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An artificial neural network ensemble method for fault diagnosis of proton exchange membrane fuel cell system

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ABSTRACT

The commercial viability of PEMFC (proton exchange membrane fuel cell) systems depends on using effective fault diagnosis technologies in PEMFC systems. However, many researchers have experimentally studied PEMFC (proton exchange membrane fuel cell) systems without considering certain fault conditions. In this paper, an ANN (artificial neural network) ensemble method is presented that improves the stability and reliability of the PEMFC systems. In the first part, a transient model giving it flexibility in application to some exceptional conditions is built. The PEMFC dynamic model is built and simulated using MATLAB. In the second, using this model and experiments, the mechanisms of four different faults in PEMFC systems are analyzed in detail. Third, the ANN ensemble for the fault diagnosis is built and modeled. This model is trained and tested by the data. The test result shows that, compared with the previous method for fault diagnosis of PEMFC systems, the proposed fault diagnosis method has higher diagnostic rate and generalization ability. Moreover, the partial structure of this method can be altered easily, along with the change of the PEMFC systems. In general, this method for diagnosis of PEMFC has value for certain applications.

1. Introduction

As civilization continues to grow and develop, there are solid reasons to expect demand for low-pollution and high-efficiency energy to grow. PEMFC (Proton exchange membrane fuel cell) which is capable of using hydrogen as an energy source can provide reliable power in a steady state. PEMFC changes the chemical energy into electric power through a chemical reaction, where the only waste product, when the reagent is pure hydrogen, is pure water. At present, PEMFC systems have been applied in many fields, especially in transportation. For example, most vehicle manufacturers are presently researching, developing, or testing PEMFC vehicles [1,2]. Many governments have also paid close attention to the continuing development of PEMFC. A PEMFC power generating system is composed of a PEMFC stack and some support systems, which make the whole PEMFC system very complex [3].

The faults in PEMFC systems may cause injuries or property damage, so the fault monitoring and diagnosis technology is an indispensable part of the whole system. N. Yousfi Steiner et al. [4] present a diagnosis procedure for water management issues in fuel cell, namely flooding and drying out, based on a limited number of parameters. Latevi Placca et al. [5] presented Fault Tree analysis for PEM (Proton exchange membrane) fuel cell degradation process modeling. In the work of Luis Alberto M. Riascos et al. [6], the Bayesian network (i.e. the graphical–probabilistic structure) is used to execute the diagnosis of fault causes in the PEMFC model based on the effects observed. Carton et al. [7] analyze and discuss the water droplet accumulation and motion in PEMFC mini-channels. Giddey et al. [8] presented a passive method of water management for a PEMFC. P.R. Pathapati et al. [9] built a new dynamic model for predicting transient phenomena in a PEM fuel cell system Carton et al. [10] design an experiment study of the parameters that affect performance of three flow plate configurations of a proton exchange membrane fuel cell. This paper presents an ANN (artificial neural network) ensemble method, which makes the fault diagnosis of PEMFC systems more simple and reliable.

2. PEMFC dynamic model

For analyzing the faults in PEMFC systems clearly, PEMFC dynamic model should be studied firstly. It is generally known that

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PEMFC is a kind of low temperature fuel cell and the operation temperature is 55 °C, so the product of reaction is liquid water. The overall reaction in the PEMFC is represented as follows [11]:

$$H_2 + \frac{1}{2}O_2 \rightarrow H_2O \tag{1}$$

2.1. Output voltage

The output voltage of a PEMFC stack can be expressed by the following equation:

$$V_{out} = N \cdot V_{cell} = N \cdot (E_{cell} - V_{act,cell} - V_{ohm,cell} - V_{conc,cell}) \tag{2}$$

where V_{out} is the output voltage of a PEMFC stack, N is the number of cells in the stack, V_{cell} is the output voltage of single cell, E_{cell} is the reversible potential of single cell.

According to Nernst equation, the reversible potential is modified as follows [12]:

$$E_{cell} = E^{\circ}_{0,cell} - k_E(T - 297.15) + \frac{RT}{2F}\ln\left[P_{H_2} \times (P_{O_2})^{\frac{1}{2}}\right] \tag{3}$$

where $E^{\circ}_{0,cell}$ is the standard reference potential at standard state (298.15 K and 1 atm pressure), k_E is the empirical constant, T is the operation temperature, P_{H_2} is the hydrogen pressure and P_{O_2} is the oxygen partial pressure.

