Application of Artificial Neural Network in Fault Detection Study of Batch Esterification Process

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Abstract - The complexity of most chemical industry always tends to create a problem in monitoring and supervision system. Prompt fault detection and diagnosis is a best way to handle and tackle this problem. There are different methods tackling different angle already proposed in literature. One of the popular methods is artificial neural network which is a powerful tool in fault detection system. In this study, a production of ethyl acetate by a reaction of acetic acid and ethanol in a batch reactor is applied. The neural network with normal and faulty event is executed on the data collected from the experiment. The relationship between normal-faulty events is captured by training network topology. The ability of neural network to detect any process faults is based on their ability to learn from example and requiring little knowledge about the system structure.

Keywords - fault detection, artificial neural network, esterification process, batch reactor

I. INTRODUCTION

The complexity of most chemical industry always tends to create a problem in monitoring and supervision system. The lacking of monitoring jeopardises the plant failure, product deterioration, performance degradation, major damage to the equipment and human health even cause the death [11]. According to the studies, inadequate managing of abnormal situations caused annual losses of $20 billion for petrochemical industry in the USA [20]. The cost will be increased when similar situation occurs in pharmaceutical, polymers and bulk chemicals. The similar accidents also will cost British economy lost around $27 billion dollars every year [16].

According to the [23-25] fault detection methods can be classified into two categories; model-based and data driven method (process history). This classification is based on the process knowledge that is required a priori [26]. The type of priori process knowledge is adopted to distinguish feature for classifying fault diagnosis system. Normally, the basic of priori knowledge is the set of failure and the relationship between the symptoms and the failures [26].

Among this two methods, model-based is very popular and powerful tools to detect any failure as early as possible [1] [8] [9] [10]. In generating model-based system, the understanding on physical fundamental is needed. In the early applications, most of the process is based on observation for a linear system and analytical redundancy [2] [13].

Recently, the potential of neural network for fault diagnosis has been demonstrated. Neural network based approach is especially suitable when accurate mathematical models are too difficult to be generated for some processes. Neural networks attempt to mimic the computational structures of the human brain.

The application of Artificial Neural Network (ANN) in fault detection and diagnosis are based on model approximation and pattern recognition as well [18] [22] [28]. Among of this method, pattern recognition is more adequate based on difficulty to perform ANN training on dynamic patterns. Pattern recognition method can provide a convenient approach to solve the fault identification problem such as to determine the size of the fault [22]. Pattern recognition classification is typically off-line procedure where the information regarding normal and faulty situation can be obtained from the training. In recent years, few literature studies had acknowledged the efficacy of ANN as pattern recognition in fault identification and fault diagnosis.

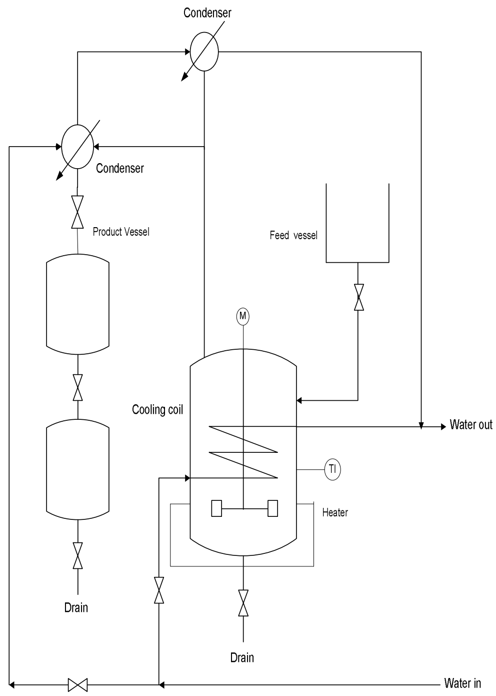
The applications of neural network can be summarized into three categories. The first is to use neural network to differentiate various fault patterns from normal operating condition, according to different measured process output data. The training of neural network can be offline or online. In the second category, neural networks are used as classifiers to isolate faults represented by process model generated residuals. The process model can be a mathematical model based on which the fault diagnosis structure utilizes some process mechanism provided by the quantitative model, and therefore facilitates the implementation and training of the neural classifier. In cases when mathematical process models are not available, a neural process model can be employed to generate residuals another network is then used to isolate faults.

