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APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN PROCESS FAULT DIAGNOSIS

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Abstract

Chemical processes are systems that include complicated network of material, energy and process flow. As time passes, the performance of chemical process gradually degrades due to the deterioration of process equipments and components. The early detection and diagnosis of faults in chemical processes is very important both from the viewpoint of plant safety as well as reduced manufacturing costs. The conventional way used in fault detection and diagnosis is through the use of models of the process, which is not easy to be achieved in many cases. In recent years, an artificial intelligence technique such as neural network has been successfully used for pattern recognition and as such it can be suitable for use in fault diagnosis of processes [1]. The application of neural network methods in process fault detection and diagnosis is demonstrated in this work in two case studies using simulated chemical plant systems. Both systems were successfully diagnosed of the faults introduced in them. The neural networks were able to generalise to successfully diagnosed fault combinations it was not explicitly trained upon. Thus, neural network can be fully applied in industries as it has shown several advantages over the conventional way in fault diagnosis.

Keywords: Artificial Intelligence, Neural Network, Fault Diagnosis, Processes, Pattern Recognition, Plant Safety

1. Introduction

In chemical plants, relationships between performance patterns and fault are generally non-linear. The use of the conventional methods will be highly difficult

Nomenclatures

F	Flow rate
P	Pressure
T	Temperature

and inaccurate [2]. Fault diagnosis and detection are essentially pattern recognition tasks [3] where sensor data which contain no readily useful message can be transformed via pattern recognition into clear information useful for decision making. The artificial neural networks can classify data effectively; it would seem that it is an appropriate tool to perform fault diagnosis in a chemical plant.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information [3]. A key element of this paradigm is the novel structure of the information processing system [4]. It is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve specific problems. ANNs, like people, learn by example [5]. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process [6]. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons as in the ANNs as well.

Artificial neural networks have many very useful properties concerning process fault diagnosis. They can handle nonlinear and undetermined processes when no process model is needed and the neural network learns the diagnosis by means of the information of the learning data [4]. Neural networks are very noise tolerant and work well with noisy measurements. The ability to generalize the knowledge as well as the ability to adapt during its use is one of its very interesting properties [6]. The use of neural networks in fault diagnosis is very straightforward. In this paper we demonstrate these features in 2 case studies involving different parts of a chemical plant.

2. Methodology- Feedforward Neural Network Model

2.1 Training

Pattern recognition can be implemented by using a feed-forward neural network that has been trained accordingly. In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually adjusted. The set of data which enables the training is called the “training set”. During the training of a network the same set of data is processed many times as the connection weights are ever refined. Detail of training can be found in [7].

When the network is used, it identifies the input pattern and tries to output the associated output pattern. The power of neural networks comes to life when a pattern that has no output associated with it, is given as an input in the validation process. In this case, the network gives the output that corresponds to a taught input pattern that is different from the given pattern. In these case studies, the input pattern represents the important variables that are affected by the existing faults and the output pattern represents the fault to be identified.

2.2 Fault diagnosis application

The development of the neural network model for the fault diagnosis studies is as follows:

1. Identification of the faults and the possible causes of the faults for the model.
2. Generation of fault data from the simulations representing normal and faulty conditions.
3. Identification of the input and output of the neural network model.
4. Classification of the training data sets and validation data sets.
5. Training the neural network by using the appropriate training data sets.
6. Validation of the neural network model for the fault diagnosis by using the testing data set.

These are the steps to be applied to the 2 case studies in the next section.

3. Case Study

3.1 Case study 1 – Production of acrylic acid

The plant chosen for case study 1 is the production of acrylic acid. Figure 1 shows the reaction part of the plant, in which propylene is converted to acrolein and then further oxidised in the reactor to acrylic acid. Vapour of propylene is mixed with oxygen and steam as the input. It is compressed and further preheated before entering the reactor. The output of this section is acrylic acid. This plant operation has been simulated by using the HYSYS program.

