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Fault Detection of PEM Fuel Cell for Vehicle Systems Using Neutral Network Models

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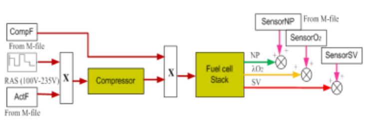
Graphical abstract



Abstract

This paper presents the neural network modeling method to perform fault detection for proton exchange membrane fuel cell dynamic systems under an open-loop scheme. These methods use a radial basis function neural network and a multilayer perceptron neural network to perform fault identification. Five types of faults which commonly happened in the vehicle systems have been introduced to the modified benchmark model developed by Michigan University. The developed algorithm of RBF and MLP network models are implemented on Matlab/Simulink environment using the healthy data sets and faulty data sets obtained from the simulation. All five simulated faults have been successfully detected where the residual is designed sensitive to fault amplitude as low as +10% of their nominal values. Thus, it is possible to apply the developed algorithm to real dynamics system of vehicles for monitoring and maintenance purposes.

Keywords: Neural network, proton exchange membrane fuel cell systems, radial basis function, multilayer perceptron, fault detection

1.0 INTRODUCTION

The worldwide energy demand is rely on the fossil fuels and therefore increasing the emission of carbon monoxide from the vehicles to the environment. The proton exchange membrane (PEM) fuel cell vehicle has been given more and more attention because nowadays it uses non-fossil based alternative fuels and produces a zero emission to the air [1]. Although prototype of fuel cell vehicles has already been introduced, it remains to reduce the cost and enhance their efficiencies [2]. Automotive fuel cell applications have more stringent fuel cell operation requirements than stationary applications [3]. Fuel cells in vehicles must operate over a wide range of conditions related to temperature, humidity and pressure [4]. Severe power degradation in the fuel cell stack during the transient phenomena in the fuel cell operation is also a problem due to load variations. Since the late 1980s, artificial neural networks have been widely implemented for fault diagnosis. They can indeed learn and approximate any continuous nonlinear function and does not need the knowledge of the physical process behind it. When they are properly trained, neural networks have strong capacity to model complex nonlinear mapping with accuracy [5]. Some researchers used it in fuel cells for different purposes in control environment [6-12]; Jemei *et al*. [6] developed a dynamic neural network in order to control a PEM fuel cell system process. Pukrushpan *et al*. [7,8] used the control strategies based on modeling to analyze and protect the fuel cell systems from oxygen starvation during the changes of stack current. Open-loop and static feedforward controller also studied by Grujicic *et al*. [9] to analyze and optimize the transient behavior of PEM fuel cell. Based on the open-loop control strategy, Kamal and Yu [10,11] have applied the fault diagnosis to the PEM fuel cell systems based on the neural network-based model. The aim of this paper is to analyze and to compare the result of fault detection under open-loop system for RBF and MLP neural network model. Besides that, to check and verify the effectiveness of the algorithm develop in order to perform fault detection of five faults occurred in the vehicle systems.

Table 1 The neural network modeling parameters

Item	RBF	MLP
Model Structure	$\hat{y}(k) = f[\hat{y}(k-1), \hat{y}(k-2), \hat{y}(k-3), u(k-1), u(k-2)]$	$\hat{y}_{mlp}(k) = f[\hat{y}_{mlp}(k-1), \hat{y}_{mlp}(k-2), \hat{y}_{mlp}(k-3), u(k-1), u(k-2)]$
	$\varphi_i = \exp\left(-\frac{\lVert x-c_i\rVert^2}{\sigma_i{}^2}\right)$	Hidden neuron input; $h_i = f\left(\sum_{i=0}^{N} w_{ij} x_i\right)$
	$c_k(t+1) = \begin{cases} c_k(t)+\alpha[x(t)-c_k(t)] \\ c_k(t) \end{cases}$	Hidden neuron output; $h_0 = \left(\frac{2}{(1+\exp(-h_i)-1)}\right)$
Training algorithms	$\hat{y} = \phi^T W$	$\hat{y}_{mlp} = w_{jk} h_o$
	$k(x) = \arg\min\left[\frac{1}{2}\sum_{k=1}^{nh}(x(t)-c_k(t))^2\right]$	Weight; $w_{jk\_new} = w_{jk)old} + (\alpha h_o e)$
	p-nearest neighbour; $\sigma_i = \frac{1}{P}\sum_{d=1}^{P}\lVert c_i(t)-c_d(t)\rVert$	Update weights; $w_{ij\_new} = w_{ij\_old} + \left(\beta\left(\frac{(1-h_o)(1+h_o)'}{2}\right)x_i\right)$
Error	$e_{mse} = \frac{1}{N}\sum_{j=1}^{N}[y(j)-\hat{y}(j)]^2$	$e = y - \hat{y}$