The gas delays effect on the fuel cell output voltage obviously, during transients of the PEMFC load. The gas delays are represented by a voltage ($E_{d,cell}$), which is a function of time [13].

$$E_{d,cell} = \lambda_e \left[i(t) - i(t) \otimes \exp\left(-\frac{t}{\tau_e}\right)\right] \tag{4}$$

where λ_e is a constant, and τ_e is the gas flow delay.

As the above discussion, the reversible potential, E_{cell} given by Eq. (3) can be modified as follows:

$$E_{cell} = E^{\circ}_{0,cell} - k_E(T - 297.15) + \frac{RT}{2F}\ln\left[P_{H_2} \times (P_{O_2})^{\frac{1}{2}}\right] - E_{d,cell} \tag{5}$$

V_{act} the voltage drop due to the fuel cell activation loss, is defined by Tafel equation as follows:

$$V_{act} = \xi_0 + a \cdot (T - 297.15) + T \cdot b \ln(I) \tag{6}$$

where ξ_0, a, b are empirical constants, I is the current density of the PEMFC.

V_{ohm} the voltage drop due to the ohmic resistance of the PEMFC, is expressed as follows:

$$V_{ohm} = I \cdot (R_{ohm,0} + k_{RI}I - k_{RT}T) \tag{7}$$

where $R_{ohm,0}$ is the constant part of the ohmic resistance of the PEMFC, k_{RI} and k_{RT} are the empirical constants.

In the process of the reaction in PEMFC, mass diffusion from the gas flow channels to the catalyst surfaces for reaction influences the concentration of the gas. V_{conc} is the voltage drop due to the above description:

$$V_{conc} = \frac{RT}{2F}\ln\left(1 - \frac{i}{i_{limit}}\right) \tag{8}$$

where i_{limit} is the limit of current density. i is the overall current density which consists of i_{out} (the output current density) and the i_{in} (the internal current loss associated with fuel crossover).

Table 1
Parameters of a PEMFC stack.

Parameter	Unit	Value
Power	W	500
Number of cells		36
Environmental T	°C	5–30
Unit dimensions	cm	22.5 × 12.5 × 17.5
Weight	kg	2.5
E_0	V	44.15
k_e	V/K	0.00085
λ_e	Ω	0.00333
τ_e	s	80.00
ξ_0	V	20.145
a	V/K	−0.1373
b	V/K	−0.000193
$R_{ohm,0}$	Ω	0.2793
i_{limit}	A/cm^2	0.468
k_{RI}		0.001872
k_{RT}		−0.0023712
R	J/mol.K	8.3143
F	C/mol	96,487
C	J/kg.K	35

2.2. Heat transfer

The main reason of the temperature variation is the heat transfer in the PEMFC, which is defined as follows [13]:

$$q_{net} = q_{chem} - q_{elec} - q_{sens} - q_{loss} - q_{cool} \tag{9}$$

where q_{net} is the net heat energy, q_{chem} is the chemical energy from the gas reaction, q_{elec} is the energy which is consumed by the load, q_{sens} is the sensible heat, q_{loss} is the heat loss due to the heat exchange between the stack and the surrounding air, and q_{cool} is the heat removing due to the artificial cooling system.

The change of stack temperature depends on the net heat energy. The temperature can be calculated by the following equation:

$$MC\left(\frac{dT}{dt}\right) = q_{net} \tag{10}$$

where M is the mass of the PEMFC stack and C is the specific heat capacity of the stack. The value of C may be determined by the individual components of the fuel cell stack such as the graphite and stainless steel. The specific heat capacity of stack is estimated from data in the references [9,13].

When some faults occur, the steady-state of PEMFC will be disappeared. The transient model is significant for this research. The transient model obtained by coupling the steady-state

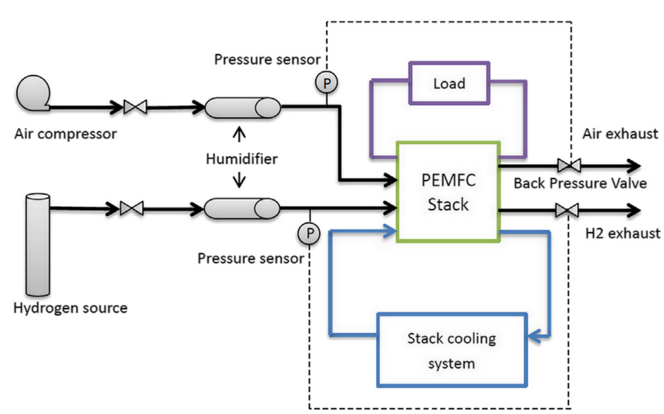

Fig. 1. Structure of a PEMFC system.

