Research on Fault Diagnosis Method of Lithium Battery Based on Fuzzy Neural Network

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Keywords: Fuzzy neural network; Lithium battery; Fault diagnosis

Abstract: Aiming at the problem that the battery lithium battery has poor generalization performance for different health conditions, a fault diagnosis method based on fuzzy neural network is proposed. The neural network is used to diagnose the battery fault, and then the fuzzy system rules are used to output three fault states of the lithium battery, namely Corresponding Capacity reduction, Increase of internal resistance, SOC Reduction, and finally simulation analysis. The effectiveness of this method for fault diagnosis of lithium battery systems is demonstrated.

1 INTRODUCTION

The domestic power battery technology is not fully mature, and the battery failure is not easy to detect at the initial stage. Therefore, it is of great practical significance to carry out fault diagnosis research on the battery system to ensure that the battery is in normal operation.

The paper use fuzzy neural network to combine fuzzy logic and neural network. The learning mechanism of neural network is used to automatically extract rules from input and output data, and the fuzzy system is easy to express human knowledge[1-3]. The characteristics can improve the traditional fuzzy controller which must rely on human thinking to adjust the membership function repeatedly to reduce the error and improve the performance. Simulation analysis shows that the fuzzy neural network can effectively judge the fault state of the lithium battery.

2 FUZZY NEURAL NETWORK

Design a five-layer feedforward neural network, see Fig 1.The first layer is the input layer, and the input value indicates that the first node of the input layer corresponds to its first component. The input and output of this layer are:

$$I_j^1 = x_j \qquad (1)$$

$$O_j^1 = I_j^1 = x_j,\ j = 1,2,\cdots,n \qquad (2)$$

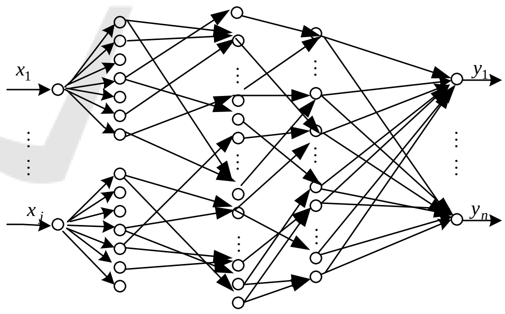

Fig. 1. Fuzzy neural networks

The second layer is the membership function layer, and the membership functions x_j belonging to the fuzzy sets of the values of the respective language variables are calculated. The membership functions are:

$$\mu_j^i = \exp\left[-\left(\left(x_j^2 - U_{ij}\right)/\left(E_{ij}\right)\right)^2\right] \qquad (3)$$

In the formula, the number of fuzzy partitions $m = 3$, U_{ij} indicating the mean of the membership function, E_{ij} indicating the standard deviation of the membership function, U_{ij} and E_{ij} are both adjustable parameters. Then the input and output of the second layer are:

$$I_j^2 = w_{ij}^{12} O_j^1 = w_{ij}^{12} x_j \qquad (4)$$

$$O_j^2 = \exp\left[-\left(w_{ij}^{12} x_j - U_{ij}\right)^2 / 2E_{ij}^2\right] \qquad (5)$$

In the formula, w_{ij}^{12} indicates the connection weight of the first node of the first layer and the second node of the second layer.

The third layer is the rule front layer. The input and output of the jth node are:

$$I_j^3 = \sum_{j=1}^{n} O_j^2 w_{ij}^{23} = \sum_{j=1}^{n} \exp\left[-\left(w_{ij}^{12} x_j - U_{ij}\right)^2 / 2E_{ij}^2\right] w_{ij}^{23} \qquad (6)$$

$$O_j^3 = 1 / \left(1 + \exp\left(-\sum_{j=1}^{n} O_j^2 w_{ij}^{23}\right)\right) \qquad (7)$$

Where, w_{ij}^{23} represents the connection weight of the second node of the second layer and the jth node of the third layer.