II. CASE STUDIES: BATCH ESTERIFICATION PROCESS

A. Process Faults

The process studies are a batch esterification for the production of ethyl acetate from a reaction of ethanol and acetic acid. This reaction is catalyzed by sulfuric acid. Esterification process is a well known reaction, simple and moderately exothermic reaction with no danger of decomposition reaction. Furthermore, this type of reaction also gets an attention from researchers to study the possible runaway reaction by applied different chemical types [19] [4] [5].

The experiment is carried out in pilot-plant batch reactor. The schematic diagram for this pilot-plant batch reactor is show in Figure 1. This pilot plant batch reactor is used to collect the data for both normal and different faulty situation. Pilot-plant batch reactor consists of reaction vessel, electric heating via heating mantle, variable speed stirrer, temperature indicator, cooling coil, feed vessel, gas feed pipe and solid discharge pipe. The maximum capacity of the reaction vessel is 20 litres.



Legend

M : motor stirrer
TI : Temperature indicator

Fig. 1 Schematic diagram of batch reactor

B. Fault Generation

Faults are defined as any non-permitted deviation from an acceptable behavior at least one of the characterization [15]. [9] [10], give their own perspective of fault definition. They mention a fault is an additional input that can disturb the system performance. Normally, a fault can be classified by temporary or permanent physical changes in the system [17].

To study the different faulty conditions, two different fault situations is generated based on process parameter changing. This generated possible fault is used to study a comparison between the normal and process fault. Two types of fault applied are incremental of catalyst concentration and catalyst volume. Both of this increment is 40% higher than the normal operations.

C. Data Collection

Data collection from the experimental part is very important in application of neural network. The experimental data should consist of a normal and different faulty phenomenon. Normally, it is impossible to have information regarding the actual process fault in real chemical process. In normal operation, this situation can be more serious when the process is still running. Additionally, it is time consuming to find out the actual faults situations. To overcome this problem, most of the researcher in this area tries to implement the generated possible faults in their research. At this stage, the researchers studied based on their proposed faults.

D. Network Architecture

The design of neural network is crucial in the process modeling. The architecture type, transfer function, number and the size of hidden layer and learning rate play an important key to determine the best neural network architecture [28]. A multilayer feedforward neural network was proposed in this study. This structure was used based on the simplicity process chooses and it is enough to classify different fault generated from the normal operations. It is also the most popular network architecture. One hidden layer was used in the neural network because it is enough to differentiate faults from the process.

Generally, Multilayer Perceptron (MLP) with single hidden layer feed forward network contains an input layer, one hidden layer and an output layer. [3] and [14] mention that networks with one hidden layer can show their ability to estimate the value with a sufficient degree of freedom as well as effectively identifying process faults or feature classification. [7] in their paper give a conclusion that single hidden layer is enough for system that have one input or the input that represented as a binary number; 1 or 0.

This suitability of this network architecture was studied by [27] and [21]. Currently, there is no simple way to determine the best architecture. Experience is the only key factor to ascertain whether it is the best or bad architecture [12].

E. *Network Training*

The network was trained in MATLAB® environment software programmed by exploiting Neural Network Toolbox model version 7.0.1. This software is chosen due to its capabilities and ability to provide solutions in technical computing [6]. Among various training algorithm available, Levenberg-Marquardt (LM) training function was selected because it has the fastest convergence ability [6]. This type of training was also implemented by [28]. In practice, the Levenberg-Marquardt (LM) routine often finds better optimal solution for a variety of problems as compared to other optimization methods.

