Jurnal Teknologi, 46(F) Jun 2007: 11–26

PROCESS FAULT DETECTION USING HIERARCHICAL ARTIFICIAL NEURAL NETWORK DIAGNOSTIC STRATEGY

MOHAMAD RIZZA OTHMAN[1], MOHAMAD WIJAYANUDDIN ALI[2*] & MOHD ZAKI KAMSAH[3]

Abstract. This paper focuses on the use of artificial neural network (ANN) to detect and diagnose fault in process plant. In this work, the ANN uses two layers of hierarchical diagnostic strategy. The first layer diagnoses the node where the fault originated and the second layer classifies the type of faults or malfunctions occurred on that particular node. The architecture of the ANN model is founded on a multilayer feed forward network and used back propagation algorithm as the training scheme. In order to find the most suitable configuration of ANN, a topology analysis is conducted. The effectiveness of the method is demonstrated by using a fatty acid fractionation column. Results show that the system is successful in detecting original single and transient fault introduced within the process plant model.

Keywords: Process fault detection and diagnosis, hierarchical diagnostic strategy, artificial neural network, fatty acid fractionation column

Abstrak. Kertas kerja ini menerangkan mengenai kegunaan jaringan neural tiruan (ANN) untuk mengesan dan membaiki kesilapan dalam loji proses. Dalam penyelidikan ini, ANN menggunakan dua lapisan dalam strategi diagnostik hirarki. Lapisan pertama mengenal pasti nod di mana kesilapan bermula sementara lapisan kedua membahagikan kesilapan yang berlaku pada nod tertentu. Arkitek model ANN adalah berasaskan beberapa lapisan rangkaian suapan hadapan dan menggunakan algoritma luncuran belakang dalam skema latihan. Untuk mendapatkan konfigurasi ANN yang terbaik, analisis topologi dilakukan. Keberkesanan kaedah ini ditunjukkan oleh kajian kes melibatkan turus pemecahan asid lemak. Keputusan menunjukkan sistem ini berjaya mengesan kesilapan tunggal dan fana yang terdapat dalam proses tersebut.

Kata kunci: Pengenalpastian dan diagnostik kesilapan proses, strategi diagnostik hirarki, jaringan neural tiruan, turus pemecahan asid lemak

1.0 INTRODUCTION

Plant operation today is becoming more complex as plants are often operated at extreme pressures and temperatures to achieve optimal performance. These extreme conditions may cause equipment failures and deviation in process that may lead to catastrophic

[1] Kolej Universiti Kejuruteraan dan Teknologi Malaysia, Locked Bag 12, 25000, Kuantan, Pahang, Malaysia
[2&3] Process Control and Safety Laboratory, Faculty of Chemical and Natural Resources Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia
* Corresponding author: Tel: +06-07-553 5602, Email: m.w.ali@fkkksa.utm.my

accidents. Although these plants are equipped with automated control, still the role played by the computer is limited and highly depended on human operators to maintain process plant integrity. In some modern high technology process plant, there may be hundreds or thousands of process variables that need to be observed. As human with limited capability, they are out of hand when handling these problems. Industrial statistics show that although major catastrophe may be infrequent, minor accidents are very common. These minor accidents cost the society billions of dollars every year [1]. Thus, to prevent this from happening, a quick detection and diagnosis of process fault is needed. An automated process fault detection and diagnosis (PFD&D) can provide a good solution to better safety in chemical process plant [2].

Fault is defined as a departure from an acceptable range of an observed variable or a calculated parameter associated with a process and it can be classified into three categories of failures or malfunctions; gross parameter changes in a model, structural changes and malfunctioning sensors and actuators [3]. In recent years, many researches have conducted process fault detection and diagnosis using various methods such as knowledge based expert system (KBES), mathematical modeling and artificial neural network (ANN). Using KBES in PFD&D has the advantage of insights into problem solving in chemical plant. However, it has its own limitations such as the tedious nature of knowledge acquisition, the inability of the system to learn or dynamically improve its performance and the unpredictability of the system outside its domain of expertise. A knowledge-based fault detection and diagnosis was also introduced through combination of heuristic knowledge (knowledge rules of operator) and procedural knowledge (mathematical models, Kalman filter algorithms and signal processing procedures) [2]. The technique, however, could be very complex when dealing with a nonlinear process. Due to these limitations, ANN can give a better solution to PFD&D because of its usefulness in representing input-output data, making predictions in time classifying data and recognizing patterns [3].

2.0 ARTIFICIAL NEURAL NETWORK

Generally when human senses something, it stimulates the nerves system and sends the input (via neurons) to the brain. Inside, the brain neurons are activated and interacted with each other to draw a conclusion or output from the brain in the form of answer or response. Thus, from this analogy, neuroscientist and computer researcher have proposed ANN, a highly interconnected neurons or nodes that mathematically interact with each other to draw output that maps the input-output pattern. Some of the advantages of using ANN include the following [4]:

(i) Pattern recognition properties – ANNs perform multivariable pattern recognition very well and this is where ANNs will probably find the most use especially in process control and fault diagnosis.

(ii) Adaptive behavior – ANNs have the ability to adapt, or learn, in response to their environment. They learn through training, where when given the input-output patterns, they adjust themselves to minimize the error.

(iii) Filtering capacity: low sensitivity to noise and incomplete information – ANNs can deal with the imperfect world, generalize and draw substance conclusions more effectively than the less flexible empirical models.