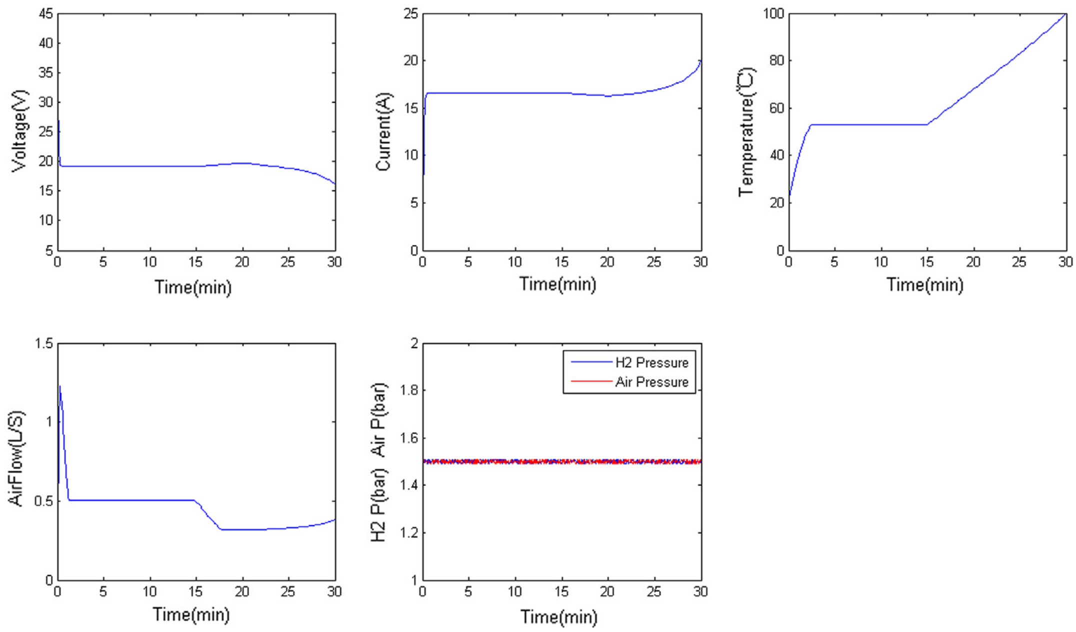

Fig. 2. Evolution of the parameters under fault in the stack cooling system.

electrochemical model and the thermal model as a function of time with the new accumulation term.

In experiments, a 500 W PEMFC stack with appropriate power is used for fault diagnosis. The parameters of this stack are presented in Table 1. Based on the previous PEMFC model analysis and these experience parameters, a transient model of the 500 W PEMFC stack is built with MATLAB software [18].

3. PEMFC systems structure

Fig. 1 illustrates a complete PEMFC system which consists of a PEMFC stack, a load, an air delivery subsystem, a hydrogen delivery subsystem and a stack cooling subsystem [20–22]. In this system, the controller maintains the P_{H_2} and P_{O_2} around 1.5 atm by changing the corresponding back pressure valve. The stack cooling system keeps the stack temperature below 55 °C. An electronic resistive load is adopted for controlling the current density of the PEMFC stack at a specified value [12,14].

4. Fault analysis

In PEMFC systems, there are two types of faults: faults that can be detected by some sensors and faults that cannot be detected directly. Both types of faults influence on the normal running of the PEMFC systems. In most cases, however, fault detection on commercial PEMFC systems is limited to detection of faults of the