The details of the training process are shown below:

- The networks are trained using the Levenberg-Marquardt training algorithm;
- Performance goal is 10^{-5};
- The maximum number of neurons: 50;
- The hidden layer contains sigmoid activation function;
- The output layer contains linear activation function;
- The trained network has 21 hidden layer neurons

III RESULT AND DISCUSSION

The result obtained is based on pattern classification between normal and faulty situation. Figure 2 shows the pattern for normal operation. It is visible that there is one smooth peak generate at network output of 0-61 samples frames. There are also some noise generated at different samples frames caused by the process transition between one faults to another.

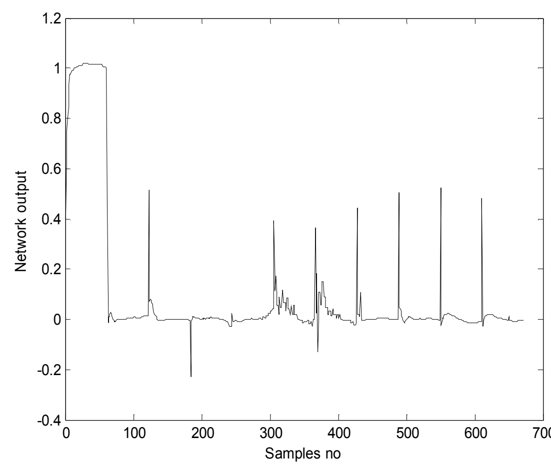


Fig. 2 Network output for normal operation

The two outputs of neural classifier are shown in Figure 3 and 4. It is clear that both two faults have been detected and isolated. The patterns generated are slightly different compared to normal operation and it is can be differentiate. One smooth peak occurs for fault no. 1 at samples frames of 123-183 whereas the peak occurs at samples frames of 245-305 for fault no. 2. The fact that classifier outputs are not zero when no fault occurs is due to errors of the neural model and noise [28].

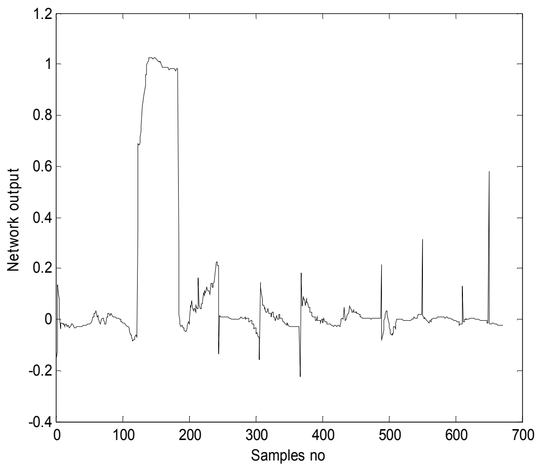


Fig. 3 Network output for fault no. 1

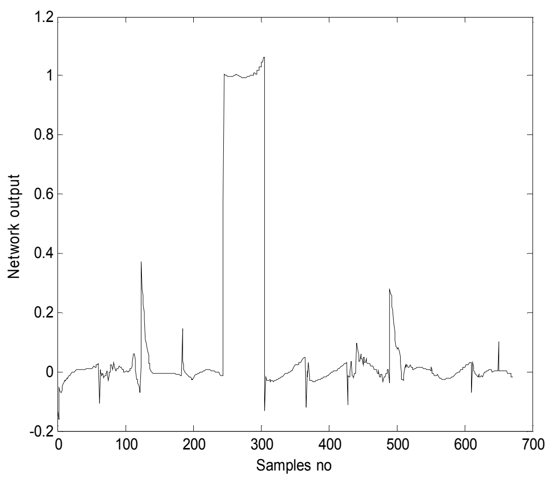


Fig. 4 Network output for fault no. 2

IV CONCLUSION

Fault diagnosis for pilot-plant batch esterification process is investigated in this work by a feed forward neural model by implementing multilayer perceptron. The effect of catalyst concentration and catalyst volume are studied and classified successfully using the neural process model. The results displayed that neural network is able to detect and isolate two fault studies with a nice pattern classification.

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