A method of battery capacity prediction based on fuzzy logic and Neural networks

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Abstract. With the wide use of lithium battery, its online monitoring and residual capacity prediction have been paid much attention. There are two methods for predicting the residual capacity of lithium batteries, namely model method and data-driven method. The traditional model method requires in-depth understanding of the material characteristics and aging mechanism of the battery. However, it is difficult to establish an accurate model due to the complex electrochemical reactions in the battery and the vulnerability to external factors. The data-driven law has been applied more widely because of its good applicability and flexibility. This paper presents a method of battery capacity prediction based on fuzzy logic and neural networks. The lithium battery data published by PCoE are selected for the test, and the results show that the prediction error of the method for the residual capacity of single battery is less than 2%, which indicates that the method has a good applicability for the complex nonlinear system of lithium battery pack, and can obtain accurate battery capacity prediction value, and it has a good application prospect.

1. Introduction

Because of its high energy density, good stability and other advantages, lithium battery has been widely used in electronic equipment, energy and power applications. The residual capacity of a single battery has a great influence on the performance of the whole lithium battery. It is very important for the efficient and safe use of lithium battery to monitor the battery pack online, predict the remaining capacity of each single battery, and replace the single battery with poor index in time.

2. Introduction of existing capacity prediction methods for lithium batteries

Lithium-ion batteries use after period of time, the energy storage capacity will gradually decline, lithium battery capacity refers to the charge after the biggest discharge ability for the load [1], the influencing factors of the lithium battery capacity is more, polarization voltage, charging current, such as monomer battery internal resistance, temperature, chemical aging, lithium-ion battery pack is composed of multiple parallel of monomer battery, the monomer battery performance directly affects the whole performance of the battery pack and efficient and safe to use, as a result, online testing and projections for single lithium battery capacity is of great significance. The lithium battery capacity forecasting method is divided into four categories: the first is based on the experience knowledge of expert system, fuzzy logic method, this method model is simple and easy to implement, need to have fewer rules, can
3. A method of battery capacity prediction based on fuzzy logic and neural networks

Relying on expert experience high universality, fuzzy logic system based on neural networks prediction accuracy and practicability of the data driven good [12], they both have strong nonlinear processing ability, no need accurate equivalent circuit model is set up, do not need high precision hardware, for lithium-ion battery pack the complex nonlinear system applicability is higher. Therefore, this paper proposes a method of battery capacity prediction based on fuzzy logic and neural networks.

The SOC prediction model based on fuzzy logic system and neural networks is composed of six layers: fuzzy input layer, fuzzifying layer, fuzzy reasoning layer, improved BPNN input layer, hidden layer and output layer. Its structure is shown in Fig. 1.

3.1. Control strategy of fuzzy controller is as follows:

To change the default, adjust the template as follows. select observation quantity and control quantity: select temperature $T$ of single battery as observation quantity 1, voltage $U$ of single battery as observation quantity 2, and monomer charging current $I$ as control quantity.

The blurring of input and output: Could be divided into 7 $T$, $U$, $I$ have a fuzzy set, $T$ {Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZO), Positive small (PS), Positive
Medium \((PM)\), Positive Big \((PB)\), \(U\) \{Zero \((ZO)\), Very Small \((VS)\), Compare Small \((CS)\), Small \((S)\), Medium \((M)\), Compare Big \((CB)\), Big \((B)\), Very Big \((VB)\)\}, \(I\) \{Negative Big \((NB)\), Negative Medium \((NM)\), Negative Small \((NS)\), Zero \((ZO)\), Positive small \((PS)\), Positive Medium \((PM)\), Positive Big \((PB)\)\}, set the scope of \(T\) is \([0,55]\), The value range of \(U\) is \([3.5,4.3]\), and the value range of \(I\) is \([-2, 2]\). The corresponding adaptive membership functions are selected and the fuzzy table is obtained.

Formulation of fuzzy rules: the formulation of fuzzy rules is the core content of fuzzy control, and the control performance is largely determined by fuzzy rules. If \(T\) and \(U\) are larger, then \(I\) is increased, and the closer to PM level, the more increase; If \(T\) is too small or too large, and \(U\) is too small, then it decreases \(I\); In other cases, it is appropriate to add or subtract less \(I\).

