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Fault Detection and Isolation for PEMFC Systems under Closed-loop Control

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Abstract— **In this work, a model-based fault detection and isolation (FDI) is developed for proton exchange membrane (PEM) fuel cell (FC) stack that is under feed-forward plus feedback control. The fault detection is achieved using an independent radial basis function (RBF) network model, whilst the fault isolation is based on the RBF classification. The novelty is that the RBF model of independent mode is used to predict the future outputs of the FC stack and a RBF classifier is used to classify five types of fault introduced to the PEMFC systems. To validate the method, a benchmark model developed by Michigan University is used in the simulation to analyze the effectiveness of the method for actuator, component and three sensor faults. The FDI results corresponding to those scenarios show that the simulated different types of fault are successfully detected and isolated.**

Keywords-Proton exchange membrane fuel cell; feed-forward; feedback; fault detection; fault isolation; radial basis function; independent model

I. INTRODUCTION

Process faults, if undetected, have a serious impact on process economy, product quality, safety, pollution level and productivity. In order to detect, diagnose and correct these abnormal process behaviors, efficient and advanced automated diagnostic systems are of great importance to modern industries [1]. Once a fault has been detected and its evolution is monitored, the severity of that fault can be evaluated and a decision can be made on the course of action to take. Monitoring creates the opportunity to strategically plan and schedule outrages and to manage equipment utilization and availability [2]. Fault detection, isolation and reconfiguration (FDIR) is an important and challenging task in many engineering applications and continues to be an active area of research in the control environment [3]. In some cases, if a fault can be quickly detected and identified, appropriate reconfiguration control actions may be taken. FDIR is a control methodology which ensures continual safe and acceptable operation of the system when a fault occurs through fault detection and isolation (FDI). Many devices depend on automatic control for satisfactory operation, and while assuring stability and performance with all components functioning properly. If the control system's structure or parameter can be altered in response to system failure, it is said to be reconfigurable [4].

There are a large number of publications on the fuel cell (FC) studies, but studies on FDI are still a few. Model-based FDI methods for PEMFC become more and more important because it involved the comparison between the observed behavior of the process with a reference model. Model-based approach gives the insight analysis of the subsystem interactions and also provides guidelines during the conduction of the experiment. The system behavior can been analyzed in depth understanding and later this information can be used for future design and development. For fault detection problem, the most effective way is by using the model-based approach based on a residual generation. Here, the difference between the actual process and estimated output of the process is used as a residual vector. In [5] presented and tested a model-based fault diagnosis methodology based on the relative residual fault sensitivity. In this method, it checks the consistency of observed behavior and then isolate the component that is in fault in different sensitivities. While, a robust fault detection based on the use of LPV observer using output zonotopes was proposed by [6]. Here, fault isolation is based on set of structured residuals that are analyzed using a relative fault sensitivity approach.

Neural networks have been proposed as an alternative method for fault diagnosis by many authors especially to tackle the nonlinear behavior. Reference [7] used a Bayesian network as an early alert to diagnose faults in the air reaction fan, faults in the cooling system, growth of the fuel crossover and internal loss current and faults in the hydrogen feed line. Alternatively, to improve reliability and durability of PEMFC systems, [8] presents a flooding diagnosis based on black-box model of elman neural network (ENN). Here, ENN is used to do a comparison between measured and calculated pressure drops. The model-based on ENN is trained with data recorded in flooding-free condition and the difference between calculated and experimental pressure drop is used as the residual. Also concern about this problem in FC, [9] presents an electric equivalent model for FC system diagnosis emphasis on FC flooding detection induced by temperature. In this paper, to tackle the efficiency of the overall PEMFC systems, a model-based FDI based on residual generation is used to implement the fault detection whilst for fault isolation a RBF networks is used as a classifier. Therefore, to make the FDI monitoring system more efficient and robust to the 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 under closed-loop system for PEMFC using an independent RBF network model which can detect five types of faults in the FC systems accordingly but also can also isolate them accurately.