(iv) Automated abstraction – ANNs can ascertain the essentials of relationships, and can do so automatically. They do not need the domain expert that knowledge-based required. Instead, through training with direct (and sometimes imprecise) numerical data, ANNs can automatically determine cause-effect relations.

(v) Potential for online use – ANNs may take a long time to train, but once trained, they can calculate results from a given input very quickly. Since a trained ANN may take less than a second to calculate results, it has the potential to be used on-line in a control system.

Advantages of ANN enable it to be applied in various areas. Such areas are business, aerospace, automotive, banking, robotics and speech recognition. In mid 1980's, researchers in the area of process safety proposed a potential approach to detect and diagnose fault using neural network. Venkatasubramanian and Chan [5] were among the earliest researchers to apply ANN in PFD&D. Since then many researchers have studied the implementation of neural network in this area such as Li *et al.* [6], Becraft and Lee [7] and Leung and Ramagnoli [8]. ANN was also used to perform several functions that might also be carried by integrating with other fault detection techniques such as knowledge based expert system [9].

3.0 RESEARCH METHODOLOGY

Figure 1 shows an overview of the development structure of ANN for the fatty acid fractionation pre-cut column. The main role of plant model is to assist in developing the system. Plant model is used to represent the real plant. For ANN model, it includes the diagnostic strategy, fault scenario simulation, moving window approach and ANN development and training.

3.1 Plant Model

A fatty acid fractionation pre-cut column as shown in Figure 2 is chosen as the case study for this work. Before entering the pre-cut column, the PKO (Palm Kernel Oil) containing fatty acid from storage tank is filtered and heated successively in a preheater by hot oil in a feed heater and put through a dryer-deaerator where air and water are removed by vacuum. It is then flashed into the pre-cut column. The vapour, consisting

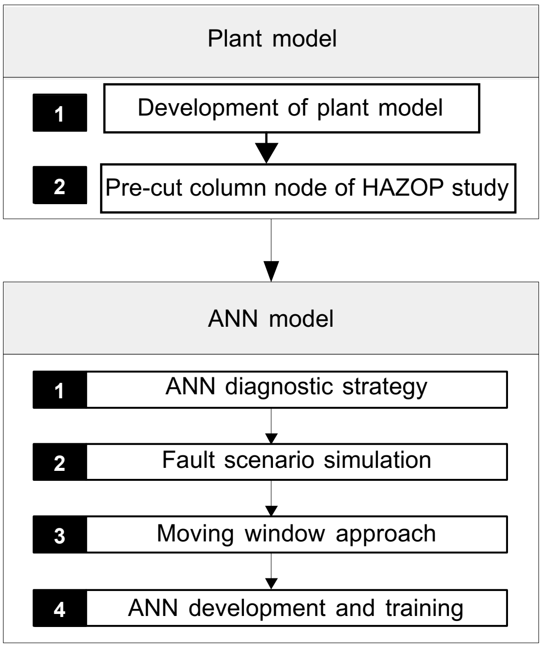


Figure 1 ANN development structure

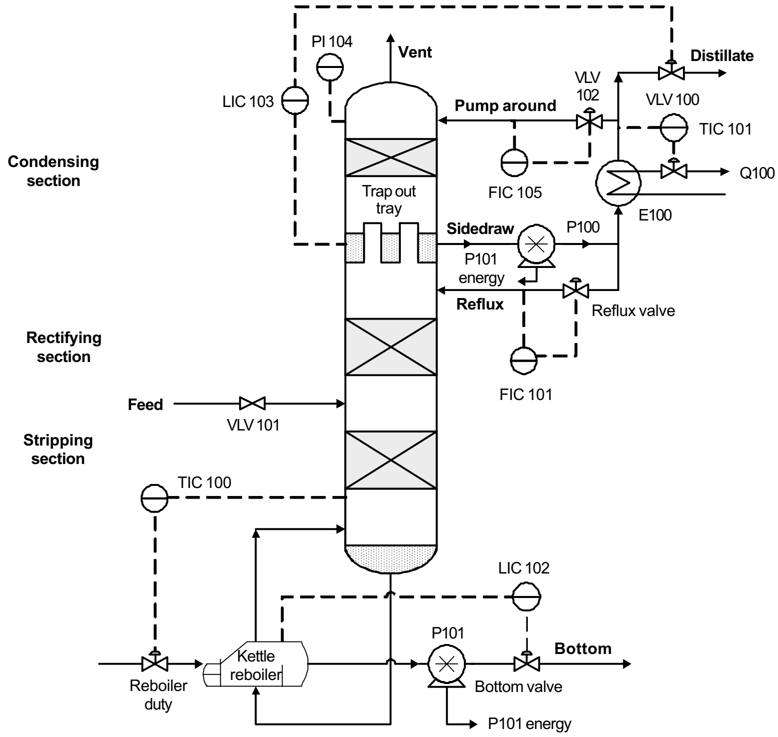


Figure 2 Process and instrumentation diagram (PID) for pre-cut column

of C6, C8 and C10 fractions, are condensed by a direct contact in the pump around section of the column. The condensed distillate is pumped by the reflux pump and cooled by cooling water in the condenser before being returned to the top of the pump around section. Part of the hot distillate is sent as reflux to the rectification section of the column. The net distillate is pumped to storage under level control. The bottoms are pumped by the bottom pump and heated by hot oil under pressure vaporization, in the reboilers. The net bottom product is pumped to the light cut column. Vacuum is maintained at the top of the column by the second stage of the pre-cut column ejector. The column has six single-input-single-output (SISO) control loops which also act as an indicator system added with top column pressure indicator to monitor the operational plant status.