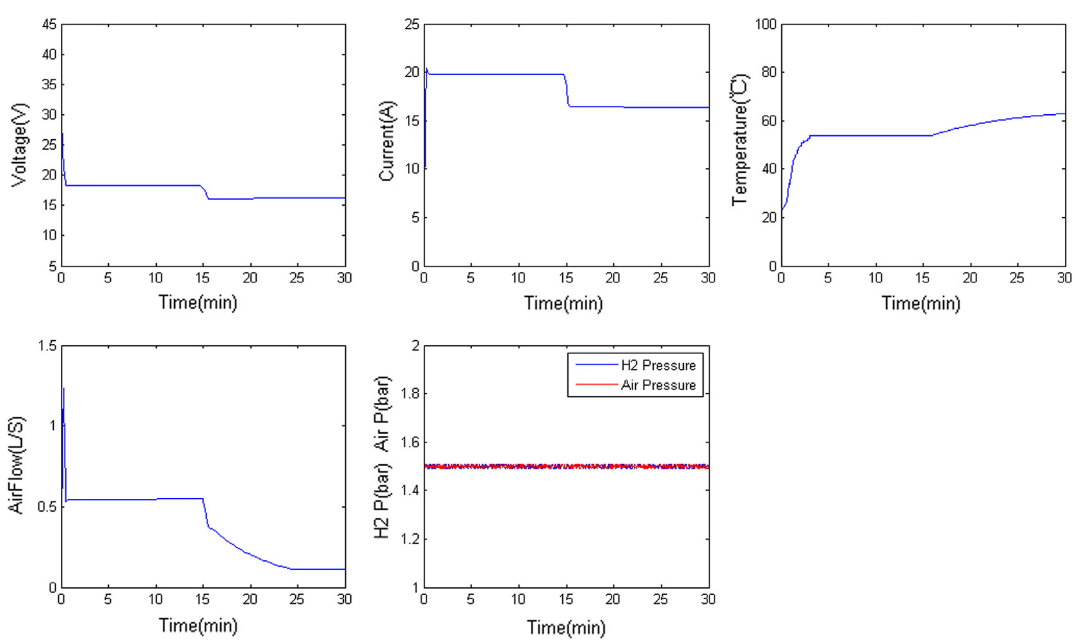

Fig. 3. Evolution of the parameters under increasing of fuel crossover.

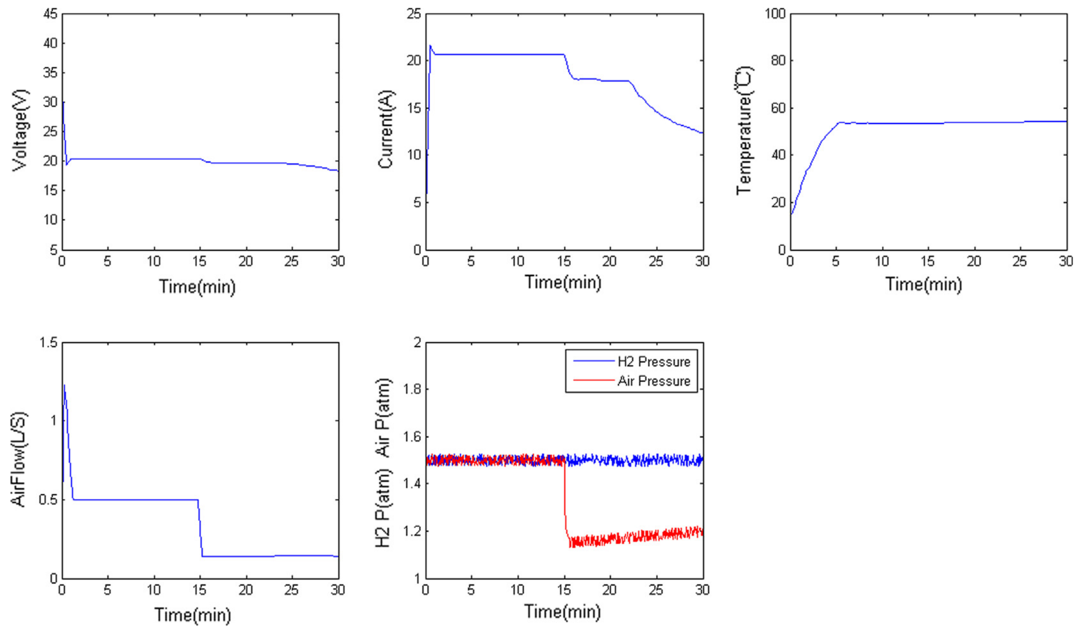

Fig. 4. Evolution of the parameters under fault in air delivery system.

first type. This paper focuses on fault detection of the second type [17].

According to the discussion about the PEMFC dynamic mode, four types of faults in the system are found and analyzed as follows.

4.1. Fault in the stack cooling system

The stack cooling system is used to maintain the temperature of the stack within the accepted range. In experiments, the normal operational temperature of the stack is about 55 °C. During the increasing of temperature, the high operational temperature can improve the performance of the PEMFC stack, but the MEA (polymer electrolyte membrane) are dying out quickly, that will case the MEA degradation [6,12].

The evolution of the parameters under the fault in the stack cooling system is shown in Fig. 2. During the first 15 min, the PEMFC stack works fine. The fault in stack cooling system happens at the 15th minute, so the q_{cool} decreases rapidly and the stack temperature increases obviously (Eq. (10)).