II. PEMFC DYNAMICS

The proton exchange membrane fuel cell (PEMFC) systems offer high efficiency and low emissions and has been become popular as an alternate power source for various application such as transportation, telecommunication, portable utilities, stationary and power generation. A typical PEMFC system normally consist of four subsystems, which include the reactant flow subsystem, the heat and temperature subsystem, the water management subsystem and the power management subsystem. The PEMFC stack is made up of 381 cells with an active area of $280cm^2$ and the stack operating temperature is at 80°C developed by University Michigan is used as a test bench.

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 behaviour of the compressor [10]:

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

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

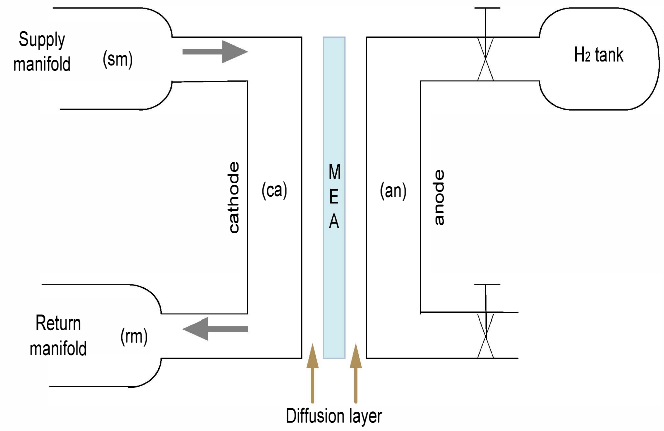

Figure 1. The fuel cell reactant supply system

The cathode supply manifold (sm) includes pipe and stack manifold volumes between the compressor and the fuel cells as shown in Fig. 1. The supply manifold pressure, *psm*, is governed by mass continuity and energy conservation equations [11]:

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

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

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. FDI METHOD WITH INDEPENDENT RBF MODEL

The basic structure of an independent radial basis function (RBF) model for PEMFC dynamic systems proposed in this work can be referred to Fig. 2. Here, two inputs and three outputs of the process with their delayed values form the 8 inputs of the RBF model, while the three process outputs are the model outputs. The chosen input output orders are according to the training experience and checking the process dynamics. The model prediction errors are generated for residual generation.

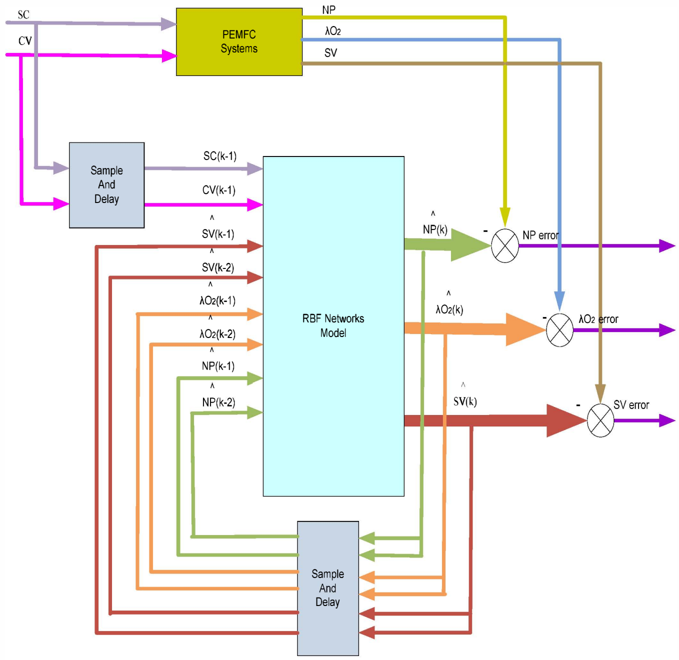

Figure 2. The structure of an independent RBF network

IV. CONTROLLER DESIGN

For air supply in the PEMFC systems, the required air flow is indicated by the desired oxygen excess ratio, λO_2 = 2. Generating rapid increase in air flow, however, requires a large amount of power drawn by the compressor motor and a affecting the system net power [12]. The combination of feed-forward and feedback control design objective is to manipulate the compressor motor input voltage, V_{cm}, in order to maintain $\lambda O_2 = 2$.