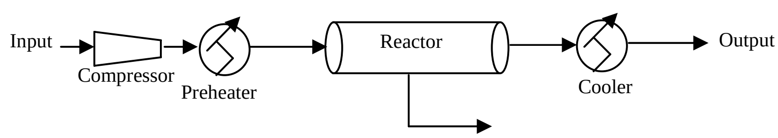


Fig. 1. Chemical Plant to be Diagnosis for Case Study 1.

Four (4) faults have been identified to be diagnosed in this case study. These faults are chosen because they are significant factors that would lead to increase in the cost of operation and decrease in profit due to loss of energy and drop of production of the plant. Below are the faults and possible causes of the failure in the plant.

Fault 1 : Performance of pump for inlet of raw materials degrades. Decrease of flow rate of feed into reactor, thus decreasing the production rate.

Fault 2 : Fouling inside the heater leads to a decrease of overall heat transfer coefficient in the system.

Fault 3 : Partial blockage in the reactor which increase the pressure drop inside reactor and reduce conversion of raw materials to product.

Fault 4 : Fouling of the heat exchanger surface in the reactor leads to a decrease of overall heat transfer coefficient in the system.

The existence of the above four faults are described and diagnosed from measurements of the outlet product flow rate, outlet product temperature and the outlet product pressure. The fault data were generated by changing the inlet flow rate of raw material, temperature of the preheated stream before entering into reactor, pressure drop inside the reactor and heat duty of reactor which changes the values of F, T and P respectively.

Table 1 shows the sample of typical input data used to train the neural network for each of the faults respectively. The 4 faults are represented by identity values for the output node 1, 2, 3 and 4 respectively. The values of F, T and P represent the input data for the neural network model. The normal condition represented by null value in each output node is also shown in the Table 1. Table 2 shows the prediction by the neural network model in terms of probability for each of the faults when presented with the validation data set. Figure 2 shows that the neural network outputs nearly match all the targets set.

Table 1. Sample Teaching Patterns for the Networks in Case Study 1.

Fault	**Input Data**			**Output Data**			
	F	**T**	**P**	**Node 1**	**Node 2**	**Node 3**	**Node 4**
1	12414	640	133.4	1	0	0	0
2	10750	587.6	134.6	0	1	0	0
3	10864	666.4	42.66	0	0	1	0
4	10799	555.2	134.4	0	0	0	1
Normal	10921	654.7	134	0	0	0	0

Table 2. Classification Matrix for the Diagnosis Fault Using the Neural Network Trained For Case Study 1.

Diagnosed Introduced	**Fault 1 (probability)**	**Fault 2 (probability)**	**Fault 3 (probability)**	**Fault 4 (probability)**
Fault 1	**0.98**	0.371	0.0043	0.0078
Fault 2	0.25	**0.703**	0.0325	0.121
Fault 3	0.0139	0.0094	**0.93**	0.0332
Fault 4	0.0066	0.0231	0.052	**0.902**

From the results in Table 2 and Fig. 2 respectively, the average results show a probability of above 0.9 for the faults that happen and a probability close to zero for those that did not happen, except for fault 2 which gave a probability of 0.7038. This is due to the similarity of the input data between fault 2 and fault 4 which reduce the efficiency of pattern recognition by the neural network for fault 2. Although the accuracy of the fault 2 is below the others the pattern of the fault can still be recognized and still show an acceptable probability close to one. The overall results imply that the artificial neural network is indeed effective in the fault detection and diagnosis of the simulated chemical plant.

3.2 Case study 2 – Production of acrolein

This case study involves a plant producing acrolein which is simulated using the HYSYS program. Figure 3 below is the simplification of the production plant, in which propylene is converted to acrolein which is the final product. Vapour of propylene is mixed with air and steam as the input, compressed and further preheated before entering the reactor. In the reactor, propylene is oxidized to acrolein. The output from the reactor goes through the purification part, which is the separator and a distillation column to separate acrolein from the other products.

Again four (4) faults have been identified to be diagnosed in this case study. Below are the faults and possible causes of the failure in the plant.

