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DETECTION OF MULTIPLE SENSOR FAULTS IN A PALM OIL FRACTIONATION PLANT USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Given the universal approximation properties, simplicity as well its intrinsic analogy to the non-linear state space form, a recurrent Elman network is derived and applied as process predictor for fault detection in process plants. In this paper, a two-stage scheme integrating a neural Elman network dynamic predictor and a feedforward neural network fault classifier is proposed to overcome the problem of multiple sensor faults. The scheme was implemented to detect sensor failures in a palm oil fractionation process. To generate the required simulation data, Hysys.Plant dynamic process simulator was employed. The use of the output prediction error, between a neural network model and a non-linear dynamic process, as a residual for detecting sensor faults is analysed. A second neural network classifier is developed to detect the sensor faults from the residuals generated, and results are presented to demonstrate the satisfactory detection of two sensor faults achieved simultaneously using this scheme.

Keywords: Fault detection; neural networks; palm oil fractionation process; sensor faults

1.0 INTRODUCTION

Changes in the physical conditions of process units, control systems or sensor failure may lead to what are generally referred to as faults. Faults in broadest sense include symptoms resulting from physical changes, such as deviations of temperature or pressure from their normal operating range, as well as physical changes themselves such as scaling, foaming, leaks and wear. Even changes in unmeasured process parameters such as heat or mass transfer coefficients can be deemed to be faults. The early detection and diagnosis of faults in industry is very important from the point of view of plant safety, as well as reduced manufacturing costs. Modern industrial plants are extremely complex, and there is a growing demand for fault tolerance, which can be achieved by an efficient fault detection and diagnosis scheme. A wide variety of techniques have been proposed to detect and diagnose faults using redundant instrumentation, Knowledge Based Expert System (KBES), process modelling statistical tools, diagraphs and combinations of these. The difficulty with these techniques is that they involve process modelling for fault diagnosis itself can be quite a difficult job because errors in the model can be interpreted as faults thus yielding false alarms, or can prevent faults from being detected when they occur.

The present study focuses on the use of the artificial neural networks (ANN) to do incipient fault detection for processes in which faults occur. A neural network can autonomously store knowledge by learning from historical fault information and has the characteristics of associative memory. Information about faults can be learnt by training the network on a set of data such as the values of process variables for normal conditions and those for identified fault conditions. The neural network in identifying systems inefficiency is directly related to the comprehensiveness of training data. The network acts as a black box into which we send inputs and from which we get outputs.

What are the advantages people see in using artificial neural networks in contrast with KBES, first principles models or other empirical models? First, ANN can be highly nonlinear, second the structure can be more complex, and hence more representative, than most other empirical models, third the structure does not have to be pre-specified, and fourth, they are quite flexible models (Himmelblau, 2000).

Applications of neural networks in fault detection and diagnosis can be broadly represented in three categories. The first is the use of networks to differentiate various faults from the normal condition, and from one another, according to different fault patterns represented in the measured input-output system data, either by off-line training (Sorsa et al., 1991) or by on-line learning of fault patterns by an adaptive network (Gomm, 1996). The second is a hybrid scheme that uses neural networks to isolate faults, based on a residual generated by a quantitative model-based method (Yu et al., 1996). The third approach uses a neural network model to predict the system output, and the prediction error is used for the residual; another neural network is then used to classify faults (Patton et al., 1994). This paper presents a study of the third scheme, applied to detect multiple sensor faults simultaneously in a palm oil fractionation plant. In the following sections, an introduction to Elman network will be presented. This will followed by the case studies with results, discussions and conclusion drawn from the work.

2.0 NEURAL NETWORK FAULT DETECTION SCHEME

The proposed fault detection scheme is hierarchical in structure. The schematic diagram of the strategy is shown in Figure 1 below. In short, there are two types of model required within this scheme. Both are developed using neural network. The first is the predictor that will always predict the "normal" or fault-free process behaviour. If faults occur, there will be residuals generated. Second, there is the fault classifier that will identify the sources of fault that takes place using residuals as an input.