A. *Feed-forward Controller*

A feed-forward control is used to control V_{cm} based on the current drawn from the FC stack. In this work, look-up table act as feed-forward control as presented in Table I with respect to the signal range of stack current ranging from 100 to 300 amperes. To design the feed-forward controller, the stack current signal is adjust at the value illustrated in Table I and fed to the FC stack while tuning the V_{cm} until $\lambda O_2 = 2$.

TABLE I. THE DESIGN OF FEED-FORWARD CONTROLLER

Stack Current (Ampere)	Compressor Voltage (Volt)	Gain = Output / Input	Stack Current (Ampere)	Compressor Voltage (Volt)	Gain = Output / Input
105	102.33	0.9746	190	163	0.8579
110	105.98	0.9635	195	166.45	0.8536
115	109.98	0.9563	200	169.85	0.8493
120	113.15	0.9429	205	173.25	0.8452
125	116.77	0.9342	210	176.65	0.8412
130	120.43	0.9264	215	179.85	0.8365
135	124.05	0.9189	220	183.25	0.8330
140	127.68	0.9120	225	186.45	0.8287
145	131.29	0.9054	230	189.65	0.8246
150	134.89	0.8993	235	192.75	0.8202
155	138.48	0.8934	240	195.95	0.8165
160	142.05	0.8878	245	199.05	0.8124
165	145.58	0.8823	250	202.05	0.8082
170	149.15	0.8774	255	205	0.8040
175	152.65	0.8723	260	208	0.8000
180	156.10	0.8672	265	211	0.7962
185	159.60	0.8627	270	214.10	0.7930

B. *Proportional-Integral-Derivative Controller*

A proportional-integral-derivative (PID) controller is used to reduce the effects the disturbances that can be measured and also to improve the response to reference signals. The PID controller equation is given by:

$$PID_{controller} = 200\left(1 + \frac{1}{0.6153\ s} + 0.05\ s\right) \quad (6)$$

Fig. 3 shows the overall control systems of feed-forward and a closed-loop control implemented in this work. In the diagram, the stack current acts as a disturbance to the PEMFC systems with a reference input set at 2 ($\lambda O_2 = 2$). The output of λO_2 need to maintain in order to avoid oxygen starvation from happening.

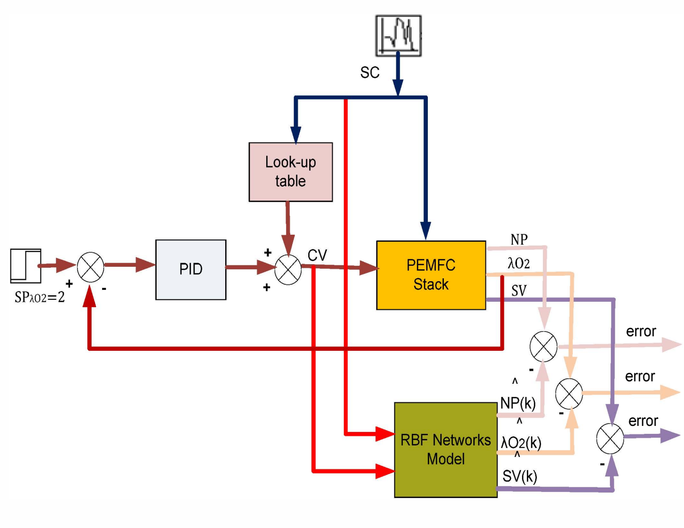

Figure 3. The overall system of FDI using feed-forward and feed-back controller

V. SIMULATING FAULTS

In this study, 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 by superimposing a -10% change of the compressor motor voltage measurement. The second is the air leak in the supply manifold which is a typical component fault. The third to fifth are three sensor faults for the three outputs, which are simulated by 10% deviation superimposed to the net power, λO_2 and stack voltage output measurements. 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.

