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Fault Detection and Isolation using RBF Networks for Polymer Electrolyte Membrane Fuel Cell

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***Abstract*—**This paper presents a new method of fault detection and isolation (FDI) for polymer electrolyte membrane (PEM) fuel cell (FC) dynamic systems under an open-loop scheme. This method uses a radial basis function (RBF) neural network to perform fault identification, classification and isolation. The novelty is that the RBF model of independent mode is used to predict the future outputs of the FC stack. One actuator fault, one component fault and three sensor faults have been introduced to the PEMFC systems experience faults between -7% to +10% of fault size in real-time operation. 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 RBF model is tested on MATLAB R2009a/Simulink environment. The simulation results confirm the effectiveness of the proposed method for FDI under an open-loop condition. By using this method, the RBF networks able to detect and isolate all five faults accordingly and accurately.

***Keywords*—**Polymer electrolyte membrane fuel cell, radial basis function neural networks, fault detection, fault isolation.

I. Introduction

NOWADAYS there is a great demand and interest in the renewable energy technology which gives motivation and encouragement to the researchers to conduct a research in this area. Among the renewable energy, fuel cell (FC) has received a lot of attention due to its potential as a future energy. Polymer electrolyte membrane fuel cell (PEMFC) is based on hydrogen technology and operates at low temperatures between the ranges of 60°C-100°C which allows the use of PEMFC in many applications such as for transportation, telecommunication and also as power generator. PEMFC gives a zero CO_2 emission which reduces the effect of pollutant directly towards the earth.

If faults occurred in the process plant, they have the ability to affect the productivity and the overall performance of the process plant. Therefore, it is important to identify, detect and isolate these faults from the process plant in order to maintain the systems operation and minimum the cost and maintenance.

The ability of neural networks to overcome the nonlinear behavior has been proposed by a few authors as a method to do fault diagnosis. Bayesian network has been proposed by [1] 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 PEMFC systems, [2] presents a flooding diagnosis based on a black-box model of elman neural network (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. In this paper, to make the FDI monitoring system more efficient and robust to five types of faults in the PEMFC systems, an independent RBF network is used for fault identification, detection and isolation. The aim of this work is to develop a FDI scheme during the online operation of PEMFC dynamic systems using an independent RBF network model which able to detect five faults and can isolate them accordingly.

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II. Polymer Electrolyte Membrane Fuel Cell Dynamic Systems

A FC is an electrochemical energy conversion device which converts the chemical reaction of hydrogen and oxygen into water and this produces electricity. It is constructed like a sandwich, with an electrolyte between two electrodes, known as anode and cathode as shown in Fig. 1. In this diagram the hydrogen is supplied to the anode side while the oxygen is supplied to the cathode side. During the chemical reaction the hydrogen atoms separate into protons and electrons. The electrons pass through the load circuit and create a flow of electricity whereby the protons migrate through the electrolyte and reunite with oxygen which produced water and heat.

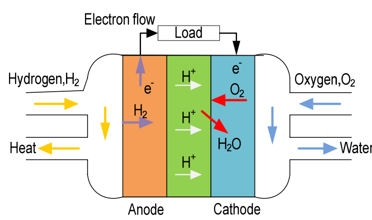

Fig. 1 PEMFC chemical reaction

A. Compressor Model

The flow and temperature out of the compressor (W_{cp} and T_{cp}) depend on the compressor rotational speed ω_{cp}. A lumped rotational model is used to represent the dynamic behavior of the compressor [3]:

$$J_{cp}\frac{d\omega_{cp}}{dt} = \tau_{cm} - \tau_{cp} \tag{1}$$

where $\tau_{cm}(v_{cm},\omega_{cp})$ is the compressor motor (CM) torque and τ_{cp} is the load torque. The compressor motor torque is calculated using a static motor equation:

$$\tau_{cm} = \eta_{cm}\frac{k_t}{R_{cm}}\left(V_{cm} - k_v\omega_{cp}\right) \tag{2}$$

where k_t, R_{cm} and k_v are motor constants and η_{cm} is the motor mechanical efficiency. The torque required to drive the compressor is calculated using the thermodynamic equation:

$$\tau_{cp} = \frac{c_p T_{atm}}{\omega_{cp}\eta_{cp}}\left[\left(\frac{p_{sm}}{p_{atm}}\right)^{(\gamma-1)/\gamma} - 1\right]W_{cp} \tag{3}$$

where γ is the ratio of the specific heats of air (=1.4), c_p is the constant pressure specific heat capacity of air (=1004 $J.kg^{-1}.K^{-1}$), η_{cp} is the motor compressor efficiency, p_{sm} is the pressure inside the supply manifold and p_{atm} and T_{atm} are the atmospheric pressure and temperature, respectively.