Fault 1 : Performance of compressor of inlet of raw material (propylene) degrades. Decreases flow rate of propylene into reactor, thus decreasing the production rate.
Fault 2 : Fouling inside the heater leads to a decrease of overall heat transfer coefficient in the system.
Fault 3 : Partial blockage in the reactor which increases the pressure drop inside reactor and reduces conversion of raw materials to product.
Fault 4 : Fouling of the heat exchanger surface in the condenser of distillation column leads to a decrease of overall heat transfer coefficient in the system.

The existence of the above four faults are identified and diagnosed from measurements of the acrolein flow rate, $F_{Acrolein;}$ water flow rate, F_{water}; outlet temperature, T_0 and outlet pressure of top product, P_0.

The fault data were generated by changing the values of the inlet flow rate of propylene, temperature of the preheater before entering into reactor, pressure drop inside the reactor and heat duty of the condenser. Table 3 shows the sample of typical input data used to train the neural network for each of the faults respectively. The 4 faults are represented by identity values for node 1, 2, 3 and respectively. The normal condition represented by null value in each output node is also shown in the Table 3. Table 4 shows the prediction by the neural network model in terms of probability for each of the fault when presented with the validation data set.

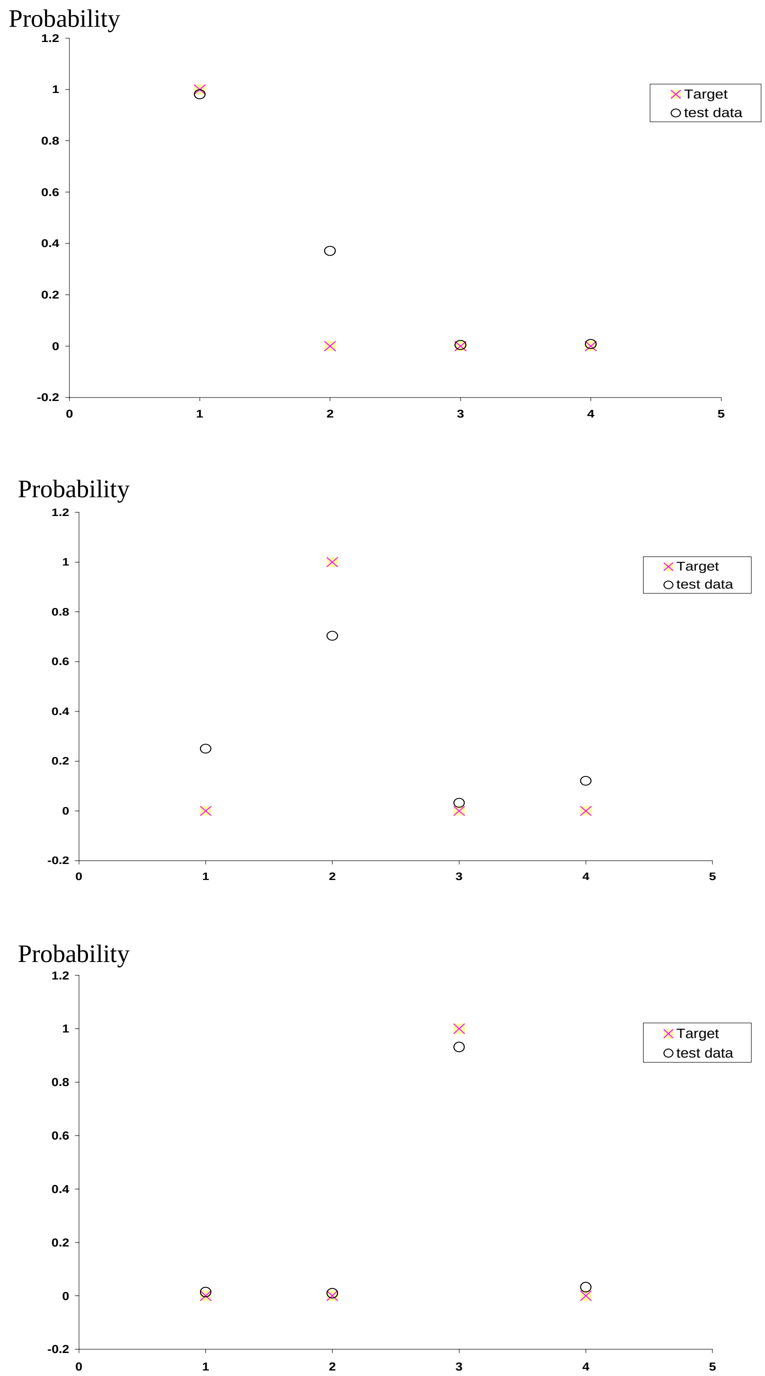
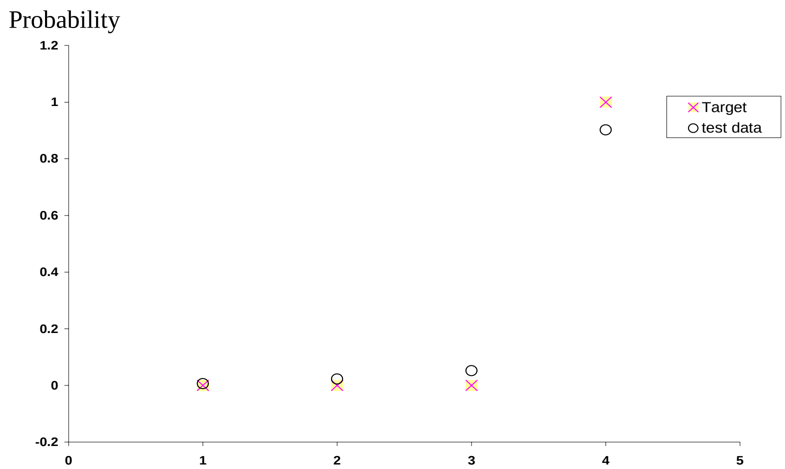