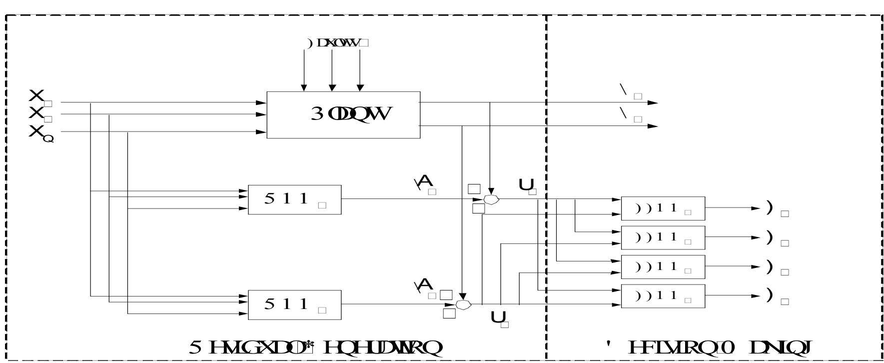

Fig.1. Model-Based Fault Detection Scheme

Most of the recent investigations into fault detection using neural networks have been simulation studies, for example (Sorsa et al., 1991; Patton et al., 1994). Real data has not been used by many researchers because contain system perturbations, measurement noise, disturbances and unmodelled system uncertainty. The avoidance of false alarms in the detection stage and the confusion of different faults in the isolation stage are therefore more difficult to achieve with real data than in computer simulations.

3.0 MODIFIED ELMAN NETWORK

In an Elman network time is represented implicitly in the network dynamics (Elman, 1990), through internal states. As shown in Figure 2 the outputs of hidden layer processing units are fed back with unity weighting on the connections into context processing units, which store states and have no other external inputs. The context processing unit outputs are fed into the hidden layer processing units through weighted connections. If each context unit also feeds its output back to itself then the network is termed a modified Elman network.

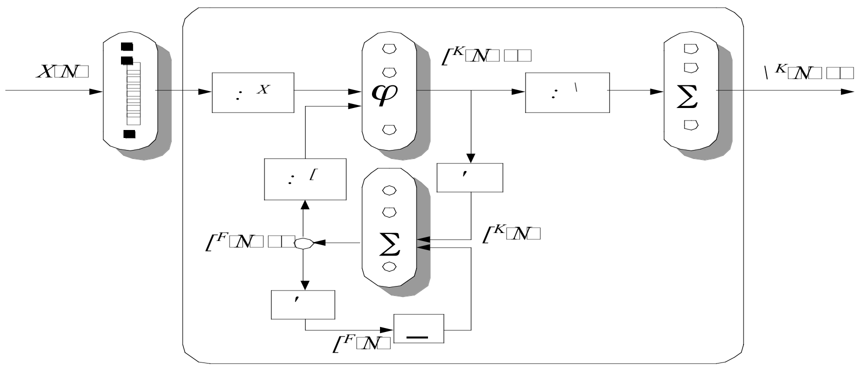

Fig.2. Block diagram of a modified Elman network.

For modelling purposes it is assumed that the plant to be controlled is a multivariable plant, with *m* inputs and *q* outputs, described by a general non-linear input-output discrete time state space model:

$$x(k+1) = f\{x(k), u(k)\} \tag{1}$$

$$y(k) = g\{x(k)\} \tag{2}$$

where $f : \Re^{n+p} \to \Re^{n}$ and $g : \Re^{n} \to \Re^{q}$ are non-linear functions; $u(k) \in \Re^{m}$, $y(k) \in \Re^{q}$ and $x(k) \in \Re^{n}$ are, respectively, the input vector, the output vector and the state vector, at a discrete time *k*.

Elman has proposed a partially recurrent network, where the feedforward connections are modifiable and the recurrent connections are fixed. Additionally to the input and the output units, the Elman network has a hidden unit, $x^{h}(k) \in \Re^{n}$ and a context unit, $x^{c}(k) \in \Re^{n}$, $W^{x} \in \Re^{nxn}$, $W^{u} \in \Re^{nxp}$ and $W^{y} \in \Re^{qxn}$ are the interconnection matrices, respectively, for the context-hidden layer, input-hidden layer and hidden-output layer. Theoretically, an Elman network with *n* hidden units is able to represent a n^{th} order dynamic system. However, due to practical difficulties with the identification of higher order systems, some modifications have been proposed. In Pham and Xing (1995) a self-connection $\alpha \in \Re^{+}$ in the context unit is introduced, improving its memorisation ability. The dynamics of the modified Elman neural network is described by the difference equations (3)–(6).

$$s(k+1) = W^{x} x^{c}(k+1) + W^{u} u(k) \tag{3}$$

$$x^{h}(k+1) = \varphi\{s(k+1)\} \tag{4}$$

$$x^{c}(k+1) = x^{h}(k) + \alpha x^{c}(k) \tag{5}$$

$$y^{h}(k+1) = W^{y} x^{h}(k+1) \tag{6}$$

where $s(k) \in \Re^{n}$ is an intermediate variable and $\varphi(\cdot)$ is an hyperbolic tangent function.

