Fault Identification of High Frequency Current Ripple of Fuel Cell Based on Learning Vector Quantization Neural Network

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ABSTRACT

In order to solve the identification problem of high frequency current ripple fault in fuel cell system, a novel fault diagnosis method based on learning vector quantization (LVQ) neural network (NN) is proposed to diagnose fuel cell. 5 single cell voltages, stack voltage, current density and current are extracted as characteristic vectors. LVQ neural network is used as pattern classifier for fault diagnosis. The experimental results show that the novel method can quickly diagnose high frequency current ripple fault. The average classification accuracy is 94.95%, which verifies the practicability and effectiveness of the proposed approach.

INTRODUCTION

Proton exchange membrane fuel cell (PEMFC) has advantages of low working temperature, high energy density and zero emission. It is widely used in the transportation fields such as trams, cars and buses. However, fuel cell stack system (FCSS) is prone to failure in actual operation. Real-time diagnosis of PEMFC faults is particularly important for improving its stability and durability [1-3].

At present, artificial neural network (ANN) methods have been widely applied to the fault diagnosis of PEMFC. Shao Meng et al. [4] have proposed back propagating neural network (BP-ANN) ensemble method. The dynamic model and experiment of PEMFC system are used to analyze the mechanism and influence of heat transfer system, hydrogen oxygen mixture and gas supply system failure. The diagnostic accuracy can be increased from 85.62% to 93.24%. M. M. Kamal et al. [5] have used radial basis function neural network (RBF-ANN) as system model for fault detection in independent mode. It is found that residuals are sensitive to faults. N. Yousfi Steiner et al. [6] have proposed PEMFC water fault diagnosis method based on the extension neural network (ENN). Based on single cell temperature and current density, Ali. Mohammadi et al. [7] have realized the location of water

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flooding and membrane drying failure. The local parameters (single cell temperature, current and voltage distribution) are estimated by the 3D fault-sensitive model and the water faults are simulated. The faults can be located within 9 segments of single cell by feedforward neural network (FNN).

However, high frequency current ripple failure hasn’t been considered in the above research work. BP-ANN uses a non-linear strategy based on gradient descent. The problem is that the result may be a local minimum rather than an actual minimum. Other optimization strategies can obtain the global minimum, but the computation is large and the efficiency is low.

Learning Vector Quantization (LVQ) neural network is an input feedforward neural network for supervised learning in training competitive layer. The algorithm is evolved from the Kohonen competition algorithm [8,9]. Compared with other pattern recognition and mapping methods, LVQ neural network has the advantage of simple network structure. Complex classification can be accomplished through the interaction of internal units. It is also easy to converge the various complex design conditions in the design domain into the conclusion. Without the normalization and orthogonalization of the input vector, only the distance between the input vector and the competition layer need be directly calculated so as to realize the pattern recognition. It is simple and easy to implement. LVQ neural network has been widely used in pattern recognition and optimization.

In this paper, a novel method for fault diagnosis of fuel cell based on LVQ neural network is presented for the first time. The 5 single cell voltages, total stack voltage, current density and current of the 1 kW fuel cell system are used as characteristic vectors. Normal state and high frequency current ripple fault status are used as network output. 60 sets of training data are selected randomly to train the designed LVQ neural network. The remaining data are used as test set to verify the reliability of the method.

FAILURE ANALYSIS OF FUEL CELL

The PEMFC system used in this paper consists of 5 single cells. The activation area of each single cell is 100 cm$^2$. The experimental platform is shown in Fig.1.

Figure 1. 1 kW PEMFC test platform [10].
The PEMFC system in Fig.1 can provide more than 1 kW electrical power. The physical parameters that can be controlled and observed by the system include the stack temperature, the temperature of air and hydrogen, the pressure, the flow rate, and the temperature and flow rate of the cooling water. These physical parameters have been controlled by the automation equipment in the appropriate range to ensure the normal operation of the fuel cell system. The nominal current density of the system is 0.7 A/cm\(^2\) and the maximum current density is 1 A/cm\(^2\). It is divided into two kinds of running states: normal operating condition and high-frequency current ripple:

Normal operating conditions: Corresponding to the operation process of PEMFC system in stable state, the data of observable variables including the total output voltage of the PEMFC system and the output voltages of 5 single cells are covered. Among them, all physical parameters have been maintained at a stable range. The current density is \(J=0.7\) A/cm\(^2\).

High frequency current ripple: In accordance with the operation process of PEMFC system under dynamic current, high frequency current ripple is introduced to simulate the connection between the energy converter and the output of the fuel cell system. The current density fluctuates approximately \(\pm 0.07\) A/cm\(^2\) in the vicinity of 0.7 A/cm\(^2\).

**FAULT RECOGNITION BASED ON LVQ NEURAL NETWORK**

LVQ neural network consists of 3 layers of neurons, namely the input layer, the competition layer and the linear output layer, as shown in Fig.2. The full connection is used between the input layer and the competition layer. The partial connection is adopted between the competition layer and the linear output layer. The number of neurons in the competition layer is always greater than the number of neurons in the linear output layer. Each competition layer neuron is connected to only one linear output layer neuron and the connecting weight is constant to 1. However, each linear output layer neurons can be connected with a plurality of competitive neurons. The values of neurons in the competing neurons and linear output neurons can only be 1 or 0. When an input mode is sent to the network, the competition layer neurons nearest to the input mode are activated. The state of the neuron is "1" and the states of the other competing neurons are "0". Therefore, the
neuron states of the linear output layer connected to the activated neurons are also "1", while the states of the other linear output neurons are "0".