2.0 FUEL CELL NEURAL NETWORK MODELS

Artificial neural network model (ANN) is a mathematical model designed to train, visualize and validate neural network model [12] and the ANN is a model-free estimator as it does not rely on an assumed form of the underlying data [13]. 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 [10].The multi-layer perceptron (MLP) networks with the back-propagation (BP) training algorithm [14] are the most commonly used type of feed-forward neural MLP has three types of layers: an input layer, a hidden layer and an output layer. In this work both networks; RBF and MLP are consist of input layer, hidden node and output layer which are used during training and testing. The model structure of the RBF and the MLP network model has been set to thirteen with three outputs are also being analyzed. The equation and parameter setting used in this work for both networks are illustrated in Table 1.

3.0 FAULT SIMULATION

The common problem with the compressor is to experience surge when it is operating near to the peak point of its efficiency where the compressor speed is increasing. The pressure in the manifold also will increase. Besides that, the meter reading of the sensor is also out of range. Due to these common problems; compressor, pressure in manifold and sensor reading have been used as faults in the vehicle systems simulated by +10% deviation superimposed to the input of compressor, the inlet manifold, the net power, λO2 and stack voltage. The inputs to the vehicle systems are randomly generated within the range of 100 A to 300 A for the current stack and 100 V to 235 V for compressor voltage. Figure 1 shows the construction of faults implemented in the Matlab/Simulink model [15].

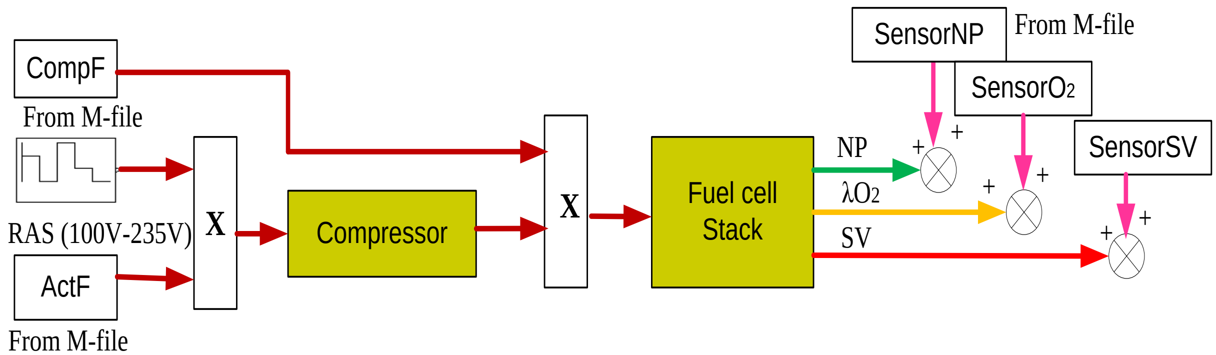


Figure 1 The Simulink block of component, actuator and sensors faults for open-loop systems

4.0 SIMULATION RESULTS

Before the algorithm for the RBF network model and MLP network model can be implemented to closed-loop control, it is tested for open-loop control due to its simplicity. From the stability point of view, the open-loop system is easier to build because system stability is not the major problem. On the other hand, stability is a major problem in the closed-loop control system, which may tend to overcorrect errors that can cause oscillations of constant or changing amplitude. Because of these reasons, both; the RBF network model and MLP network model have been tested under open-loop condition. By applying the residual generator equation given by equation in (1), 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 [15].

$$re = \sqrt{e_{NP}^{2} + e_{\lambda O2}^{2} + e_{SV}^{2}} \qquad \text{(Eq. 1)}$$

