Fault Diagnosis for Fuel Cell Stack using Independent MLP Neural Network

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Abstract—This paper presents a new method of fault diagnosis for fuel cell stack dynamic systems using independent multilayer perceptron (MLP) neural network to perform fault detection and isolation. The novelty is that the MLP model of independent mode is used to predict the future outputs of the fuel cell stack. One actuator fault, one component fault and three sensor faults have been introduced to the fuel cell systems experience faults of +10% of fault size. To validate the results, a benchmark model developed by Michigan University is used in the simulation to investigate the effect of these five faults. The developed independent MLP model is tested on MATLAB R2000a/Simulink environment. The simulation results confirm the effectiveness of the proposed method for fault diagnosis. By using this method, the MLP network able to detect and isolate all five faults accordingly and accurately.

Keywords—Fuel cell stack, multilayer perceptron neural network, independent model, fault diagnosis

I. INTRODUCTION

Fault diagnosis is one of the important tasks in safety-critical and intelligent control systems in Patton et al. (1994). Fault diagnosis has received a lot of theoretical and practical attention over the last few decades. Diagnosis is a complex reasoning activity, which currently one of the domains where artificial intelligence techniques have been successfully applied as these techniques use association rule, reasoning and decision making processes as would the human brain in solving diagnostic problems. The problem of fault detection and diagnosis in dynamic systems has received considerable attention in last decades due to growing complexity of modern engineering systems and ever increasing demand for fault tolerance, cost efficiency and reliability by Willsky (1976) and Basseville (1988).

The potential of neural networks for fault diagnosis in nonlinear systems has been demonstrated in recent years. Neural networks provide an excellent mathematical tool for dealing with nonlinear problems (Narendra and Parthasarathy, 1990). Bayesian network has been proposed by Riascos et al. (2006) as an early alert to diagnose faults in the air reaction fan, inside the cooling system and also in the hydrogen feed line. The authors also used it to diagnose the growth of the fuel crossover and internal loss current. To improve reliability and durability of fuel cell systems, Escobet et al. (2009) presents a flooding diagnosis based on a black-box model of ENN. Here, ENN is used to do a comparison between measured and calculated pressure drops where the ENN is trained with a flooding-free condition and the difference between calculated and experimental pressure drop is used as the residual. Also in Kamal and Yu (2013), the fault diagnosis of fuel cell stack using RBF network is used to perform fault detection and isolation. In this paper, to make the fault diagnosis more efficient and robust to five types of faults in the fuel cell stack, an independent MLP network is used for fault diagnosis.

The aim of this work is to develop a fault diagnosis scheme under open-loop system for fuel cell stack using an independent MLP network model which able to detect five faults and can isolate them accordingly.

II. FUEL CELL STACK SYSTEMS

A fuel cell is an electrochemical energy conversion device which converts the chemical hydrogen and oxygen into water and in the process produces electricity. It is constructed like a sandwich, with an electrolyte between two electrodes, known as anode and cathode (Kamal and Yu, 2013).

![Fuel cell chemical reaction](Fig. 1)

Electron flow

Hydrogen, H₂ → Anode → e⁻ → H₂O → Cathode → O₂ → Oxygen, O₂ → Water → Heat

Fig. 1 Fuel cell chemical reaction

Hydrogen is fed to the anode, and oxygen is fed to the cathode. Activated by a catalyst, hydrogen atoms separate into protons and electrons where the electrons go through the load circuit and creates electricity. As shown in Fig. 1, the protons migrate through the electrolyte and reunite with oxygen which produced water and heat.

III. MULTILAYER PERCEPTRON NEURAL NETWORK

The MLP networks with back-propagation training algorithm by Rumelhart et al. (1986) are the most commonly used type of feedforward neural network. MLP has three types of layers: an input layer, a hidden layer and an output layer. Here, three layers MLP has been used as the architecture based
on justification made by Lippmann (1987) which stated that three layers of MLP is adequate on the basis. The input-output mapping for the MLP network can be described as:

\[ h_i = f \left( \sum_{j=0}^{N} w_{ij} x_j \right) \]  

(1)

where \( h_i \) is output from each hidden neuron \( J \) and \( w_{ij} \) is the weight connecting the input, \( x_i \) and hidden input and \( f \) is the tangent sigmoid activation function. The output of hidden neuron, \( h_o \) is calculated by

\[ h_o = \left( \frac{2}{1 + \exp(-h_i)} - 1 \right) \]  

(2)

where the activation function take the inputs and squash the outputs into the range of -1 and 1. The output of network, \( \hat{y}_{mlp} \) is given by:

\[ \hat{y}_{mlp} = w_{jk} h_o \]  

(3)

where \( w_{jk} \) is the weight connecting the output layer and the output of the hidden neuron.