4.2. Increasing of fuel crossover

In the case of fuel crossover phenomenon, some hydrogen can transfer through the membrane and react directly with oxygen to produce heat only. In normal condition, there is only a few

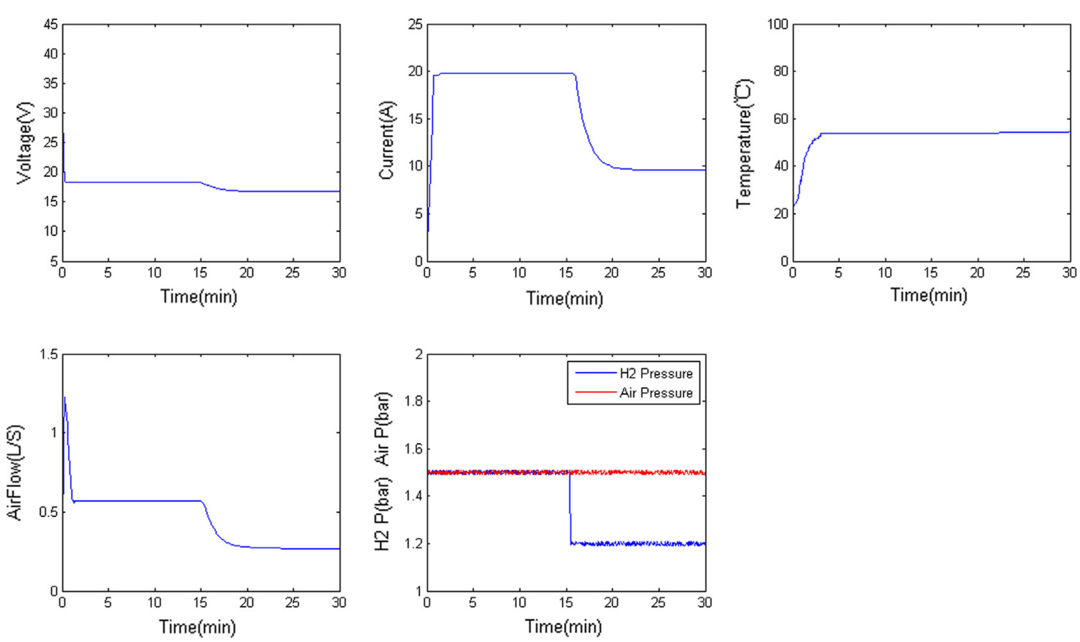

Fig. 5. Evolution of the parameters under fault in air delivery system.

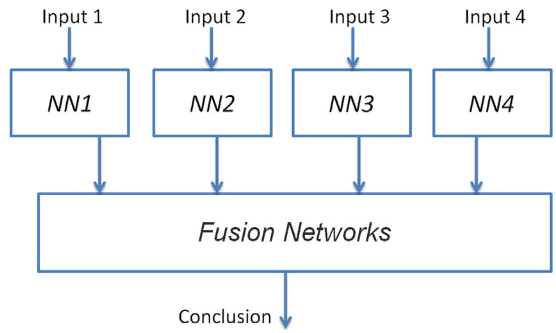

Fig. 6. Basic framework of a network ensemble.

hydrogen which transfers through the membrane, so i_{in} is very small. Increased local temperature increases MEA degradation [6].

Fig. 3 illustrates the evolution of the parameters under the increasing of fuel crossover. While the increasing of fuel crossover inside the PEMFC, there is a rise in stack temperature at the meantime.

4.3. Fault in air delivery system

There are two main faults in the air delivery system: the leak of air channel and the fault in the air compressor. Both faults lead to the following consequences: first, air pressure drops obviously, which lowers the effect of the reaction in the PEMFC. Second, the faults lead to the decrease of the oxygen which should react with the hydrogen, and then the decrease of the oxygen leads the decrease of current directly. The last consequence is the accumulation of liquid water which should be blown away by the airflow. A great accumulation of water flood the electrodes which makes gas diffusion difficult and affects the performance of the stack [4,6].

Fig. 4 illustrates the evolution of the parameters when the fault in air delivery system occurs. Air pressure reduces from 1.5 atm to 1.2 atm at the 15th minute.