4.0 PROCESS DESCRIPTION

The application of neural network in fault detection and diagnosis is implemented to a palm oil fractionation plant. The process consists of five distillation columns connected in series. A simplified schematic diagram of the plant is provided in Figure 3(a). The feed to the plant is Palm Kernel Oil (PKO), which contains fatty acids from C6 - C18.

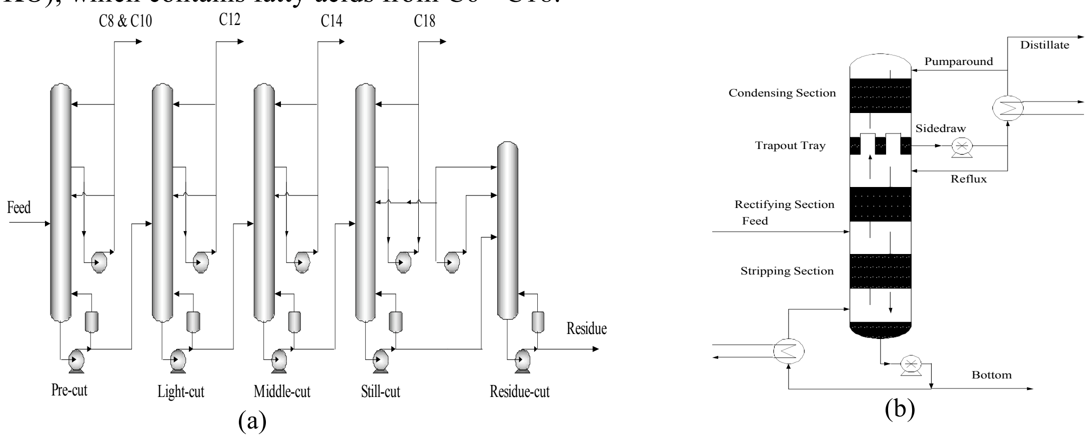

Fig.3. Schematic Diagram of a Fractionation Process (a) and a Typical Packed Column (b)

In the pre-cut column, light products consisting of mainly C8 and C10 and a trace of C6 are recovered in the overhead. The bottom stream is fed to the light-cut column where C12 is separated from the rest of its constituents. The bottom product then enters the middle-cut column where C14 and C16 are recovered leaving the C18 to be purified from the rest of the oil constituents in the still-cut column. In the residue cut column, C18 is recovered and recycled back to the previous column. All the distillation columns operate at highly vacuum conditions that are generated using steam ejectors. The columns are packed with structured packing to provide the desired separation properties.

Due to high operating temperatures, thermal oil is used for heating in the reboilers. A sectional view of a typical column is shown in Figure 3(b). The column is equipped with a pump-around system. Liquid collected on the trap-out tray is drawn out from a side-draw stream. The stream is split into two – a reflux stream and a stream that goes through an external cooler. The cooled stream is split again into two streams, one returning to the column as a recycle and one as the distillate. The pump-around system provides a means for the vapour in the column to be condensed through direct contact with the cooled liquid from above.

5.0 RESULTS AND DISCUSSIONS

This study focused on the malfunctions of the process caused by the failure of the temperature and pressure sensors in the pre-cut column. Faulty conditions are simulated using the HYSYS.Plant software to generated two sensor failures happen in certain time. Sensor failures are created causing the normal process operation to shift to a faulty operation mode. Effects of these faults are expressed by the top column pressure and bottom stage temperature in the pre-cut column.