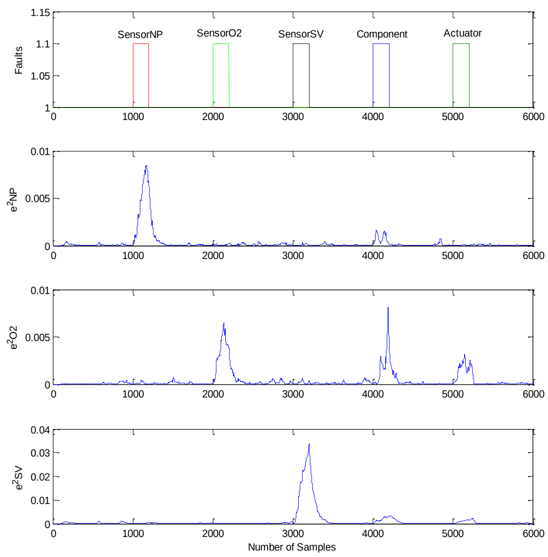
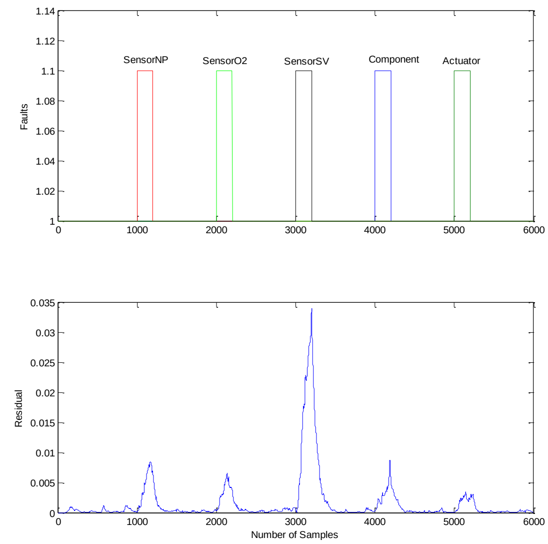
where eNP is the filtered modeling error of net power, eλO2 is the filtered modeling error of λO2 and eSV is the filtered modeling error of stack voltage.

The filtered squared error signals pattern for both networks is quite similar as shown in Table 2(a). However, fault cannot be detected straight away due to more than one faults occurred their output signals. Therefore, Table 2(b) presented the fault detection of five faults after performing the residual generator as in equation (1). The result in Table 2 shows the simulation graph of RBF network and MLP network when performing fault detection analysis. From the observation all five faults are detectable and give quite similar outputs results in terms of the residual signals where the amplitude of sensorsv for RBF is nearly to 0.035 while the amplitude of sensorsv for MLP network is nearly to 0.04.

5.0 CONCLUSION

The main study of this work is to clarify and check the effectiveness of RBF and MLP network models algorithm in performing the fault detection under open-loop condition. The simulation results show that the +10% faults in three sensors, actuator, component are successfully detected. The results for both networks show that these two algorithms able to detect and identify five faults with similar amplitude. Thus, both algorithms developed from these two neural network models are able to perform fault detection in order to detect the common scenarios happen inside the vehicle systems.

Table 2 Fault detection in open-loop control

<table>
<tr><th>Neural Network model</th><th>(a) Squared error signals</th><th>(b) Residual signals</th></tr>
<tr><td>RBF model</td><td>
</td><td>
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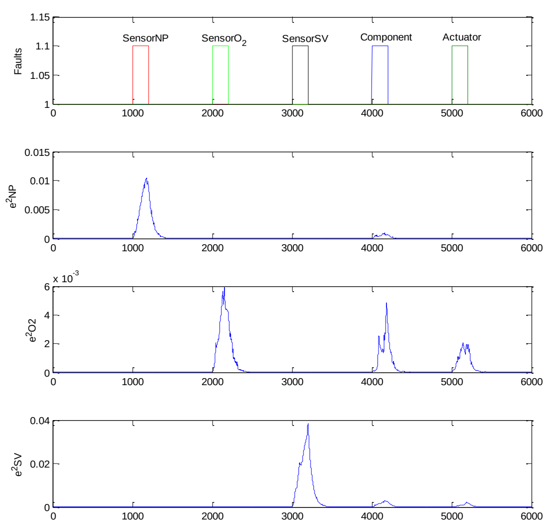
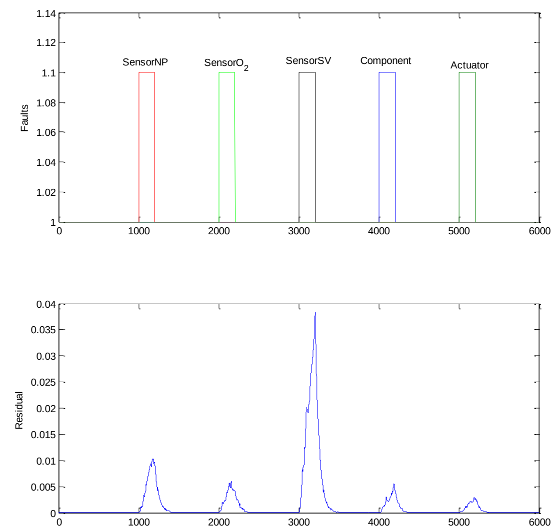
<tr><td>MLP model</td><td>
</td><td>
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References