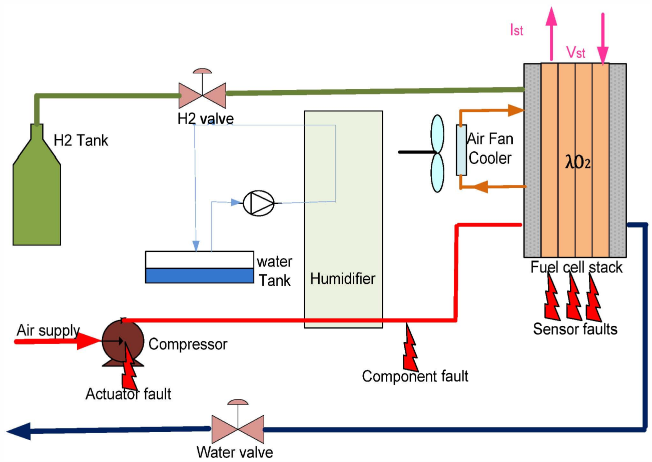

Figure 4. The schematic of PEMFC systems with five types of faults

1) *Actuator fault:* Mostly centrifugal compressor is used in FCs are susceptible to surge and choke that limit the efficiency and performance of the 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 -10% of the total compressor motor voltage from the sample intervals, k=2500-2550 to reflect the scenario of the fault which happens at the actuator part.

2) *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:

$$\frac{dp_{sm}}{dt} = \frac{\gamma R_a}{V_{sm}}\left(W_{cp}T_{cp} - W_{sm,out}T_{sm} - \Delta l\right) \tag{7}$$

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 -10% change of the pressure inside the supply manifold. The fault occurs at the sample intervals, *k* = 2000-2050.

3) *Sensor faults:* Net power, λO_2 and stack voltage sensors are considered experiencing over-reading faults. The faulty sensor data used was the data from the collected data set, superimposed with a 10% change of the measured net power over the sample interval, k = 500-550, a 10% change of the measured λO_2 over the sample intervals, k = 1000-1050 and a 10% change of the measured stack voltage over the sample intervals, k = 1500-1550.

VI. FAULT DETECTION AND ISOLATION

A. Fault Detection

Though the filtered squared model prediction error for each output could be used as fault detection signal, a residual signal is generated by combine these prediction errors, so that the sensitivity of the residual to each fault can be significantly enhanced, and consequently the false alarm rate would be reduced. The residual in this work is defined as in (8).

$$re = \sqrt{e_{NP}^2 + e_{\lambda O2}^2 + e_{SV}^2} \tag{8}$$

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. The signal with faults is clearly been identified and less influences by a noise signal.

B. Fault Isolation

RBF classifier is a nonlinear static network. The network is trained with a set of data collected under each of the five faults and no-fault condition. 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, 3000 samples of data were collected with the first fault occurring during *k* = 500~550, the second fault occurring during *k* = 1000-1050, and etc. Then, the generated filtered and 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 3000 rows and 5 columns. The entries from the 500th row to the 550th 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 II.

TABLE II. THE TARGET MATRIX IN TRAINING THE RBF CLASSIFIER

Rows	**X_0**				
500~550	[1	0	0	0	0]
1000~1050	[0	1	0	0	0]
1500~1050	[0	0	1	0	0]
2000~2050	[0	0	0	1	0]
2500~2550	[0	0	0	0	1]

VII. SIMULATION RESULTS

A random amplitude signals (RAS) of stack current used as disturbances to the PEMFC systems has been injected to the FC stack. At the same time, the constructed table described in the previous section act as a feed-forward control is the input to compressor motor. The RAS excitation signals of stack current are generated randomly to cover the whole range of frequencies and entire operating space of amplitude in the PEMFC systems.