Simulation of the column was carried out using HYSYS.Plant. Due to the non-conventional nature of the palm oil distillation system, the development of the flowsheet for the simulation has not been straightforward. For example, one of the long-chained fatty acid, caprylic acid (C8) is not found in HYSYS Component Properties Library. As such, C8's properties have to be estimated by HYSYS Hypothetical Component Manager. One has to provide as much data as possible so the estimation will be realistic. HYSYS.Plant does not support packed column as such, the equivalent tray (HETP) calculation was used. Similarly, model of a direct contact internal condenser based on packed column is also not available within the standard library and modifications have also been implemented. Proper initial values should be chosen for these streams; otherwise the system might converge to different values, which is not desirable due to the non-linearity and unstable characteristics of the process (HYSYS, 2000).

In this study, the ANN model development efforts were carried out using the neural network toolbox available within MATLAB software.

5.1 Process Predictor

A number of important issues must be addressed when dealing with the development of the neural network predictor. The first step was selecting the input variables and output variable for the neural network estimator. The inputs were selected based upon their availability in the actual industrial column and their effects on the top stage pressure and bottom column temperature. The inputs have been identified to consist of 12 variables; C12 composition, C8 composition, reflux flowrate, top stage temperature, bottom flowrate and distillate flowrate as well as a one-sampling-interval-delayed signal of each these variables. The output variables are top stage pressure and bottom column temperature.

Plant test data generation was designed and conducted in Hysys.Plant with emphasis to capture the dynamic behaviour of the column. A data set consisting of 2000 data points was obtained. The data was divided into two sets, a training set and a validation set.

The next stage concerned with the development of an artificial neural network (ANN) model that correctly mapped the input variables to the output variable. Elman network with structure shown in Figure 2 had been chosen to train the data. The Elman networks have been developed consist of *tansig* (hyperbolic tangent) neurons in its hidden (recurrent) layer, and *purelin* (linear) neurons in its output layer. With this combination, the network can approximate any function even with a finite number of discontinuities to an arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity.

Network training was implemented using gradient descent with momentum and adaptive learning backpropagation algorithm. The network was cross-validated at every batches training and thus the cross-validation errors of the network were monitored throughout the training. Network weights and biases were selected based on the minimum cross-validation error achieved in the training.

Table 1.0
Optimum network structures and their validation errors

	PREDICTOR			**CLASSIFIER**				
	MIMO	MISO (P)	MISO (T)	MIMO	MISO F1	MISO F2	MISO F3	MISO F4
Nodes	8	10	13	12	17	8	16	12
Error	4.4294e-3	2.3580e-3	1.9602e-3	5.3041e-4	6.1140e-7	6.7334e-6	2.8168e-5	1.0982e-5

The results in Table 1 revealed that MISO networks for process predictor have better prediction ability compared to MIMO network. The optimum network structures were established with 10 and 13 hidden neurons for top pressure predictor and bottom temperature, respectively. Figure 5 displays the performance of ANN in tracking the actual process data during the training and validation stages. Good performance in the validation set indicated that the network was able to represent the behaviour of the process in different operating conditions than that of the training set. In other words, the network is capable of estimating the product composition based on “unseen” data.

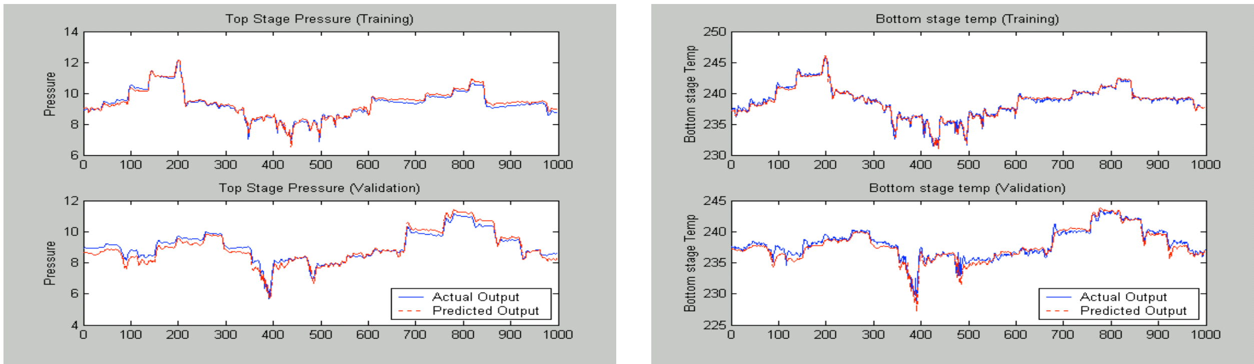

Fig. 5. Result of training and validation for process predictor

5.2 Fault Classifier

The fault classifier was constructed using feedforward neural network (FFNN) with single hidden layer. Network training was implemented using Levenberg-Marquardt learning algorithm. The network was also cross-validated at every batch of the training.