Ling [10] has developed a plant model for the pre-cut column using a commercial process simulator, HYSYS.Plant^{TM}. Data simulation of various scenarios is used to develop and train the ANN model. Furthermore, the plant model is also used to test and validate the system. A complete description of the pre-cut column model can be found in Ling [10], Ahmad *et al*. [11] and Abd Hamid [12].

To create fault scenarios, the pre-cut column is divided into several sections or nodes. The node of study specifies the extent of the analysis such as the nature of the process and the inherent hazards, novelty of the operation, the complexity of the control system and the relationship to other operating units. In this work, the pre-cut column is divided into seven nodes as described in Table 1.

Table 1 Node definitions

Node no.	Definition
1	From column to reboiler before circulate back to column.
2	From reboiler to bottom product pump (P101) and bottom valve before discharge to light cut column.
3	From sidestream to reflux pump (P100) and circulate reflux back to column.
4	From P100 to heat exchanger (E100) and VLV 102.
5	From heat exchanger (E100) to VLV 102 before pump around back to column.
6	From heat exchanger (E100) to VLV 100 before discharge to storage tank.
7	Feed stream.

Various conditions at specific node are defined by imposing changes to a process variable. The conditions are simulated based on two classes of failures; structural changes and malfunctioning of sensors and actuators. When a given fault affects a plant, a process parameter or variable is directly affected by it; then, this original perturbation propagates itself throughout the plant taking the process variables away from their normal values [13]. For this work, 18 fault scenarios are identified related to a specific nodes which include pump failures, changes in feed stream, incorrect controller

Table 2 Faults scenarios employed in the plant model

	Parameter	Node	Type of fault
F1	LIC102	2	Incorrect controller setpoint (+15%)
F2	TIC100	1	Incorrect controller setpoint (–0.5%)
F3	TIC100	1	Incorrect controller setpoint (+1%)
F4	LIC103	6	Incorrect controller setpoint (–20%)
F5	LIC103	6	Incorrect controller setpoint (+20%)
F6	TIC101	4	Incorrect controller setpoint (–5%)
F7	TIC101	4	Incorrect controller setpoint (+5%)
F8	FIC105	5	Incorrect controller setpoint (–5%)
F9	FIC105	5	Incorrect controller setpoint (+5%)
F10	FIC101	3	Incorrect controller setpoint (–5%)
F11	FIC101	3	Incorrect controller setpoint (+5%)
F12	Node 3	3	Pipe leakage (3%)
F12a	Node 3	3	Pipe leakage (5%)
F13	Node 4	2	Pipe leakage (10%)
F14	Feed stream	7	High feed flowrate (+1%)
F15	Feed stream	7	Low feed flowrate (-5%)
F16	P101	2	Pump failure (Off)
F17	P100	3	Pump failure (Off)

set points and pipe leakage. The characteristics of the fault scenarios are depicted in Table 2.

3.2 ANN Model Element

The design of the ANN diagnostic strategy which consists of two levels is shown in Figure 3. The first level or main ANN is trained to identify the particular node where the faulty scenario originated. Each of the second level's nodes is trained to further isolate the type of fault that actually occurred.

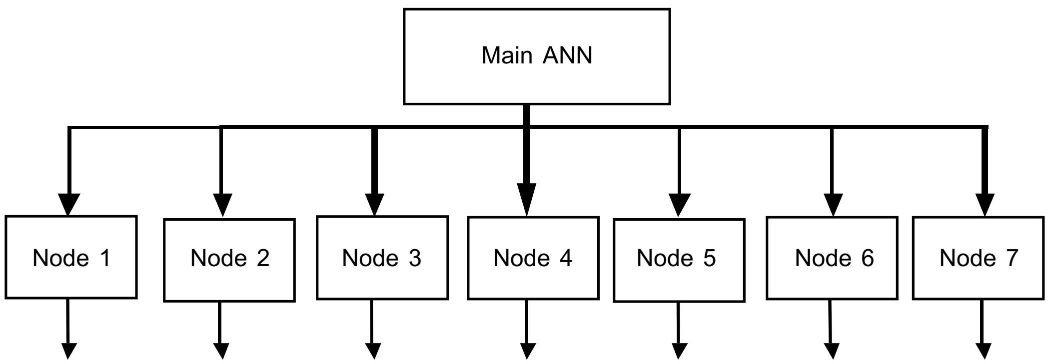


Figure 3 Structure of neural network hierarchical structure

The input variables used in the development of the neural network model are based on the measurement sensors of the column, as they resemble the real behaviour of the plant. The variables are bottom temperature, bottom level, reflux flow, pump around flow, cooler temperature, trap-out tray level, top column pressure, heat exchanger (E100), power, P100 Energy, P101 Energy and kettle reboiler power duty.

Moving window approach is used to track dynamic data and detect transient states of fault [6]. As shown in Figure 4, two separate windows move forward with time - at each time increment the windows move by Δt, which is called the sampling rate. The right side of the windows corresponds to the current time, t. The time span of the windows is $L_f\Delta t$ and $L_y\Delta t$, respectively, where L_f and L_y are integers and not necessarily equal to each other.

These integers are called window lengths. Each moving window cuts a set of dynamic data into several overlapping pieces. The segmented data are presented to a neural network with L_y +1 nodes in the input layer and L_f + 1 in the output layer. If the number of measurements, m, and the number of single faults, n, to be diagnosed is larger than one, the above approach is extended by increasing the nodes in input and output layers by m and n times, respectively. In this work, L_f and L_y are taken as 5. In short, the moving time window approach generates many patterns, and the networks are asked, after learning these patterns, to diagnose the fault from a short piece of the transient information.