Fuzzy decision making: the control quantity \(I\) we finally need to obtain is the output of the fuzzy control. I can be composed of the matrix \(X\) composed of the membership function of \(T\), the matrix \(Y\) composed of the membership function of \(U\) and the matrix \(Z\) composed of the membership function of \(I\):

\[
I = X \times Y \times Z
\]

3.2. BP neural networks (BPNN) running process
The running process of BP neural networks (BPNN) is divided into two parts: forward propagation signal and back propagation error. Forward propagation refers to the process in which the input signal is transmitted from the input layer to the output layer through the hidden layer. Back propagation error refers to the process of transferring the error from the output layer to the input layer and adjusting the connection weight and bias value through the gradient descent algorithm.

In the process of forward propagation, when a sample is input, the feature vector of the sample is obtained, the input value of the perceptron is obtained according to the weight vector, and then the output of each perceptron is calculated using the sigmoid activation function, which is then used as the input of the next perceptron, and so on, until the output layer.

In the process of back propagation, in order to obtain the weight vector, we continuously adjust the weight vector by minimizing the loss function, and then solve the weight vector by the following steps:

First, we need to define the loss function. \(1/2\) in (1) is to facilitate calculation:

\[
E(\vec{w}) = \frac{1}{2} \sum_k (t_k - O_k)^2
\]

Next, all weights in the network are randomly initialized.

Then perform the following operations for each training sample:

According to the input of the instance, calculate from front to back to get the output of each unit of the output layer, and then calculate the error term of each unit of each layer in reverse from the output layer.

For each unit \(k\) of the output layer, calculate its error term:

\[
\delta_k = O_k(1 - O_k)(t_k - O_k)
\]

For each hidden unit \(h\) in the network, calculate its error term:

\[
\delta_h = O_h(1 - O_h) \sum_k w_{kh}\delta_h
\]

Update each weight:

\[
w_{ji} = w_{ji} + \eta \delta_j x_{ji}
\]

\[
\Delta w_{ji} = \eta \delta_j x_{ji}
\]

BPNN has the following disadvantages:
Local minimum value: for multi-layer network, the error surface may contain multiple different local minimum values, and gradient descent may lead to local minimum value.

Too much weight: when there are too many hidden nodes and more layers, the weight increases exponentially. The increase of the weight value means the increase of the corresponding space dimension.

Easy overfitting: too many times of training and too high spatial dimension are easy to overfitting.

Therefore, in order to get a better solution, the BPNN algorithm is improved by using momentum weight adjustment method. The specific approach of momentum weight adjustment method is to add a part of the last weight adjustment amount to the weight adjustment amount calculated according to the error, as the actual weight adjustment amount of this time, that is, add a momentum coefficient β before \( w_{ji} \) in (4), and become:

\[
w_{ji} = \beta w_{ji} + \eta\delta_j x_{ji}
\]

In (6), \( x_{ji} \) represents the input from node i to node j; \( w_{ji} \) represents the corresponding weight; \( k \) represents the node belonging to the output layer, and here represents the output node SOC; \( \delta_k \) represents the error term of the hidden layer; \( w_{kh} \) represents the weight of each error \( \delta_k \), that is, the weight from hidden unit h to output unit k; Activation layer function uses sigmoid function, \( O_h(1 - O_h) \) is the derivative of the function; \( \Delta w_{ji} \) represents the updating laws; \( \eta \) represents the learning rate; \( \eta \) represents momentum coefficient.

4. Experimental verification and analysis

This article selects the NASA Prognostics CoE (PCoE) research center open lithium battery data set to validate the proposed battery capacity forecasting method based on fuzzy logic and neural networks. The parameters of the experimental battery are as follows: the battery model is 18650 with the nominal capacity of 2Ah. The battery is charged to 4.2V with the current of 1.5A at room temperature, and the battery is transferred to the constant voltage mode until the charging current drops to 20mA. Then the current of 2A is used to discharge the current continuously to the cut-off voltage to complete A complete charging and discharging process. In the experiment, the data of the B6 battery when the charge and discharge times are 50-110 times are selected as the training data set, and the data when the charge and discharge times are 120-170 times are selected as the verification data set. The training data are shown in Table 1, which shows battery temperature, voltage, current and corresponding actual battery capacity values measured when the battery discharged at full capacity for 4.148 minutes (time T1), 25.17 minutes (time T2) and 46 minutes (time T3), respectively.