Sensor faults were simulated as if there were sudden failures of the measurement systems resulting in measurements bias. The magnitudes of the sensor biases were used as indicators for severity of the sensor fault. Since in the operation of the palm oil fractionation process, bottom stage temperature and top column pressure are the two important variables to be controlled, these variables were considered as the focus of this work. Both positive and negative bias measurements of these sensors were simulated for fault detection. Table 2 shows the list of process faults involved and their operating limits.

Table 2.0
List of Sensor Faults and Their Operating Limits

Sensor	Description	Operating limit
F1	Column Temperature Sensor +ve bias	245 ^{o}C
F2	Column Temperature Sensor –ve bias	230 ^{o}C
F3	Top Column Pressure Sensor +ve bias	15 kPa
F4	Top Column Pressure Sensor –ve bias	5 kPa

All these faults influence not only the performance of the control loops within the plant, but also the stability of the process. For example, when reboiler temperature is changed to 5%, bottom stage temperature and top column pressure deviated up to 2.7% and 4.6% from their operating limits, respectively. Some of these impacts are shown in Figure 6 below.

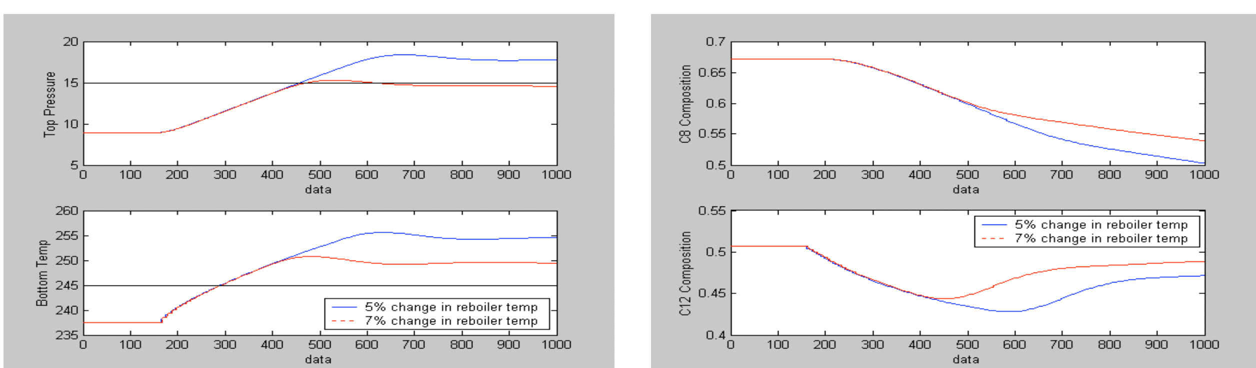

Fig. 6 Sensitivity analysis when 5% and 7% change in reboiler temperature

Inputs for fault classifier come from process predictor in the form of residual signal. The residual vector has different structures for different faults. This feature can be used to detect these faults. A FFNN classifier was developed with two inputs and four outputs (corresponding to the four faults being considered). At the output layer, output nodes indicate the classes of sensor fault occurred. The classifier developed in this work is used to detect two faults simultaneously. Therefore two output nodes are expected to respond when sensor faults occurred.

The output data for sensor faults were designed to spread linearly between 0 and 1 with the index 0 and 1 being used to represent the process during normal condition and violation of process limit respectively. Here, the output data corresponds to operation limit was assigned a value of 0.8.

The FFNN classifier can either be composed of a set of MISO networks or a single MIMO network. The performances of the selected MISO and MIMO networks for the fault classifier are displayed in Table 1. MISO networks showed better generalisation ability compared to the MIMO counterpart. Thus, the MISO networks were selected as the fault classifier with optimum structure of 17, 8, 16 and 12 hidden nodes for F1, F2, F3 and F4 classifier, respectively.

The results obtained shows that the success of the classifiers in detecting multiple faults happened to the plant. Figure 7 and Figure 8 show the output from the classifier exceed the index 0.8 indicate the violation of operating limit and the cause of the violation.