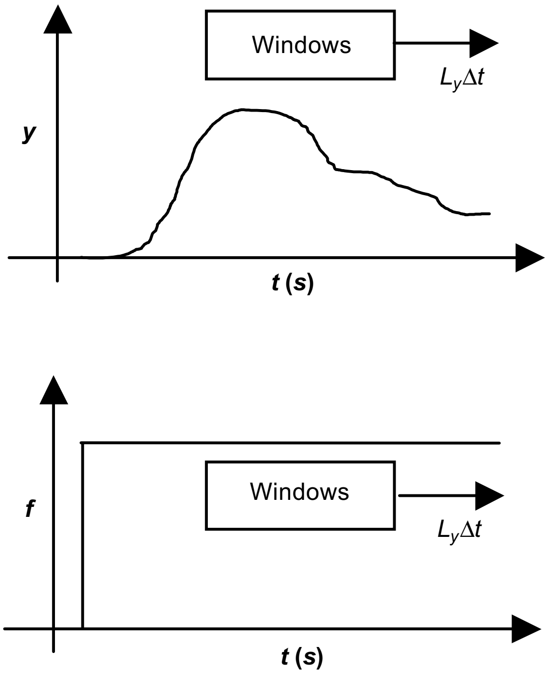


Figure 4 Moving window approach [6]

3.2.1 Architecture of ANN

The neural network model used in this study is implemented in two stages of hierarchical diagnostic strategy. For the first level, the network is designed to recognize 18 fault scenarios. The target or output vector is a 7-element vector with a '1' in the position of the nodes it represents and '0' everywhere else. In other words, the output value is set to '0' to indicate no fault and '1' to indicate the presence of fault. For the second level, there are seven individual neural network models, one for each node to further isolate the type of fault that occurred within the node. The design concept is the same as the first level, differs only in the input and output elements. The architectures for the neural network model both for first level and second level are based on the feedforward multilayer networks incorporating the backpropagation algorithm for training. The first level ANN is trained to identify particular plant node where the fault originates. There are seven measurements to be used as input to the first level neural network model. The number of neurons in the input layer, N_{input} is equivalent to the number of measurements, m times (L_y +1). The input used for each model in the second level is different, where only appropriate measurements within the node are used. The second level network also incorporates additional input measurements not presented to the first level network, thus provides a greater degree of resolution of the fault type. The output layer of each neural network model represents its own specific fault type. The number of hidden layers and number of hidden nodes used in training have a significant effect on the efficiency and accuracy of ANN. An increase in the number of hidden layers increases the learning iterations but does not guarantee a good performance [5]. Presently, neural networks with one hidden layer are primarily used in training of both level one and level two. Transfer function used in the hidden layer is *tansig* whereas *purelin* is used in the output layer.

Preprocessing is a method to recondition the input and output data in order to make the network more efficient. Typically, sensor measurement data; e.g. temperature, flowrate and pressure, in a chemical process plant vary significantly in magnitude, and therefore, must be appropriately conditioned and similar in magnitudes. Before presented to the neural network model, input data and targeted output data is preprocessed so that it always falls in a specified range. In MATLAB, the function *premnmx* is used to scale inputs and outputs so that they fall in the range of –1 to 1. The outputs can be converted back to their original values by using the routine *postmnmx*. Noted that whenever the trained network is used with new inputs, they should be processed with the minimum and maximums that were computed for the training set using routine *trainnmx*.

In order to find the most suitable configuration for the neural network models, it is necessary to conduct topology analysis. The aim of topology analysis is to find suitable configuration of ANN structure that gives lowest mean square error (MSE). For the first level network, three types of training algorithms; *trainrp* (Resilient Backpropagation), *traingdx* (Gradient Descent with Momentum and Adaptive Learning Backpropagation) and *trainscg* (Scaled Conjugate Gradient) are used in training. The number of hidden nodes is also iteratively changed from 28 to 33 for each specific training algorithm. The training is conducted for 500 epochs. Type of training algorithm with hidden nodes that give the lowest MSE is chosen as the optimum configuration for the development of the neural network models. Table 3 shows the lowest MSE value achieved by each training algorithm for specific hidden nodes.

Table 3 Comparison of MSE between types of training and hidden nodes

Type of training algorithm	Number of hidden nodes	MSE after 500 epochs
trainscg (Scaled Conjugate Gradient)	28	0.0717
	29	0.0689
	30	0.0741
	31	**0.0615**
	32	0.0692
	33	0.0676
trainrp (Resilient Backpropagation)	28	0.1217
	29	0.1080
	30	0.1084
	31	0.0922
	32	0.0682
	33	0.1011
traingdx (Gradient Descent with Momentum and Adaptive Learning Backgpropagation)	28	0.2134
	29	0.2238
	30	0.2209
	31	0.2201
	32	0.2424
	33	0.2129

From the table, it can be seen that *trainscg* with 31 hidden nodes produces the smallest MSE value after 500 epochs, compared to other training methods and hidden nodes. Hence, Scaled Conjugate Gradient training algorithm with 31 hidden nodes is used to develop the neural network model. The chosen first level neural network structure is trained again with the conditioned fault scenario data until the network converges to MSE value of 0.005 or until the MSE is relatively constant over several iterations. Using the same neural network structure, all second level neural networks are trained. The training is conducted until it converges to MSE value of 1.0×10^{-6} or constant over several iterations. Table 4 lists the MSE values and the number of epochs required for each individual model in second level ANN.