| Number of charge | T1 TEMP. (°C) | T1 U (V) | T1 I (A) | T2 TEMP. (°C) | T2 Voltage (V) | T2 Current (A) | T3 TEMP. (°C) | T3 U (V) | T3 I (A) |
|------------------|---------------|----------|----------|---------------|----------------|----------------|---------------|----------|----------|
| 50               | 25.59         | 3.889    | 1.506    | 26.19         | 4.039          | 1.507          | 28.29         | 4.199    | 1.478    |
| 60               | 25.60         | 3.885    | 1.507    | 26.27         | 4.036          | 1.507          | 28.39         | 4.199    | 1.506    |
| 70               | 25.81         | 3.917    | 1.507    | 26.90         | 4.078          | 1.507          | 29.01         | 4.199    | 1.168    |
| 80               | 25.40         | 3.940    | 1.507    | 27.20         | 4.113          | 1.507          | 28.81         | 4.197    | 0.944    |
| 90               | 25.73         | 3.959    | 1.507    | 27.42         | 4.142          | 1.507          | 28.54         | 4.198    | 0.843    |
| 100              | 26.07         | 3.969    | 1.507    | 27.99         | 4.159          | 1.507          | 28.80         | 4.199    | 0.802    |
| 110              | 26.57         | 3.956    | 1.507    | 28.13         | 4.138          | 1.507          | 29.51         | 4.199    | 0.922    |

Table 2 shows the temperature, voltage and current data of the B6 battery selected in the experiment when the number of charge and discharge is 120-170 times, as well as the prediction capacity of the
method in this paper, the prediction capacity of the fuzzy method, the prediction capacity of the neural networks method and the actual capacity.

**Table 2. Measurement data of lithium battery with different cycle times and prediction of full capacity**

| Number of charge | TEMP. (°C) | U (V) | I (A) | Practical capacity (Ah) | Predictive capacity (Ah) | Fuzzy method capacity (Ah) | Neural networks capacity (Ah) |
|------------------|------------|-------|-------|--------------------------|--------------------------|-----------------------------|-------------------------------|
| 120              | 25.873     | 3.947 | 1.506 | 1.511                    | 1.511                    | 1.525                       | 1.533                         |
| 130              | 25.731     | 3.959 | 1.507 | 1.481                    | 1.493                    | 1.458                       | 1.46                          |
| 140              | 25.543     | 3.966 | 1.506 | 1.463                    | 1.478                    | 1.475                       | 1.433                         |
| 150              | 25.518     | 3.976 | 1.506 | 1.437                    | 1.448                    | 1.450                       | 1.420                         |
| 160              | 26.576     | 3.956 | 1.507 | 1.415                    | 1.437                    | 1.425                       | 1.440                         |
| 170              | 26.243     | 3.975 | 1.507 | 1.430                    | 1.433                    | 1.383                       | 1.378                         |

Fig. 2 shows the comparison between the predicted value and the actual value of the battery capacity prediction method based on fuzzy logic and neural networks, the battery capacity prediction method based on fuzzy logic, and the battery capacity prediction method based on neural networks. Fig. 3 shows the battery capacity prediction error.

**Fig. 2. Predicted values of the three prediction methods**
Fig. 3. Errors of three prediction methods

As can be seen from Fig. 3, the prediction error of fuzzy logic method and neural networks method is large, the fluctuation range is between 0% and 4%, the precision is not high, and the convergence is not strong. The error fluctuation range of the proposed method is between 0% and 2%, the predicted value is closer to the real value, and it has better convergence.

5. Conclusion
Aiming at the problem of lithium battery capacity monitoring and prediction, based on analyzing the advantages and disadvantages of various prediction methods, a battery capacity prediction method based on fuzzy logic and neural networks is proposed in this paper. Experimental results show that the prediction method presented in this paper has higher prediction accuracy and better stability than the traditional prediction method, and its maximum error is less than 2%. In addition, the method proposed in this paper does not need to establish complex and difficult to accurately estimate the model, it has good application value.

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