Later, a data set with 3000 samples is acquired from the plant when the five faults are simulated to the plant as described in previous section. The simulation result of three PEMFC outputs and the corresponding five faults is shown in Fig. 5. It shows the squared filtered model prediction error for the three output variables. As can be seen, there are more than one faults occurred in these three outputs.

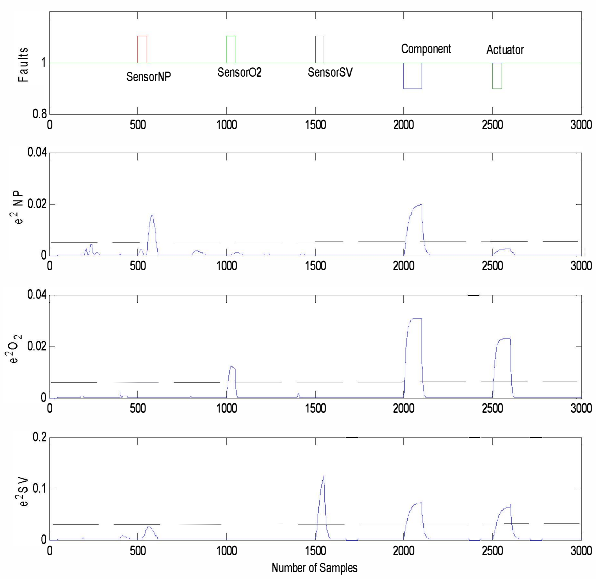

Figure 5. Filtered model predicted errors

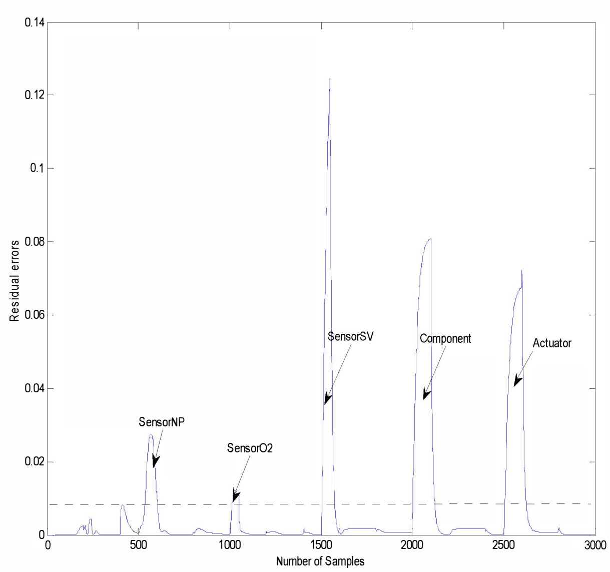

Figure 6. The fault classification of residual generator

In order to do fault classification, the residual generation as stated in equation (8) was applied. Here, the fault occurrence can clearly identified and detected with their respective threshold after the implementation. It is observed in Fig. 6 that all five faults of +10% for three sensors and -10% for component and actuator faults are clearly detected.

The target matrix in Table II was used in training of the RBF classifier. The centres and widths of the network were chosen using the K-means clustering algorithm and the p-nearest centre algorithm. The weights were trained with using the RLS algorithm with the following data, μ= 0.99999, $w(0) = 1.0\times10^{-6}\times U_{(nh\times3)}$, $P(0)=1.0\times10^{8}\times I_{(nh)}$; where I is an identity matrix and U is an ones matrix. The RBF networks model only used the three rows of the PEMFC outputs matrix which contain the values of net power, λO_2 and stack voltage. After training, a similar data set with also 3000 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. 7.

