Engineering Applications of Artificial Intelligence 28 (2014) 52–63

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Fault detection and isolation for PEM fuel cell stack with independent RBF model

M.M. Kamal [a], D.W. Yu [b], D.L. Yu [a,*]

[a] Control Group, School of Engineering, Liverpool John Moores University, Liverpool, UK
[b] Department of Automation, Northwest University at Qinhuangdao, Qinhuangdao, China

ARTICLE INFO

Article history:
Received 18 December 2012
Received in revised form
30 September 2013
Accepted 7 October 2013
Available online 2 December 2013

Keywords:
Fault detection
Fault isolation
PEMFC
RBF networks
Independent model

ABSTRACT

Neural networks have been successfully used to model nonlinear dynamic systems. However, when a static neural network model is used in system fault detection and the model prediction error is used as the residual, the residual is insensitive to the fault if the neural network used is in dependent mode. This paper proposed the use of a radial basis function network in independent mode as the system model for fault detection, and it was found that the residual is sensitive to the fault. To enhance the signal to noise ratio of the detection the recursive orthogonal least squares algorithm is employed to train the network weights. Another radial basis function network is used to isolate fault using the information in the residual signal. The developed method is applied to a benchmark simulation model of the proton exchange membrane fuel cell stacks developed at the Michigan University. One component fault, one actuator fault and three sensor faults were simulated on the benchmark model. The simulation results show that the developed approach is able to detect and isolate the faults to a fault size of $\pm 10\%$ of nominal values. These results are promising and indicate the potential of the method to be applied to the real world of fuel cell stacks for dynamic monitoring and reliable operations.

1. Introduction

If faults occurred in a process plant, they will affect the productivity, quality, safety and performance of the control systems of the plant. Therefore, early detection of possible faults would minimize the downtime, increase the safety of plant operations, prevent damages to the equipment, minimize the operation cost and also the maintenance. Fault detection and isolation (FDI) for dynamic control systems of nonlinear plants has become an important and challenging task in many engineering applications and continues to be an active area of research in the control environment (Hwang et al., 2010).

In process engineering, most plants have nonlinear dynamics in nature (Basseville, 1988) and may also be multivariable and complex, the observer-based FDI methods (Frank, 1990; Isermann, 1984; Patton, 1994) would therefore be very difficult to apply to these systems. Researchers have been tuned to some other alternatives and one of which is the artificial intelligent method. For example, Frank and Koppen-Seliger (1997) studied fuzzy logic and neural network applications for fault diagnosis. They used a dependent neural network for residual generation and fuzzy logic for residual evaluation. Simeón et al. (2010) used classical multivariable statistical techniques for FDI of several manufacturing and process plants. Ng and Srinivasan (2010) used the multi-agent method in which principle component analysis (PCA), self-organizing map (SOP) and Bayesian network were combined to do FDI for the Tennessee Eastman process and also distillation unit to classify the temperature change and disturbance during start-up. Bayesian network was also used as a classifier to do fault diagnosis in the Tennessee Eastman process by Verron et al. (2010), where a fault database was constructed. Three kinds of fault are analyzed in terms of unit step and random signal excitation. Subrahmanya and Shin (2013) used recurrent neural network (RNN) to distinguish faults occurring in actuator, component and sensors. In recent years, Polycarpou and Helmicki (1995) proposed a framework to estimate faults occurring in the system dynamics, in which an estimator was added to the state space model. The error between the model and the plant outputs was used to update the estimator that is used to estimate the fault. The RBF network has been used as the estimator in their work and the Levenberg–Marquart algorithm by Chong and Zak (2013) as an updating algorithm. This method has been widely recommended for further research, but its drawback is that the difficulty of developing an accurate nonlinear state space model for the plant makes it difficult for real applications.

Patton et al. (1994) proposed an approach for detecting and isolating faults in a nonlinear dynamic process using neural networks. Firstly, a multi-layer perceptron network was trained to

* Corresponding author.
E-mail address: D.Yu@ljmu.ac.uk (D.L. Yu).

0952-1976/$ - see front matter
http://dx.doi.org/10.1016/j.engappai.2013.10.002

predict the future system states, then the residual was generated using the differences between the actual and predicted states. Secondly, another neural network was used as a classifier to isolate faults from these state prediction errors. However, this method used the neural network model in its so-called dependent mode (see definition given in Narendra and Parthasarathy (1990)), i.e. the past state of the process was used as a part of the network input. In this way, the network model was trained using the nominal process data for state prediction. Then, when a fault occurred, the fault would cause the process state to be contaminated (the value was affected). This contaminated process state was then fed into the network model, the predicted state would tend to the real process state, and consequently the residual would tend to zero (insensitive to the fault) when the model mismatch and noise effects were omitted. In addition to the above analysis, this point was also affirmed by Yu et al. (1999), where the simulation data clearly disclosed that the neural network model of the dependent mode generated residual that was insensitive to the fault. Besides, the method described by Patton et al. (1994) was not practical for most nonlinear systems as some of the states may not be measurable, while the design of nonlinear state observer is very difficult.