The fourth layer is the rule back layer, the input and output are:

$$I_j^4 = \sum_{j=1}^{n} O_j^3 w_{ij}^{34} = \sum_{j=1}^{n} w_{ij}^{34} / \left(\exp\left(-\sum_{j=1}^{n} O_j^2 w_{ij}^{23}\right)\right), j = 1,2,\cdots,n \qquad (8)$$

$$O_j^4 = O_j^3 / \sum_{j=1}^{3^n} O_j^3, \qquad (9)$$

In the formula, w_{ij}^{34} indicates the connection weight of the ith node of the third layer and the jth node of the fourth layer; 3 indicates that the fuzzification level is level 3.

The fifth layer is the output layer, which represents the output variable. After deblurring, the network output is obtained:

$$O_j^5 = \sum_{j=1}^{n} w_{ij}^{45} O_j^4 \qquad (10)$$

Where, w_{ij}^{45} represents the connection weight of the ith node of the fourth layer and the jth node of the fifth layer.

3 LEARNING TRAINING ALGORITHM

Use BP algorithm network to adjust weights w_{ij}^{12} 、w_{ij}^{23} 、w_{ij}^{34} 、w_{ij}^{45} 、U_{ij} 、E_{ij} .

Define The network output error function[4-5]:

$$O_p = 0.6 \sum_j \left(a_j - b_j\right)^2, j = 1,2,\cdots,n \qquad (11)$$

a_j is the expected output of the network, b_j is the actual output of the network, and n is the number of output categories.

Suppose G_j^i is the error back-propagation signal the jth node of the ith layer of the network, then the layers can be expressed as:

Output layer

$$G_j^5 = \frac{\partial O_p}{\partial O_j^5} = a_j - b_j \qquad (12)$$

Fourth floor

$$G_j^4 = G_j^5\left[U_{ij} O_i^4 \sum_k^L E_{ik} O_i^4 - \sum_k^L U_{ij} E_{ik} O_i^4\right] / \left[\sum_k^L E_{ik} O_i^4\right]^2 \qquad (13)$$

In the formula, U_{ij} represents the mean value of the membership function, E_{ij} represents the standard deviation of the membership function, L is the number of output categories.

the third floor

$$G_j^3 = \sum_j^n G_j^5 \left[U_{ij} O_i^4 \sum_k^L E_{ik} O_i^4 - \sum_k^L U_{ij} E_{ik} O_i^4 \right] / \left[\sum_k^L E_{ik} O_i^4 \right]^2 \quad (14)$$

Second floor

$$G_j^2 = G_j^3 \sum_j^n \left(\left(1 - G_j^3\right) U_{ij} E_{ij} \right)^2 \quad (15)$$

The weight is calculated as:

w_{ij}^{12} is 1

$$w_{ij}^{23} = \frac{\eta}{m} \sum_{x \in n} G_j^2 / \sum_j \sum_{x \in n} G_j^2 \quad (16)$$

$$w_{ij}^{34} = \left(a_j - b_j\right) \times \eta \frac{\exp\left(-G_j^3\right)}{\left(1 + \exp\left(-G_j^3\right)\right)^2} \quad (17)$$

$$w_{ij}^{45} = \eta \sum_j \frac{1}{U_{ij}} \exp\left(-G_j^4\right) \quad (18)$$

U_{ij} , E_{ij} are the parameters in the second layer, find a step:

$$a_{ij}(k+1) = a_{ij}(k) + \Delta a_{ij} = a_{ij}(k) + \eta \left(\frac{\partial E_p}{\partial a_{ij}(k)} \right) \quad (19)$$

$$b_{ij}(k+1) = b_{ij}(k) + \Delta b_{ij} = b_{ij}(k) + \eta \left(\frac{\partial E_p}{\partial b_{ij}(k)} \right) \quad (20)$$

When E_p less than a given threshold ε , learning training stops. If the desired output has not been reached, the weight parameter is adjusted according to the formula until the predetermined requirement is reached.

4 SIMULATION

In this paper, the CBP2450 battery pack in reference[6] is used as the research object. The charge and discharge experiments are designed by using the ITECH series of DC electronic load and DC voltage source. The specific battery parameters are shown in Tab 1.