[1] Yang, D., Ma, J., Xu, L., Wu, M. & Wang, H. 2006. The Effect of Nitrogen Oxides in the Air on the Performance of Proton Exchange Membrane Fuel Cell. *Journal of Electrochimica Acta*. 51: 4039-4044.

[2] Hatti, M. & Tioursi, M. 2009. Dynamic Neural Network Controller Model of PEM Fuel Cell System. *International Journal of Hydrogen Energy*. 34: 5015-5021.

[3] Chen, F. Chu, H. & Soong, C. 2005. Effective Schemes to Control the Dynamic Behavior of the Water Transport in Membrane of PEM Fuel Cell. *Journal of Power Sources*. 140: 243-249.

[4] Jianfeng, H., Liangfei, X., Xinfan, L., Languang, L. and Minggao, O. 2009. Modeling and Experimental Study of PEM Fuel Cell Transient Response for Automotive Applications. *Tsinghua Science and Technology*. 14: 639-645.

[5] Yousfi Steiner, N., Hissel, D., Mocuteguy, P. and Candusso, D. 2011. Diagnosis of Polymer Electrolyte Fuel Cells Failure Modes (Flooding & Drying Out) by Neural Networks Modeling. *International Journal of Hydrogen Energy*. 36: 3067-3075.

[6] Jemei, S., Hissel, D., Pera, M. C. and Kauffmann, J. M. 2003. On-board Fuel Cell Power Supply Modeling on the Basis of Neural Network Methodology. *Journal of Power Sources*. 124: 479-486.

[7] Pukrushpan, J. T., Stefanopoulou, A. G. and Peng, H. 2004. Control of Fuel Cell Breathing. *IEEE Control Systems Magazines*. 24: 30-46.

[8] Pukrushpan, J. T., Peng, H. and Stefanopoulou, A. G. 2004. Control-Oriented modeling and analysis for automotive fuel cell systems, J. of Dynamic Systems, *Measurement and Control.* 126: 14-25.

[9] Grujicic, M., Chittajallu, K. M., Law, E. H. and Pukrushpan, J. T. 2004. Model-based Control Strategies in the Dynamic Interaction of Air Supply and Fuel Cell. *Journal of Power and Energy*. 487-499.

[10] Kamal, M.M. & Yu, D. 2013. Intelligent Fault Detection and Isolation for Proton Exchange Membrane Fuel Cell Systems. *World Academy Science*, *Engineering & Technology.* 7: 153-157.

[11] Kamal, M. M. & Yu, D. 2014. Fault Diagnosis for Fuel Cell Stack Using Independent MLP Neural Network. *2nd International Conference on Innovations in Engineering and Technology.* 72-75.

[12] Nazari, J. & Ersoy, O.K. 1992. Implementation of Back-Propagation Neural Network with MatLab.

[13] Chang, D. H. & Islam, S. 2000. Estimation Of Soil Physical Properties Using Remote Sensing and Artificial Neural Network. *Remote Sensing of Environment.* 74: 534-544.

[14] Rumelhart, D. E., Hinton, G. E. & Williams, R. J. 1986. Learning Internal Representations by Error Propagation. *Parallel Distributed Processing*. 318-362.

[15] Mahanijah, M. K., Yu, D. W. & Yu D. L. 2013. Fault Detection and Isolation Based on Feedforward-Feedback Control for Oxygen Excess of Fuel Cell Stack. *Proceedings of the 19th International Conference on Automation & Computing*.