mean corresponding to 4 large cycles, that is, (x1[0]+x2[0]+x3[0]+x4[0])/2, (x1[1]+x2[1]+x3[1]+x4[1])/4, and so on. Thus, 200 average values are calculated, which are used to measure the accuracy of the model in 200 epoch training. The errors of 200 cycles are shown:

In the graph, the fluctuation of error is very intense. It is difficult to see the difference between the points. In order to show the difference in the data during the training process more clearly, the result is operated by Exponential sliding average process. The formula is as follows:

$$S_t = \begin{cases} Y_1, t = 1 \\ \alpha \cdot Y_t + (1-\alpha) \cdot S_{t-1}, t > 1 \end{cases} \tag{13}$$

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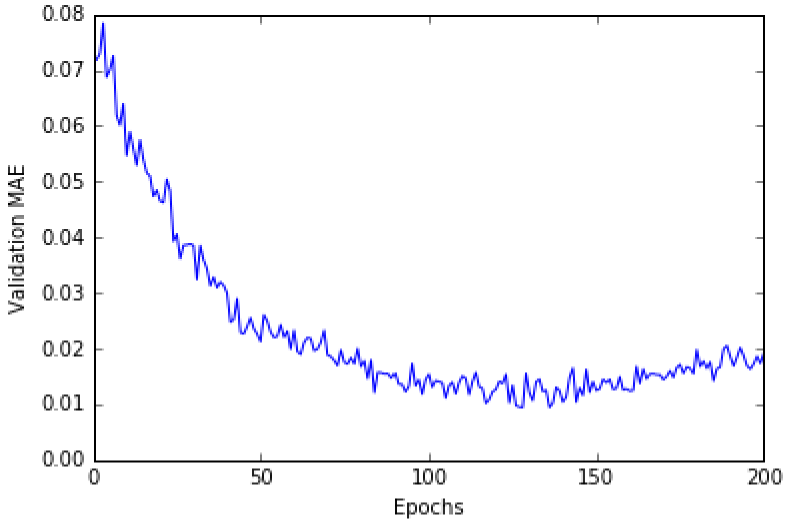

Fig. 8 Training error curve

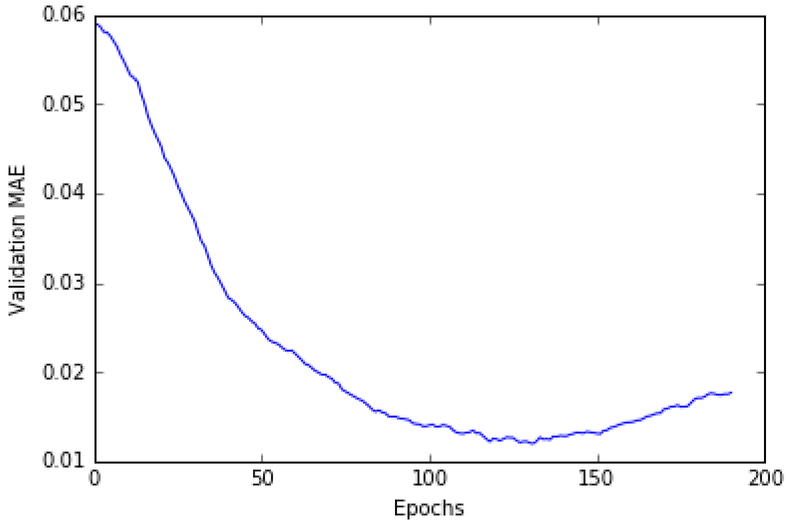

Fig. 9 Improved training error curve

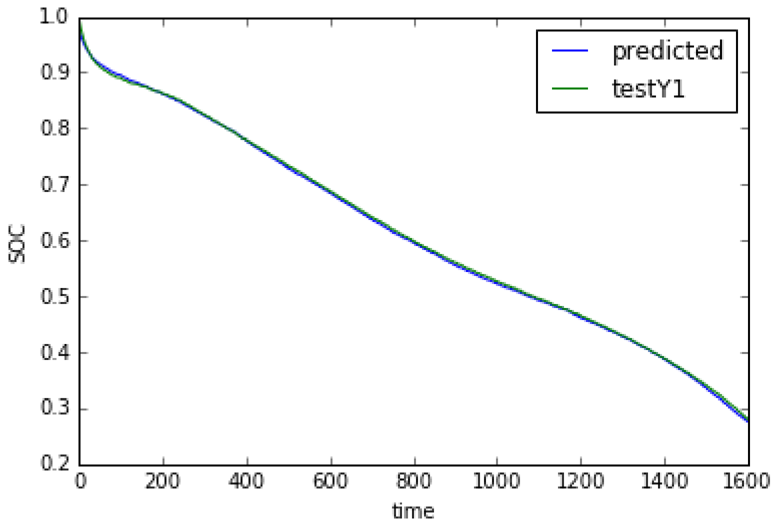

Fig. 10 Tthe true and predicted values after adding k-flod cross-validation

The Exponential sliding average method has the effect of smoothing the data of repeated beats, so that the hidden trend of the repeatedly changing data can be clearly identified. As shown in Fig.9, the data become a curve with obvious trend after moving average. It can be found when epochs value is 130, the calibration error is at the lowest point, and then the error continues to increase. Therefore,

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the number of cycles of training can be set at about 130, where the model with best accuracy can be made.

The network structure, weights and offset values are saved after the model training is completed. The saved model is called to verify the running on the dataset, and the fitted curve of the SOC predicted value and the SOC real value is shown in the following figure:

The network performance indicators of the BP neural network added to the K-fold cross-validation on the five verification sets are shown in Table 4.

Table 4 The error value of the improved model on the five validation sets

Error function	First validation set	Second validation set	Third validation set	Fourth validation set	Fourth validation set
MSE(%)	0.49	0.32	0.26	0.82	0.12
MAE(%)	0.39	0.52	0.12	0.24	0.98
MAX(%)	0.61	0.74	0.75	0.34	0.41

It can be seen from the Fig.10 and Table 4 that the prediction accuracy of the BP neural network optimized by the K-fold cross-validation algorithm is much better than the BP neural network without optimization. The prediction error is mostly controlled within 1%. Compared with the prediction error of BP neural network without optimization (about 10%), it has been greatly improved. It can be seen from the discharge prediction curve shown in the Fig.10 that the improved network prediction curve can track the measured curve more accurately. The prediction curve without optimization is seriously deviated from the test curve. The model has been entirely able to predict the SOC value of a lithium ion power battery within an acceptable error range.

4. Conclusion

Aiming at the nonlinear problem of lithium ion power battery state of charge (SOC) estimation, a lithium ion power battery state prediction model based on BP neural network and K-fold cross-validation are established in this paper, with its model accuracy tested. The feasibility of predicting the battery SOC value is examined. Compared with the traditional BP neural network model, the prediction accuracy of the model is improved to 99%, which can meet the actual needs and prove it true the feasibility of the method.

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