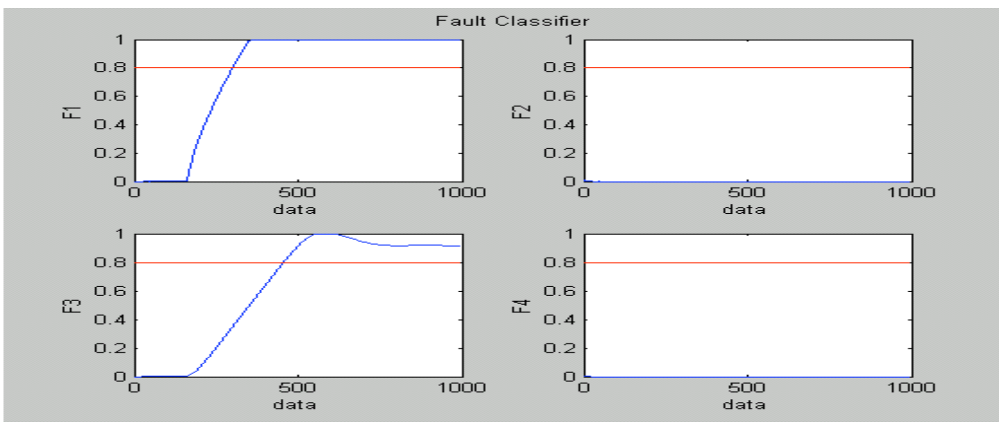

Fig. 7. Detection of faults F1 and F3 when +6% change in reboiler temperature.

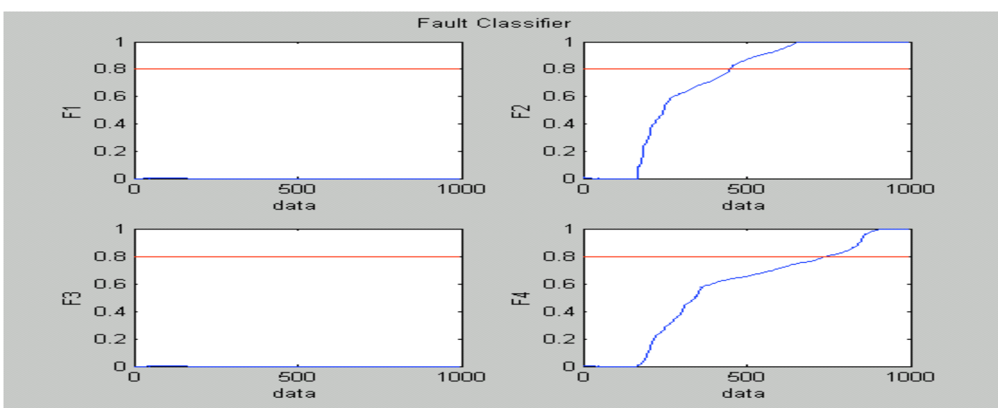

Fig. 8. Detection of faults F3 and F4 when -3.4% change in reboiler temperature

In Figure 7, when 6% change in reboiler temperature happened, F1 and F3 deviated up to 3.1% and 9.9% and the classifier's outputs reached the index 0.8 to trigger alarms telling that bottom stage temperature and top column pressure have exceed their operating limits. Similarly, when -3.4% change in reboiler temperature happened, F2 and F4 deviated up to 3.5% and 6.3% from their operating limits and exceed the index 0.8. This shows that the process faults were successfully detected. Similar observations were established when other fault patterns were introduced. In all cases, the proposed scheme had been successful in detecting multiple failures. However, due lack of space, the results are not shown here.

6.0 CONCLUSION

In this paper the application of a modified recurrent Elman network as process predictor have been presented. In the development of the process predictor, MISO model is more superior compared to MIMO model. In the development of fault classifier, feedforward neural network have been used and the results revealed that MISO networks are better than MIMO network because MISO model was easier and faster to train. Multiple faults detection for a palm oil fractionation plant is investigated here using a neural network predictor and neural network classifiers. Neural network models have effectively been applied as both the process predictor and fault classifier. The detection scheme has been successfully applied in multiple faults detection under dynamic state. The dynamic detection scheme presented here is useful in fault monitoring because rather than having a discrete detection, continuous detection allows operators to anticipate potential process failures. The scheme was able to detect multiple sensor faults in various places in the process such as top column pressure and bottom stage temperature. With an early detection, the engineer has a change to stop the faulty condition before it grows into a full malady.

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