In Fig.2, $p$ is the input mode of the R dimension; $S^1$ is the number of neurons in the competition layer; $IW^{1,1}$ is the connection weight coefficient matrix between the input layer and the competition layer; $n^1$ is the input of neurons in competition layer; $a^1$ is the output of competitive layer neurons; $LW^{2,1}$ is the connection weights matrix between the competition layer and linear output layer; $n^2$ is the input of linear output layer neurons; $a^2$ is the output of the linear output layer neurons.

The LVQ neural network algorithm is a kind of learning algorithm which trains the competition layer under the supervised state, so the LVQ algorithm can be considered as an algorithm to improve the self organizing feature mapping algorithm into supervised learning. Vector quantization is a technique of data compression using the intrinsic structure of input vectors. LVQ is a supervised learning technique which can classify input vectors on the basis of vector quantization. Kohonen improved the self-organizing feature mapping algorithm into supervised learning algorithm. The training process of the algorithm begins by randomly selecting an input vector and the correct category of the vector from the "calibration" training set.

The basic idea of the algorithm: The nearest competition layer neurons are computed from the input vectors, so that the linear output layer neurons connected to them are found. If the class of input vectors is consistent with the corresponding categories of the linear output layer neurons, then the corresponding competition layer neuron weights move along the input vectors. Conversely, if the category of the two is inconsistent, the corresponding neuron weights of the competition layer move along the inverse direction of the input vector. The steps of the basic algorithm:

Step 1: The weight $w_{ij}$ and learning rate $\eta (\eta > 0)$ of the input layer and the competition layer are initialized;

Step 2: The input vector $x = (x_1, x_2, \cdots, x_R)^T$ is input to the input layer. The distance between the competing layer neuron and the input vector is calculated:

$$d_i = \sqrt{\sum_{j=1}^{R} (x_j - w_{ij})^2} \quad i=1,2,\cdots,S^1$$  \hspace{1cm} (1)

In the formula, $w_{ij}$ is the weight between the neuron $j$ of the input layer and the competing layer i.

Step 3: The competition layer neuron with the minimum distance from input vectors is selected. If $d_i$ is the smallest, the class label of the linear output layer neuron connected with it is $C_i$.

Step 4: The class label corresponding to the input vector is denoted as $C_x$. If $C_i = C_x$, the weights are adjusted as follows:

$$w_{ij\_new} = w_{ij\_old} + \eta (x - w_{ij\_old})$$  \hspace{1cm} (2)

Otherwise, the weights are updated as follows:

$$w_{ij\_new} = w_{ij\_old} - \eta (x - w_{ij\_old})$$  \hspace{1cm} (3)
DIAGNOSTIC EXAMPLES AND ANALYSIS

The 5 single cell voltages, total stack voltage, current density and current of the 1 kW fuel cell system are used as the input of the network. The normal state and fault state of high frequency current ripple are the output of the network. The trained LVQ neural network is trained with the training set data, then the test set data is tested and the test results are analyzed. The design steps are shown in Fig.3.

![Flow diagram of design procedure.](image)

The 1 kW fault diagnosis data set consists of 100 sets of data. Among them, data of normal state is 50 groups, data of high frequency current ripple fault state is 50 groups. 48 sets of data are randomly selected as training set, 12 sets of data are as verification set and 40 sets of data are as test set, as shown in Fig.4. After 5-fold cross validation, the optimal number of neurons is 10.

![Composition table of fault diagnosis data sets.](image)

![Identification results of the confusion matrix.](image)
In order to express the recognition rate of the model, the confusion matrix is introduced as shown in Fig.5. For a 2 class classification problem, the confusion matrix is a $2 \times 2$ matrix. The rows of the confusion matrix represent the actual category, and the columns indicate the forecast category. The element $M(i, j)$ in the matrix indicates that a sample of $M(i, j)$ with actual category of $i$ is predicted to be a sample of class $j$. In the ideal case, the prediction category for each sample is correct, then the confusion matrix becomes a diagonal matrix. As can be seen from Fig.5, the ratio of the correct forecast of each sample is 95.8%.

The classification results of test set are shown in Fig.6. Among them, $N$ represents normal state and $F$ denotes high frequency current ripple failure. The results show that there are two sets of data misdiagnosis in the 40 sets of test set data. (1 group of normal operation state is mistakenly diagnosed as high frequency current ripple fault. 1 group of high frequency current ripple fault is mistakenly diagnosed as normal operation.). The average diagnostic accuracy is 94.95%.

**SUMMARY**

LVQ neural network is used to realize the fault diagnosis of fuel cell. The 5 single cell voltages, total stack voltage, current density and current of the 1 kW fuel cell system are used as characteristic vectors. The normal state and high frequency current ripple fault state are used as network output. The results of the 40 groups of test sets indicate that: The accuracy of the normal state classification is 94.44%. The classification accuracy of high frequency current ripple fault is 95.45%. The average fault recognition rate is 94.95%. The new findings of the research are that the novel approach can quickly identify the high-frequency current ripple fault of fuel cell.

**REFERENCES**

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