4.4. Fault in hydrogen delivery system

In theory, the higher the hydrogen pressure, the better the performance of the stack. When the fault in hydrogen delivery system occurs, the reduction of hydrogen pressure reduces the current density directly and degrades the performance of the stack. The hydrogen pressure should be maintained at 1.5 atm. Fig. 5 illustrates that the hydrogen pressure reduces from 1.5 atm to 1.2 atm at the 15th minute, and then other parameters change obviously.

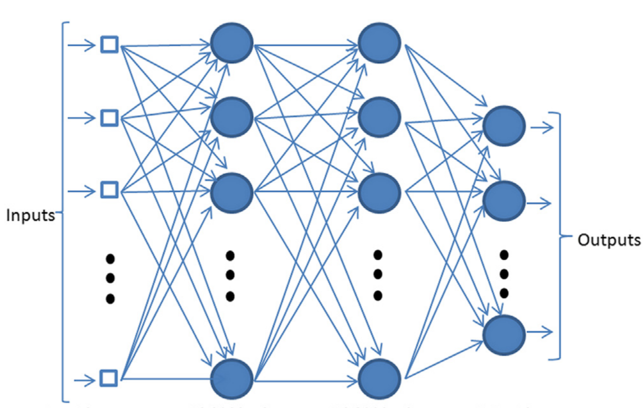

Fig. 7. Structure of the BP artificial ANN.

Table 2
Parameters of the sub-NNs.

	NN1	NN2	NN3	NN4
Network type	BP	BP	BP	BP
Nodes	6–13–4	3–7–4	6–13–4	3–8–4
Inputs	$V(t)$, $I(t)$, $V(t-1)$,$I(t-1)$, $V(t-2)$,$I(t-2)$	$T(t)$, $T(t-1)$, $T(t-2)$	$F(t)$, $F(t-1)$, $F(t-2)$	$P_{H_2}(t)$, $P_{O_2}(t)$, $P_{H_2}(t-1)P_{O_2}(t-1)$, $P_{H_2}(t-2)$,$P_{O_2}(t-2)$

5. Artificial neural network ensemble method

In 1990, the ANN ensemble was proposed by Hansen and Salamon. This method improves the generalization capability and reliability of the ANN system through training several ANNs for the same task, and then combining their outputs. The ensemble method is composed of individual generating and conclusion generating. Also, the individual generating steps include neural network selection and parameter determine. The most profound difficulty about the fault diagnostics of the PEMFC systems is the high coupling of these variables. The ANN ensemble provides an accurate and practical method [15,16,19].

5.1. Architecture of the artificial neural network ensemble

Fig. 6 illustrates the basic framework of the network ensemble. Firstly, each sub-ANN in the ensemble is trained using the corresponding training samples. Then, the outputs of these sub-ANNs are combined to produce the outputs of the whole ensemble. The number of the sub-ANNs should be determined based on the parameters of PEMFC systems.

5.2. Sub-ANNs design

An ANN ensemble is composed of several sub-ANNs. The structure of each sub-ANN directly affects the diagnosis effect of the ANN ensemble, so all sub-ANN should follow the following principles: first, the correlation among these sub-ANNs should be as small as possible. Second, the correlation among the inputs of the sub-ANNs should be as small as possible [15].

In this paper, sub-ANNs based on the types of signals are adopted, because the different sub-ANNs take as input the different signals. This approach is conducive to ensuring the irrelevancies among the inputs of the sub-ANNs.

In the PEMFC systems, there are six variables which can be detected directly. They are V_{out}, I, T, F_{air}(Air Flow), P_{H_2} and P_{O_2}. According to the above discussion, four sub-ANNs are used for composing the ANN ensemble. The evolutions of these variables are the functions of time, after some faults occurring. For better capturing the evolution of each variable, three values about each parameter in three moments are used (e.g. $V(t)$, $V(t-1)$, $V(t-2)$ are the values about the output voltage in three moments respectively).

There are many types of ANN that can be used for fault detection. By a series tests, this work eventually chooses BP-ANN (Back-Propagating ANNs) for four sub-ANNs of the ANN ensemble. The topology of the BP (Back-Propagating) network is defined by the organization of the neurons. The multilayer Perceptron network is organized by setting the number of neurons in the input and output layer according to the specific application, and experientially determine the amount of hidden layers and neurons. Connections between two different neurons are called weights. Moreover each one has a bias that makes it work or not work depending on the level of the input signal. The ith neuron's input is formed by the numerical combination of the weight, the bias, and the output