Table 4 MSE values and the number of epochs for second layer ANN model

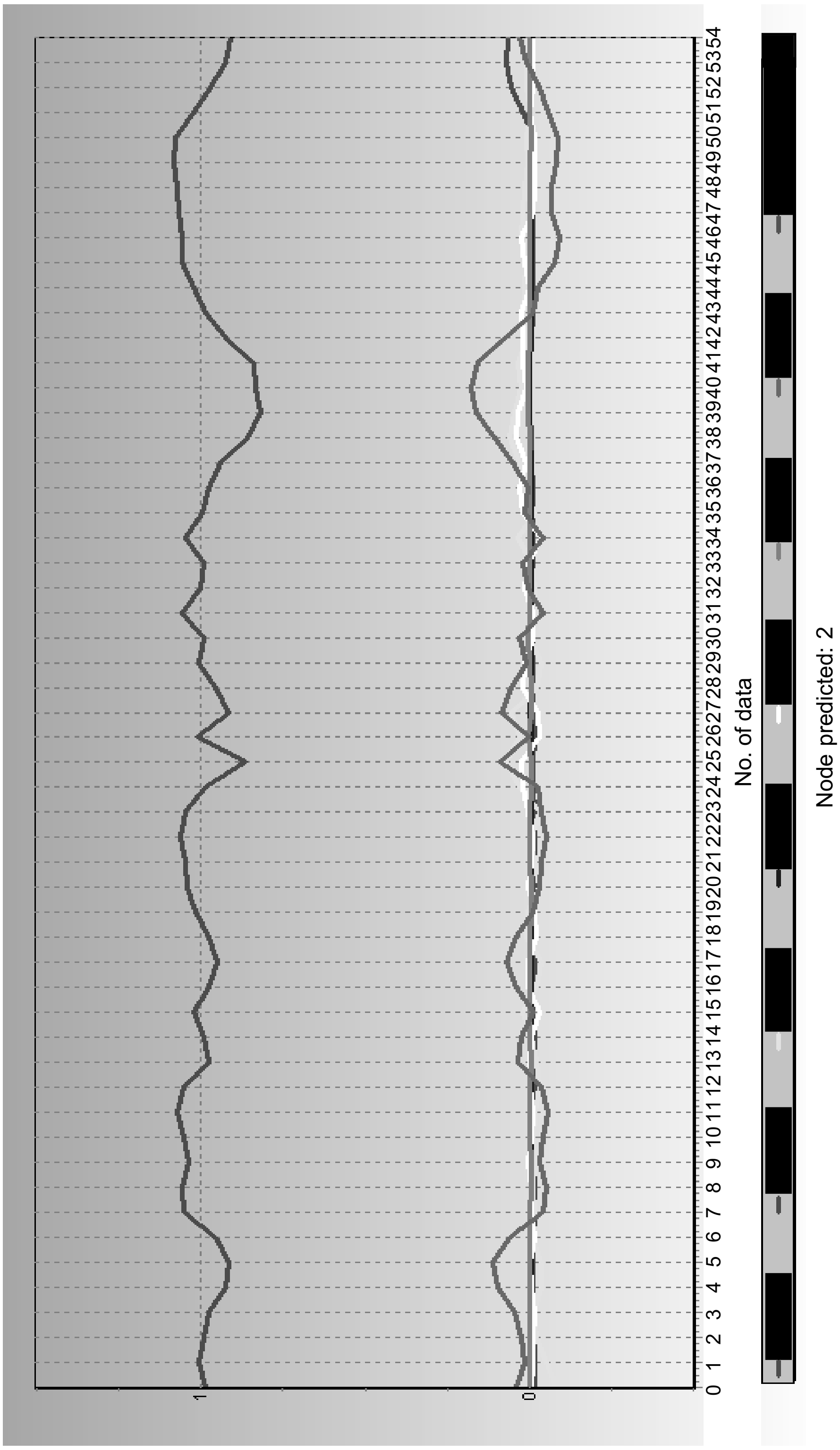
ANN model	MSE	Epochs
ANN 1	9.9998e-007	2123
ANN 2	9.9989e-007	2436
ANN 3	5.9623e-006	5001
ANN 4	9.9894e-007	1970
ANN 5	9.9875e-007	1559
ANN 6	9.9964e-007	2646
ANN 7	3.1488e-006	5001