IV. SIMULATING FAULTS

In this study, five faults are introduced to a known test-bench PEMFC based on the model developed in Michigan University by Pukrushpan et al. (2004). One actuator fault, one component fault and three sensors fault which are simulated having +10% change of fault size from the nominal values. The fuel cell stack simulator was modified in Kamal and Yu (2011) to include five possible fault scenarios which may occur during the normal operation of fuel cell systems. Fig. 3 shows the five faults introduced to the overall PEMFC systems.

V. FAULT DIAGNOSIS

The implementation of fault diagnosis is done in the MATLAB R2000a/Simulink environment. In this work, a data set with 6000 samples is acquired from the plant when the five faults are simulated to the plant. The fault diagnosis can be divided into two parts: fault detection and fault isolation.

A. Fault Detection

By applying fault detection, it determines that problems have occurred in the fuel cell stack. In order to do this, the filtered squared model prediction error for each output is used as fault detection signal, where a residual signal is generated by the combination of these prediction errors. The sensitivity of the residual to each fault can be significantly enhanced, and consequently the false alarm rate would be reduced. The residual error in this work is defined as in equation (4) as in Kamal and Yu (2012).

\[ re = \sqrt{e_{NP}^2 + e_{\lambda O_2}^2 + e_{SV}^2} \]  

(4)

where \( e_{NP} \) is the filtered modeling error of net power, \( e_{\lambda O_2} \) is the filtered modeling error of \( \lambda O_2 \) and \( e_{SV} \) is the filtered modeling error of stack voltage.
B. Fault Isolation

RBF classifier is used to perform fault isolation using the MLP residuals error signals. The five outputs are arranged in this way: The target for any one output is arranged to be “1” when the corresponding single fault occurs, and to be “0” when this single fault does not occur. In this study, 6000 samples of data were collected with the first fault occurring during \( k = 1001 \sim 1200 \), the second fault occurring during \( k = 2001 \sim 2200 \), etc. Then, the generated filtered squared model prediction error vector from the fault detection part was used as the input data of the RBF classifier. Correspondingly, the target matrix \( X_0 \) has 6000 rows and 5 columns. The entries from the 1001\(^{th}\) row to the 1200\(^{th}\) row in the first column are “1”, while the other entries are “0”. The arrangement for the column 2 to 5 is done in the same way. This is shown as in Table I.

<table>
<thead>
<tr>
<th>Rows</th>
<th>( X_0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1001~1200</td>
<td>[1 0 0 0 0](^T)</td>
</tr>
<tr>
<td>2001~2200</td>
<td>[0 1 0 0 0](^T)</td>
</tr>
<tr>
<td>3001~3200</td>
<td>[0 0 1 0 0](^T)</td>
</tr>
<tr>
<td>4001~4200</td>
<td>[0 0 0 1 0](^T)</td>
</tr>
<tr>
<td>5001~5200</td>
<td>[0 0 0 0 1](^T)</td>
</tr>
</tbody>
</table>

VI. SIMULATION RESULTS

The random amplitude signals (RAS) of stack current used as disturbances to fuel cell stack has been injected. The RAS excitation signals of stack current are generated randomly to cover the whole range of frequencies and the entire operating amplitude in the fuel cell systems. The simulation result of three fuel cell outputs and the corresponding five faults is shown in Fig. 4. It shows the squared filtered model prediction errors for the three output variables. As can be seen, it is easily to detect that there is a fault due to sensorNP at \( k=1001 \) and sensorSV at \( k=3001 \) due to the fault size is higher than the others. However it is hardly to define which faults occurred in the output signals of oxygen excess output because there are more than one fault signals inside it.

Based on the result obtained in Fig. 4, in order to identify the types of faults occurred, the residual generator as stated in equation (4) was applied. Here, the fault occurrence can clearly identified and detected with their respective threshold after the implementation. It is observed in Fig. 5 that all five faults of three sensors, component and actuator faults are clearly detected.

The target matrix in Table I was used in training of the RBF classifier. After training, a similar data set with also 6000 samples, with the same five faults simulated, was collected. These data was applied to the fault detection part and then the isolation part with the trained RBF classifier. The five outputs of the classifier are displayed in Fig. 6.
VII. CONCLUSIONS

This work presents the development of fault diagnosis using an independent MLP network model to perform fault detection and the RBF network as a classifier to do fault isolation. The simulation results show that the with +10% faults size of the nominal values, all these five faults are successfully detected and isolated. It is important to detect and isolate the malfunction devices in the systems for troubleshooting and maintenance. By applying this step, the malfunction devices can easily be monitored and replaced in order to save time and safety purposes.

REFERENCES

http://dx.doi.org/10.1016/j.jpowsour.2008.12.014