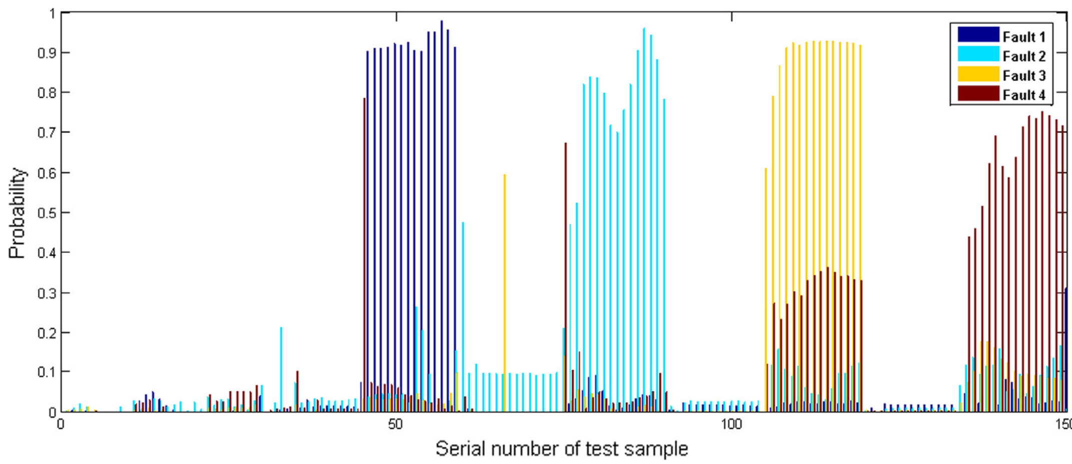

Fig. 8. Probability of faults diagnosis: fault1 is the fault in the stack cooling system; fault2 is increasing of fuel crossover inside; fault3 is the fault in air delivery system; fault4 is the fault in hydrogen delivery system.

signals from the previous neurons. Each neuron's input signal is described by the following formula:

$$\text{Input}_i = \sum_{j=1}^{k} w_{ij}x_j + b_j \tag{11}$$

where Input_i is the input signal of the ith neuron, k is the number of neurons in the prior layer, w_{ij} is the weight between the ith neuron and the jth neuron in the prior layer, x_j is the output signal of the jth neuron in the prior layer, b_j is the bias of the jth neuron in the prior layer.

Fig. 7 illustrates the structure of a BP-ANN with two hidden layers and one output layer. This neural network is full-connection. The structures of four sub-ANNs are presented in Table 2. In this paper, the values of the weight and bias provided to the BP network are updated using the Levenberg–Marquardt optimization with the error goal of 0.001.

5.3. Combining network

Combining network combines these outputs of the sub-ANNs into the final result. This paper uses the Lagrange multiplier method to combine these sub-ANNs. The main idea of the Lagrange multiplier method is that it takes the square sum as the object function and the weight coefficient is determined by optimizing the accuracy of the ANN ensemble.

$$P_i = [p_{1i}, p_{2i}, \cdots, p_{ni}]^* \quad r_i = [r_{1i}, r_{2i}, \cdots, r_{ni}]^* \tag{12}$$

where P_i is the failure vector of the ith sub-ANN, r_i is the weight vector of the ith sub-ANN for all faults.

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nm} \end{pmatrix} \quad R = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix} \tag{13}$$

where P is the fault matrix, R is weight coefficient matrix, n is the number of the faults, m is the number of the sub-ANNs.

The function of the combining network is presented as follows:

$$Y = P \cdot R \tag{14}$$

where Y is the output of the combining network.

According to Eq. (13), the probability of the jth fault is calculated by the following equation:

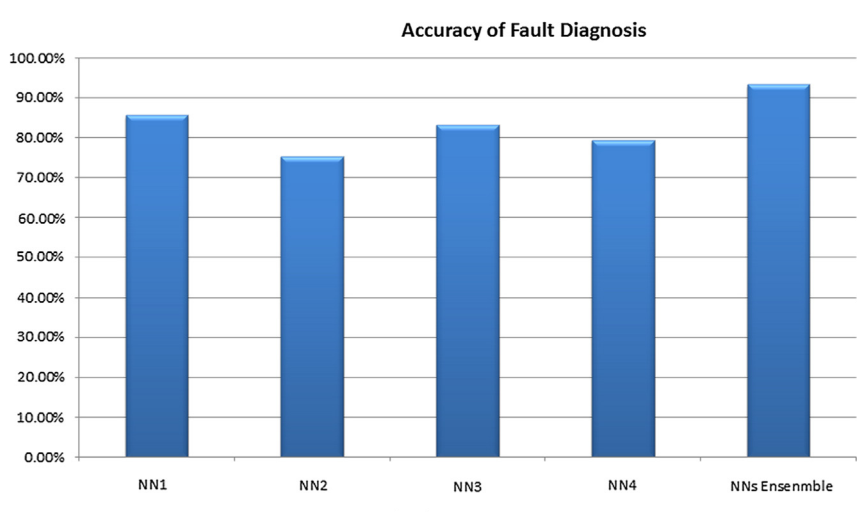

Fig. 9. Accuracy of fault diagnosis.