B. Supply Manifold Model

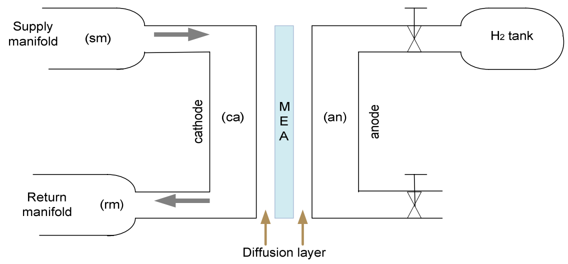

Fig. 2 The fuel cell supply system

The cathode supply manifold (sm) includes pipe and stack manifold volumes between the compressor and the fuel cells as shown in Fig. 2. The supply manifold pressure, *psm*, is governed by mass continuity and energy conservation equations [4]:

$$\frac{dm_{sm}}{dt} = W_{cp} - W_{sm,out} \tag{4}$$

$$\frac{dp_{sm}}{dt} = \frac{\gamma R_a}{V_{sm}}\left(W_{cp}T_{cp} - W_{sm,out}T_{sm}\right) \tag{5}$$

where R is the universal gas constant and M_a^{atm} is the molar mass atmospheric air at ϕ_{atm}, V_{sm} is the manifold volume and $T_{sm} = \frac{p_{sm}V_{sm}M_a^{atm}}{Rm_{sm}}$ is the supply manifold gas temperature.

III. Radial Basis Function Neural Networks

A neural network provides a general way to model a nonlinear system with memory and it has been used by many researchers to describe the relationship between the input and output of monitored systems. Radial basis function (RBF) neural networks is a forward network consist of three layers which are the input layer, hidden layer and output layer. RBF networks used a k-means clustering algorithm which the incoming weights from the input layer become centre of clusters of input vectors. The k-means clustering algorithm determines the closest centre of the RBF networks. The input-output mapping for the RBF network can be described as:

$$y(x) = \sum_{i=1}^{K} w_i\phi_i(x) \tag{6}$$

The Gaussian function is the most common equation used in the RBF neural network.

$$\varphi = \exp\left(-\frac{\|x-c\|^2}{\rho^2}\right) \tag{7}$$

where c is the radial basis centre, ρ is the variance of the Gaussian function, and x is the input vector.

The training session of the RBF network uses the error in the output values to update the weights connecting the layers until a minimal error is achieved. The minimal error is in the index of mean square error (MSE) [5] defined by the following equation:

$$MAE = \frac{1}{N}\sum_{j=1}^{N}(e-\hat{e})^2 \tag{8}$$

where e is true value and ê is the estimated value.

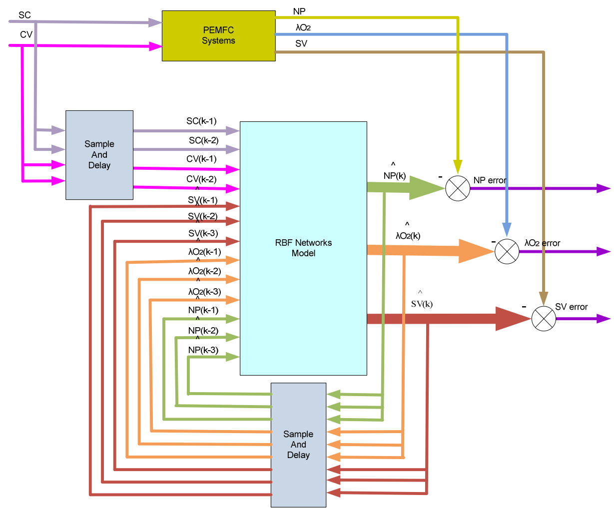

Fig. 3 The independent RBF networks

The basic structure of an independent RBF networks for PEMFC dynamic systems proposed in this work can be referred to Fig. 3. Here, two inputs and three outputs of the process with their delayed values form the 13 inputs of the RBF model, while the three process outputs are the model outputs [6]. The chosen input output orders are according to the training experience and checking the process dynamics. The model prediction errors are generated to implement the FDI procedure.