The insensitive residual generated by static network of dependent mode can be avoided where the process sensor faults should be treated was proposed by Yu et al. (1999). In their work, a semi-independent MLP network was used with the predicted output by the network model used to replace process output in the network input. Then, the model predicted output was reset by the real process output on every period of time to reduce the growing model prediction error. This was called semi-independent mode. The residual generated in this way was sensitive to the fault but the prediction error is bigger and the residual is not smooth, and a filer had to be used to smoothen the residual. A higher threshold had to be used due to the increased model prediction error and therefore some faults with small amplitude would then not be detected.

In the field of PEMFC, most approaches for fault detection used a model-based approach which involved the comparison of the observed behavior of the process to a reference model. In the aspect of hydrogen safety and efficiency for PEMFC, Ingimundarson et al. (2008) and Lebbal and Lecoeuche (2009) have developed a computer simulation tool which can be used to detect and monitor faults in the hydrogen stations. Xue et al. (2006) proposed a model-based condition monitoring scheme that employs the Hotelling T^2 statistical analysis for fault detection of PEMFC. This model-based robust condition monitoring scheme can deal with the operating condition variation, various uncertainty in a fuel cell system and measurement noise.

FDI for the PEMFC systems is challenging due to its nonlinear nature. Thus, a method needs to be developed which can tackle the above problems in a simple and effective way. This is the motive of this paper. The novelty of this work lies in using the independent RBF network to model the fuel cell stacks, and generating the residual. By acquiring process data under different disturbances and with or without faults, the network model can be trained to make the residual of FDI monitoring system more sensitive to the faults and more robust to the disturbance. To enhance the model accuracy while reducing the false alarm rate, the recursive orthogonal least squares (ROLS) algorithm is employed to train the RBF model. For fault isolation, another RBF network is used to classify the different features of different faults on the residual vector. By setting appropriate number of hidden layer nodes, the clearness of the isolation can be maximized. The Michigan benchmark model is used as the benchmark to evaluate the proposed method with and without faults occurring in the process. The Michigan model has been modified to introduce one component fault, one actuator fault and three sensor faults. Simulation results approved the effectiveness of the method for detection and isolation of the faults with the fault size as small as $\pm 10\%$ of their nominal values. The rest of paper is arranged as follows: Section 2 presents the dynamics of the PEMFC systems. The RBF neural network model is presented in Section 3. These are followed by fault detection in Section 4 and fault isolation in Section 5. Finally, conclusions are discussed in Section 6.

2. Proton exchange membrane fuel cell dynamics and faults

A fuel cell consists of two electrodes; a negative electrode (anode) and a positive electrode (cathode) separated by an electrolyte. Fuel cells convert the chemical energy of the hydrogen fuel (on the anode side) into electric energy while through a chemical reaction with oxygen (on the cathode side) produce water and heat as end product. Hydrogen atoms separate into protons and electrons once the chemical reaction happens. The electrons go through the load which contains a flow of electricity while the protons migrate through the electrolyte to the cathode side, where they reunite with oxygen to produce water and heat as shown in Fig. 1. To maintain the desired air supply, the air supply needs to replenish the air to maintain the oxygen partial pressure. The air supply system consists of an air compressor, an electric motor and pipes or manifolds between the components. The compressor not only achieves desired air flow but also increases air pressure which significantly improves the reaction at the membranes, and thus the overall efficiency and power density (Pukrushpan et al., 2004a).

2.1. 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 (Pukrushpan et al., 2004a):

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

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:

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

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.

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

where γ is the ratio of the specific heats of air ($=1.4$), c_p is the constant pressure specific heat capacity of air ($=1004\ \mathrm{J\ kg^{-1}\ K^{-1}}$), η_{cp} is the motor compressor efficiency, p_{sm} is the pressure inside

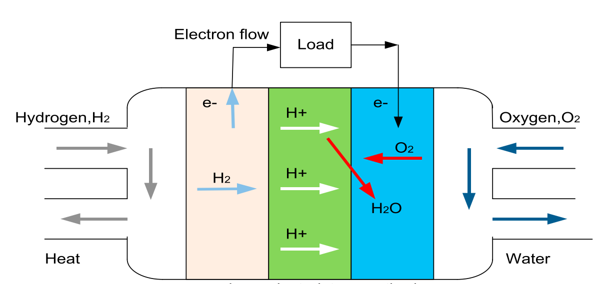

Fig. 1. PEMFC chemical reaction.