4.0 DIAGNOSTIC PERFORMANCE RESULT

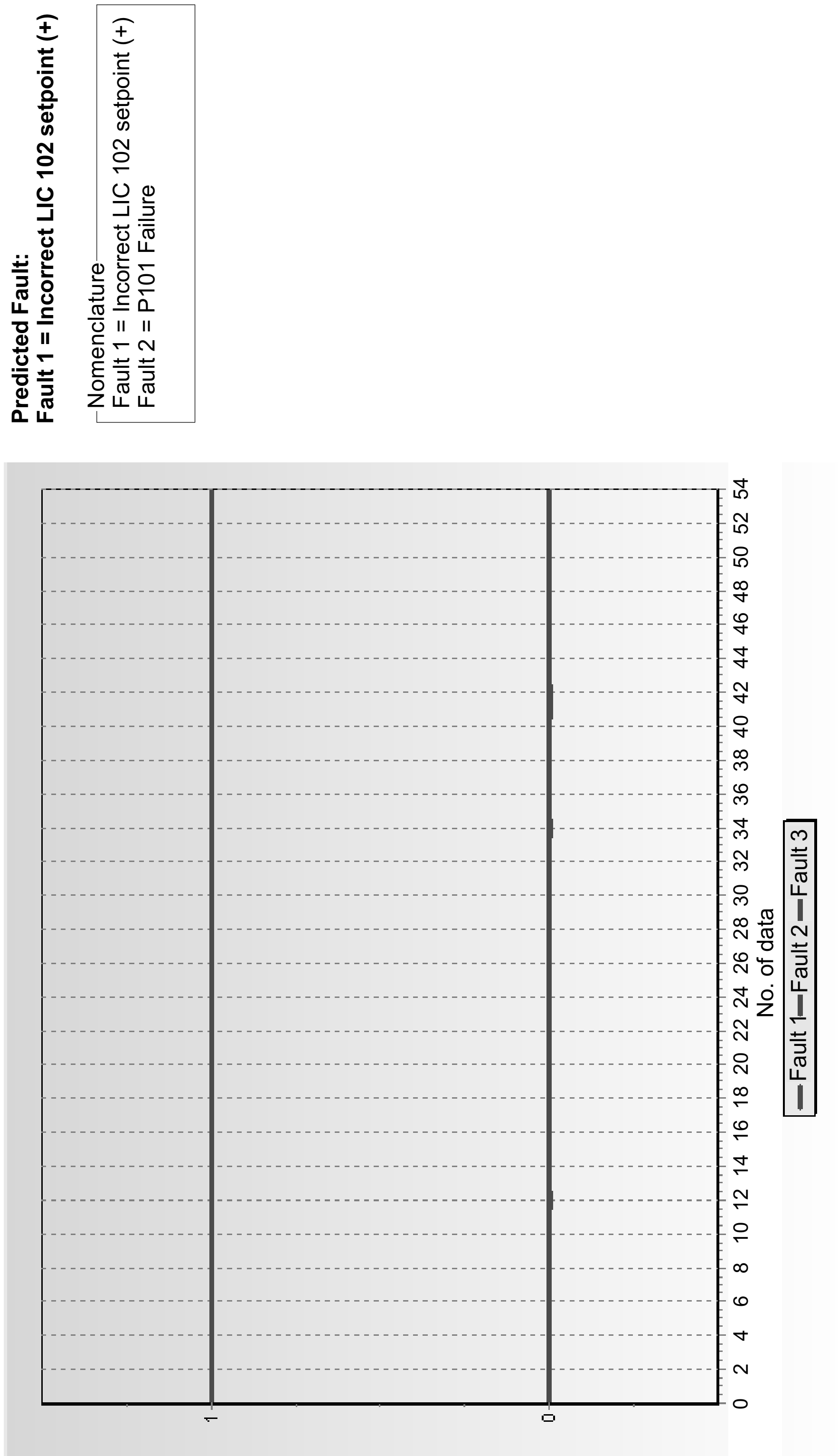
This section describes the ability of the hierarchical neural network in detecting and diagnosing process fault. To illustrate the network capability, 18 original single fault conditions and its transient state are described. Detection and diagnosis of transient data means that the system monitors the process and gives its diagnosis while the process is in transients. Each original single fault used to train the network is subjected into the network model to be generalized. For example, when Fault 1, 15% increase in LIC 102 controller set point is introduced to the network model, it successfully detected the fault. Figure 5(a) and 5(b) show the residual generated from 1st and 2nd level ANN, respectively.

Similar result is obtained when Fault 3, 20% decrease in feed temperature, is introduced into the pre-cut column. In all cases, similar results are obtained when the network is subjected to other fault patterns. This result is to be expected, as these are the fault scenarios that are used to train the ANN model. With no noise present, the system has no problem producing the correct diagnosis. It shows that the hierarchical ANN module is capable of diagnosing the fault correctly.

To investigate the diagnostic performance for transient states, the sensor data for all scenarios are obtained by introducing the specific fault after time, *t* and let it run for about 20 to 60 minutes. That data is then introduced to the network model to be analyzed. To illustrate this, the plant model is simulated in normal condition for about 20 minutes before Fault 6 is introduced to the plant model. The simulation stops after 60 minutes. The data obtained is then subjected into the model for generalization process. From Figure 6, it shows that the system correctly diagnoses the fault. Figure 6(a) shows that Node 4 is where the fault originated. Furthermore, it also correctly predicts the type of fault occurs; incorrect TIC 101 set point (–) as shown in Figure 6(b). The examples illustrate that the hierarchical ANN module is capable not only in diagnosing the original single fault correctly but also its transient state.