IV. Simulating Faults

In this work, five faults are introduced to a known test-bench PEMFC based on the model developed in Michigan University. First one is an actuator fault, which is simulated having a -7% change of the compressor motor voltage measurement. The second is the air leak in the supply manifold which is a typical component fault also at -7%. The sensor faults for the three outputs, which having a +10% change measurements of net power and λO_2 while a +5% change in stack voltage. The PEMFC simulator was modified to include five possible fault scenarios which may occur during the normal operation of PEMFC systems. Fig. 4 shows the five faults introduced to the overall PEMFC systems [6].

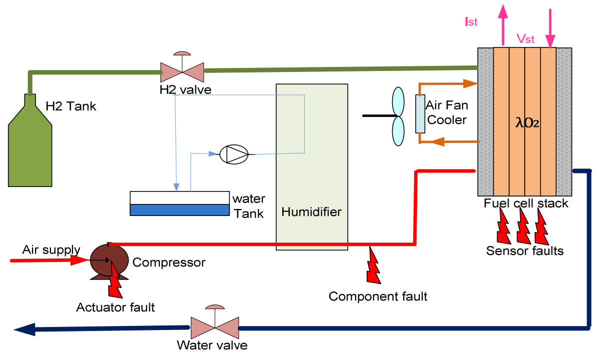

Fig. 4 The schematic of PEMFC systems with five types of faults

A. Actuator Fault

Most centrifugal compressor is used in FCs are susceptible to surge and choke that limit the efficiency and performance of the compressor. The air flow must be ensure that the partial pressure of oxygen does not fall below a critical level at the cathode, on the other hand, it must also minimize the parasitic losses of the air compressor. The compressor voltage will be changed if the compressor experience surge and choke and affected the air flow in the supply manifold. The compressor motor performance is reduced by -7% of the total compressor motor voltage from the sample intervals, T=500-600 to reflect the scenario of the fault which happens at the actuator part.

B. Component Fault

Air leakage in the supply manifold makes the pressure in the cathode decrease. Therefore to collect the FC stack data subjected to the air leak fault, equation (5) is modified to:

$$\frac{dp_{sm}}{dt} = \frac{\gamma R_a}{V_{sm}}\left(W_{cp}T_{cp} - W_{sm,out}T_{sm} - \Delta l\right) \quad (9)$$

where Δl is used to simulate the leakage from the air manifold, which is subtracted to increase the air outflow from the supply manifold. Δl=0 represents that there is no air leakage in the supply manifold. The air leakage is simulated by -7% change of the pressure inside the supply manifold. The fault occurs at the sample intervals, k = 1500-1600.

C. Sensor Faults

Net power, λO_2 and stack voltage sensors are considered experiencing over-reading faults. The faulty sensor data has a change of +10% at the measured net power over the sample interval, k = 2500-2600, a +10% change of the measured λO_2 over the sample intervals, k = 3500-3600 and a +5% change of the measured stack voltage over the sample intervals, k = 4500-4600.

V. Fault Detection and Isolation

The implementation of FDI is done in the MATLAB R2009a/Simulink environment. In this work, a data set with 5000 samples is acquired from the plant when the five faults are simulated to the plant. The block diagram of FDI proposed in this work is displayed in Fig. 5.

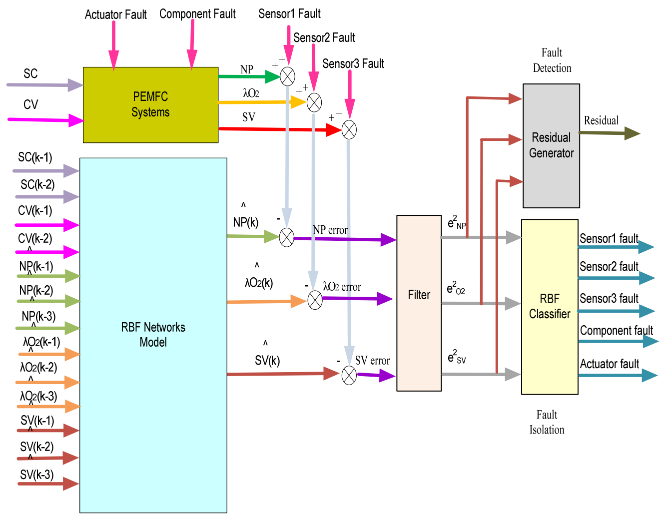

Fig. 5 Block diagram of the proposed FDI using the RBF networks

A. Fault Detection

By applying fault detection, it determines that problems have occurred in the PEMFC systems. 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 [7]:

$$re = \sqrt{e_{NP}^2 + e_{\lambda O2}^2 + e_{SV}^2} \quad (10)$$

where e_{NP} is the filtered modeling error of net power, $e_{\lambda O2}$ is the filtered modeling error of λO_2 and e_{SV} is the filtered modeling error of stack voltage.

B. Fault Isolation

RBF classifier is used to perform fault isolation. 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, 5000 samples of data were collected with the first fault occurring during k = 500~600, the second fault occurring during k = 1500-1600, 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 5000 rows and 5 columns. The entries from the 500th row to the 600th 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 I
THE TARGET MATRIX IN TRAINING THE RBF CLASSIFIER

Rows	Xo				
500-600	[1	0	0	0	0]
1500-1600	[0	1	0	0	0]
2500-2600	[0	0	1	0	0]
3500-3600	[0	0	0	1	0]
4500-4600	[0	0	0	0	1]

VI. SIMULATING RESULTS

The random amplitude signals (RAS) of stack current used as disturbances to the PEMFC systems has been injected to the FC stack. The RAS excitation signals of stack current are generated randomly to cover the whole range of frequencies and the entire operating amplitude in the PEMFC systems. The simulation result of three PEMFC outputs and the corresponding five faults is shown in Fig. 6. It shows the squared filtered model prediction errors for the three output variables. As can be seen, there are more than one faults occurred in these three outputs.

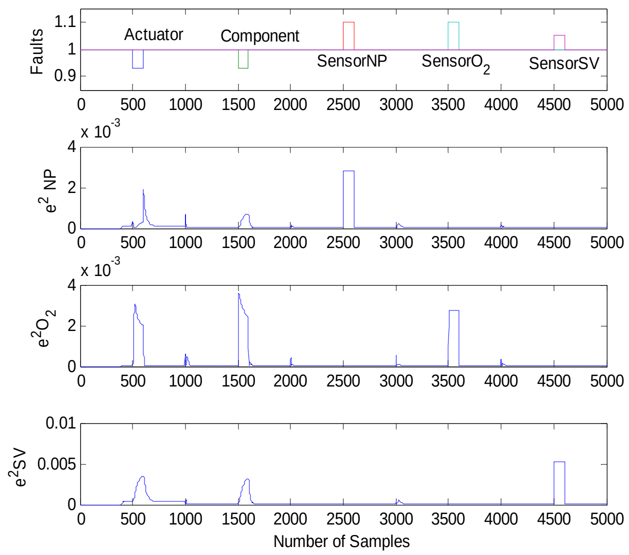

Fig. 6 Filtered model predicted errors

Based on the result obtained in Fig. 6, in order to identify the types of faults occurred, the residual generator as stated in equation (10) was applied. Here, the fault occurrence can clearly identified and detected with their respective threshold after the implementation. It is observed in Fig. 7 that all five faults of three sensors, component and actuator faults are clearly detected.