Tab. 1. The Battery Parameters

Production Model	Nominal Voltage/V	Nominal Capacity/AH
CBP2450	25.6	50
Size/mm	**Quality/kg**	**Internal Resistance/mΩ**
355×312×135	19	10
Working Temperature	**Storage Temperature**	**Ambient Humidity**
-20~50	-40~60	5~95

Fuzzy neural network has 3 nodes in the first layer, and selects voltage, current and temperature as network input; the second layer has 8 nodes; the third and fourth layers are fuzzy rules and the post is also 10 nodes; the fifth layer has 4 nodes. It corresponds to four states of lithium battery, including three major fault states and normal states, such as Corresponding Capacity reduction, Increase of internal resistance, and SOC Reduction.

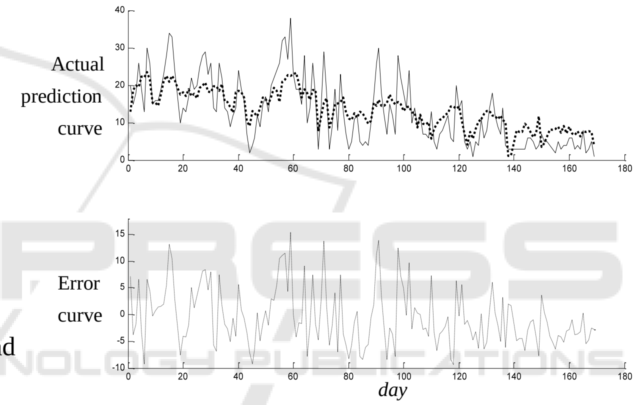

Fig. 2 Composite prediction result

Select 180 data to be as training and testing samples, and predict the actual curve and error curve, the result is Fig.2.

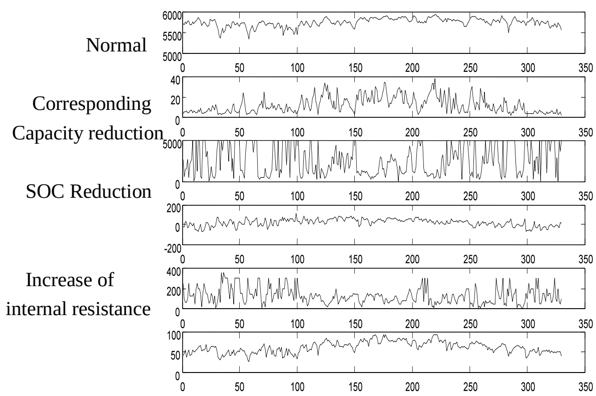

Fig. 3. Fuzzy neural networks prediction

Fig. 3 is a fuzzy neural network prediction, the function output corresponds to the discharge capacity. In the sample size, the battery discharge capacity can reach 100%. In order to facilitate the observation error, the error curve is drawn by the difference between the predicted output and the expected output to predict the lithium battery fault diagnosis. According to the prediction output , the lithium battery fault could be diagnosed and the result is credible.

After constructing the network, 150 training samples are input for training. In order to avoid over-learning, the training error precision is set, and the learning process is stable and convergent. After 75 cycles, the allowable error range has been reached. The BP network training error curve is shown in Fig. 4.

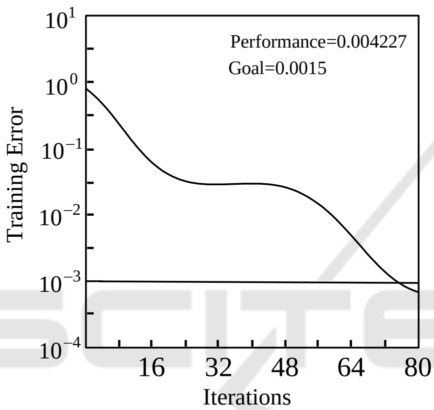

Fig. 4 Training error curve.

5 CONCLUSION

Based on the complexity and uncertainty of lithium battery faults in electric vehicles, this paper proposes a lithium battery fault diagnosis method based on fuzzy neural network. The method makes a preliminary diagnosis of lithium battery fault through neural network, and then uses the combination rule to fuse different neural network outputs, which can successfully diagnose the fault state of the lithium battery, and the diagnostic accuracy is higher than the single fault diagnosis method, and the diagnosis is improved. Sexuality, the result of the diagnosis is met, and the accurate judgment of the fault state of the lithium battery of the electric vehicle is obtained.

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