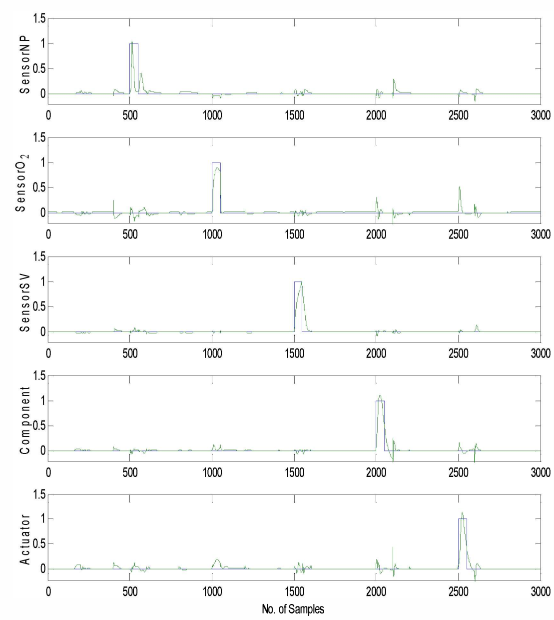

Figure 7. The fault isolation for five faults during training

From the fault isolation signals in Fig. 7 it is clearly observed that all considered five faults have been isolated. The RBF classifier successfully suppressed the corresponding output value for the no-fault-occurring period, while promoted the corresponding output value for the fault-occurring period. It is noticed in Fig. 7 that the fault isolation signals are very noisy and that would cause false alarm. Then, the RBF classifier outputs are filtered and the filtered signals are displayed in Fig. 8. It is obvious that the filtered fault isolation signals are much smoother and the robustness of the signal to modeling errors, interactions between variables and noise is greatly enhanced. 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.

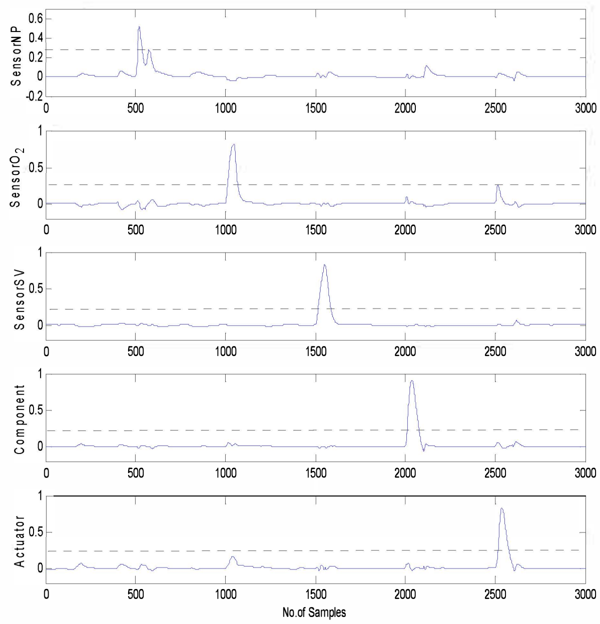

Figure 8. The location of five faults in the PEMFC systems

VIII. CONCLUSIONS

A combination of feed-forward and feedback controller is designed to regulate the λO_2 during the changes of stack current in the FC stack. FDI has been developed for the PEMFC under the closed-loop control. Five faults are simulated and diagnosed. The simulation results show that the new approach using the residual generation to do fault detection and the RBF classifier to apply fault isolation is successfully implemented. The 10% faults in the actuator, component and three sensors can be clearly detected and isolated. Here, the fault condition is considered occurred as a single fault at a time. But this result can be extended to the fault condition of multi-faults occurring simultaneously. The extension for fault detection part is straightforward, while for fault isolation needs more complex training of the fault classifier. The developed method has a big potential to be applied to real world dynamic systems. Also, the method is not limited to FC systems, and can be applied to other multivariable nonlinear dynamic systems with some modifications.

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