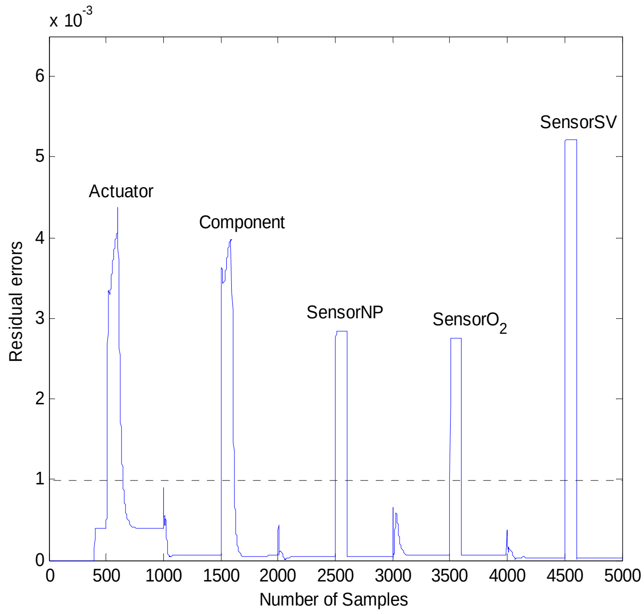

Fig. 7 Fault detection of five faults using the residual generator

The target matrix in Table I was used in training of the RBF classifier. After training, a similar data set with also 5000 samples, with the same five faults simulated, was collected. These data was applied to the fault detection part and then to the isolation part with the trained RBF classifier. The five outputs of the classifier are displayed in Fig. 8.

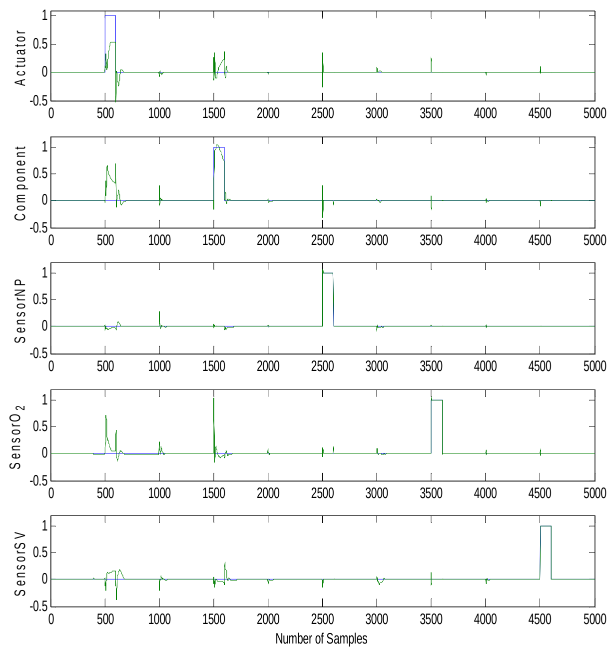

Fig. 8 The fault isolation for five faults during the training process

The output of this signals are filtered and the filtered signals are displayed in Fig. 9. By implemented the RBF classifier, the five faults are isolated according to individual fault with respect to certain threshold value.

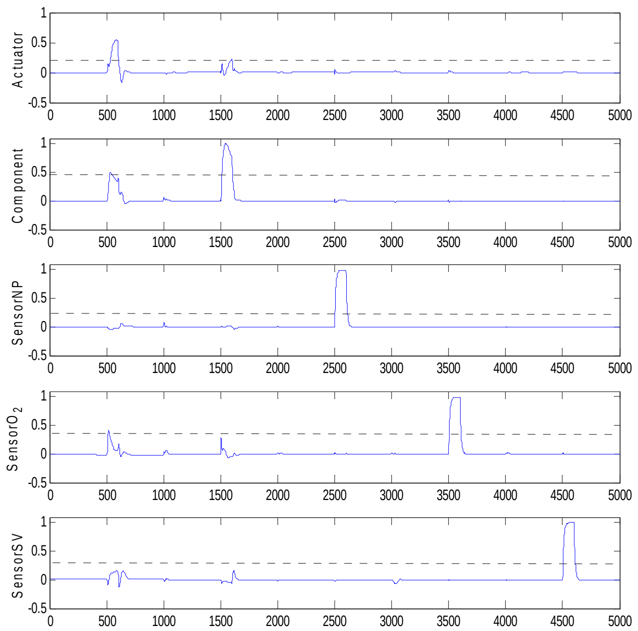

Fig. 9 The location of five faults in the PEMFC systems

VII. Conclusion

This work presents the development of FDI using an independent RBF network model which has been investigated under an open-loop scheme. Here, the RBF network has been used to perform fault identification, classification and isolation. The simulation results show that the -7% faults in the actuator, component, +5% fault in sensorSV and +10% two other sensors are successfully detected and isolated. It is important to isolate the malfunction devices in the systems for easy troubleshooting and maintenance purposes. By doing this step, the device can easily be replaced and any appropriate action can be taken quickly and therefore it can save time and increase productivity.

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