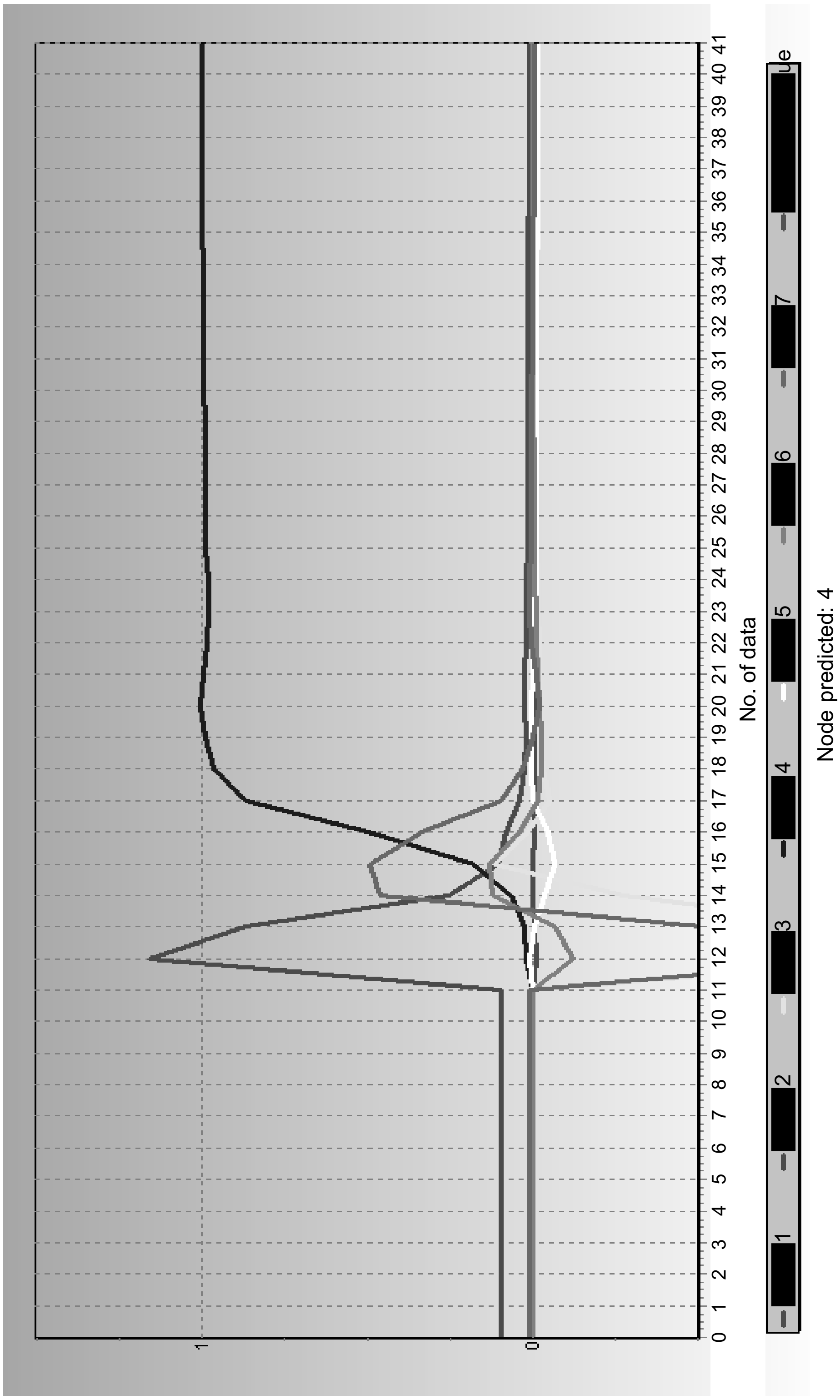

1
0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54
No. of data
Node predicted: 2

(a)