$$Y_j = p_{j1}r_{1j} + p_{j2}r_{2j} + \cdots + p_{jm}r_{mj} \tag{15}$$

where Y_j is the probability of the jth fault.

In order to improve the result of the fault diagnosis, an operator "$\mp$" is defined as follows:

$$a \mp b = a + b - ab \tag{16}$$

Eq. 14 is improved as follows:

$$Y_j = p_{j1}r_{1j} \mp p_{j2}r_{2j} \mp \cdots \mp p_{jm}r_{mj} \tag{17}$$

The advanced combining method takes into account the results of the all sub-ANNs and reflects reality roundly.

Fig. 8 shows the probabilities of faults diagnosis using the ANN ensemble method. There are 150 points in test sample data. From 1st to 45th, 61st to 75th, 91st to 105th, 121st to 135th, there are no faults occurred. From 46th to 60th, the fault in the stack cooling system occurs. From 76th to 90th, fuel crossover increases. From 106th to 120th, the fault in air delivery system occurs. From 136th to 150th, the fault in hydrogen delivery system occurs.

6. Result and discussion

The unsteady-state of the PEMFC systems appears, when there are faults occur. It is necessary to build a transient model for researching the transient phenomena which are caused by faults in the PEMFC systems. The simulant results have shown that the model is capable of predicting transient behavior in flow rates, voltage, and temperature and pressure.

By some random samples to test, the accuracies of the sub-ANNs are presented in Fig. 9. The accuracies of these sub-ANNs are distributed on the interval from 75.24% to 85.62%, and the accuracy of ANN ensemble increases to 93.24%. The overall performance of the ANN is significantly improved by the ANN ensemble method. The phenomena of misinformation and failing to report in fault diagnosis are significantly reduced.

Above all, the framework of the ANN ensemble can adjust department structure of the PEMFC systems. Each sub-ANN can be removed from the network ensemble or added to the network ensemble, but that does not affect others. When some new monitoring units are added to the PEMFC systems, what we just need to do is designing and training some suitable sub-ANNs, then adding these sub-ANNs to the ANN ensemble. Comparing with the single huge network for fault diagnosis, the ANN ensemble can conspicuously reduce duplication of effort.

7. Conclusions

A dynamic model of the PEMFC systems is analyzed and simulated by MATLAB. Based on the dynamic model, this paper discusses four faults in the PEMFC systems (Fault in the stack cooling system; Increasing of fuel crossover; Fault in air delivery system; Fault in hydrogen delivery system), and then the evolutions of the parameters under these faults are respectively illustrated in Figs. 2–4, and Fig. 5. Simulation results presented above clearly indicate the dynamic change of a PEMFC. According to the research above, the mechanism and effect of the faults in the PEMFC systems are clearly presented. An ANN ensemble method is used for the fault diagnostics of the PEMFC (proton exchange membrane fuel cell). The ANN ensemble method based on BP-ANN and the Lagrange multiplier method is designed and simulated by MATLAB.

Over all the results indicate that faults in the PEMFC seriously influence the normal operation of the PEMFC, and fault diagnosis is an essential part of a PEMFC system. This paper details the mechanism and effect of the faults. The ANN ensemble method is used is a utility tool for faults diagnosis of the PEMFC systems. The accuracies of the normal BP networks applied to fault diagnosis are distributed on the interval from 75.24% to 85.62%. This method can improve the accuracy to 93.24%, and greatly reduce the phenomena of misinformation and failing to report in fault diagnosis. Due to the open framework of this method, the partial structure of this method can be altered easily, along with the change of the PEMFC systems. With a few modifications, the faults diagnosis of the PEMFC systems can easily connect to the faults diagnosis of some complex hybrid systems which contains PEMFC systems. Above all, this method can be considered as a widely applicable method for faults diagnostic of the PEMFC systems.

In the further work, to improve the performance of the ANN ensemble method, more sample data needs to be included. And more research into the practical application of this method should be carried out.

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