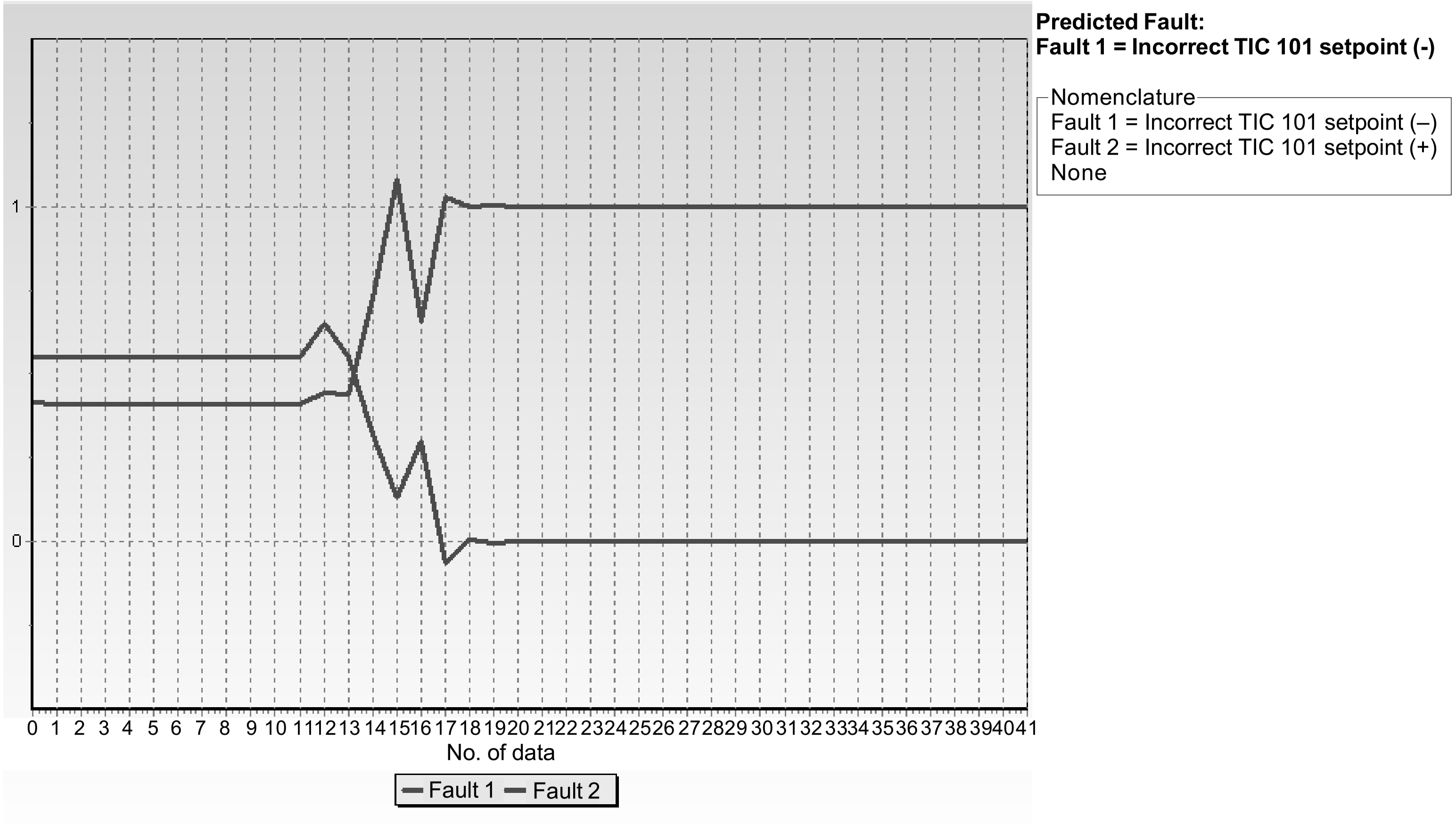


(b)

Figure 5 (a) Result of 1st level ANN and (b) Result of 2nd level ANN


No. of data
Node predicted: 4
1
0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
1
2
3
4
5
6
7

(a)



(b)

Figure 6 (a) Results of 1st level ANN and (b) Result of 2nd level ANN

5.0 CONCLUSIONS

This paper outlines the development of process fault detection and diagnosis using hierarchical ANN diagnostic strategy. This strategy manages to shorten the training time and narrow the diagnostic focus of the system from node to type of fault occurs in the node. The use of time moving window approach shows that the method is suitable with hierarchical neural network in capturing the dynamic of the process plant. From the results, it shows that the neural network models are capable of diagnosing original single fault scenarios and also give its diagnosis while in transient state. However, the use of this method is limited to selected abnormal events that occur in a fatty acid fractionation pre-cut column only. To extend the capability of the system, more work need to be done. For example, online implementation is left open for further research and it is also recommended to design a more robust neural network model to tackle multiple and noisy fault scenarios.

ACKNOWLEDGEMENTS

The authors would like to thank Universiti Teknologi Malaysia (through the IRPA Grant Vot 74036) for sponsoring this research.

REFERENCES

[1] Venkatasubramanian, V., R. Rengaswary, K. Yin, and S. N. Kavuri. 2003. A Review of Process Fault Detection and Diagnosis Part I: Quantitative Model-Based Methods. *Computers and Chemical Engineering*. 27: 293-311.

[2] Korbicz, J., D. Ucinski, A. Pieczynski, and G. Marczewska. 1994. An Integrated Approach to Fault Detection and Diagnosis in Power Plant. *IFAC Fault Detection, Supervision and Safety for Technical Processes*. Espoo, Finland.

[3] Himmelblau, D. M. 1978. *Fault Detection and Diagnosis in Chemical and Petrochemical Processes*. New York: Elsevier North-Holland Inc.

[4] Baughman, D. and Y. Liu. 1995. *Neural Network in Bioprosessing and Chemical Engineering*. San Diego, CA: Academic Press.

[5] Venkatasubramanian, V. and K. A. Chan. 1989. A Neural Network Methodology for Process Fault Diagnosis. *AiChE Journal*. 35(12): 1993-2002.

[6] Li, R., J. H. Olson, and D. L. Chester. 1990. Dynamic Fault Detection and Diagnosis Using Neural Networks. Intelligent Control. Proceedings of 5th IEEE International Symposium on Intelligence Control. 1169-1174.

[7] Becraft, W. R. and P. L. Lee. 1993. An Integrated Neural Network/Expert System Approach for Fault Diagnosis. *Computers and Chemical Engineering*. 17(10): 1001-1014.

[8] Leung, D. and J. Ramognali. 2000. Dynamic Probabilistic Model-Based Expert System for Fault Diagnosis. *Computers and Chemical Engineering*. 24: 2473-2492.

[9] Hoskins, J. C., K. M. Kaliyur, and D. M. Himmelblau. 1991. Fault Diagnosis in Complex Chemical Plants Using Artificial Neural Network. *AIChE Journal*. 37(1): 137-141.

[10] Ling, L. Y. 2004. Plantwide Control of a Fatty Acid Fractionation Column. Master's Thesis. Universiti Teknologi Malaysia.

[11] Ahmad, A. and M. K. Abd Hamid. 2002. Detection of Sensor Failure in a Palm Oil Fractionation Plant Using Artificial Neural Network. Proceedings of the International Conference on Artificial Intelligence in Engineering and Technology. Kota Kinabalu, Sabah. 739-745.

[12] Abd Hamid, M. K. 2004. Multiple Faults Detection Using Neural Network. Master's Thesis. Faculty of Chemical and Natural Resources Engineering, Universiti Teknologi Malaysia.

[13] Tarifa, E. E., D. Humana, S. Franco, S. L. Martinez, A. F. Nunez, and N. J. Scenna. 2002. Fault Diagnosis for MSF Using Neural Networks. *Desalination*. 152(1-3): 215-222.