Fig. 2. Fault Diagnosis Results for Case Study 1. **(Continued on next page)**



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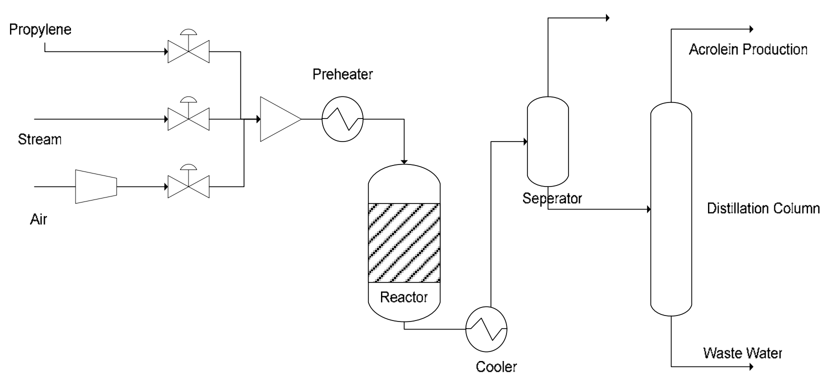

Fig. 3. Chemical Plant to be Diagnosed in Case Study 2.

Table 3. Sample Teaching Patterns for the Networks in Case Study 2

Fault	Input Data				Output Data			
	$F_{Arcolein}$	F_{water}	T_o	P_o	Node 1	Node 2	Node 3	Node 4
1	74.8	395.8	52.7	100	1	0	0	0
2	65.79	386.8	52.7	100	0	1	0	0
3	65.98	386.97	52.7	100	0	0	1	0
4	66.93	384.93	51.79	97	0	0	0	1
Normal	66.93	367.95	52.7	100	0	0	0	0

Table 4. Classification Matrix for the Diagnosis Fault Using the Neural Network Trained in Case Study 2

Diagnosed Introduced	Fault 1 (probability)	Fault 2 (probability)	Fault 3 (probability)	Fault 4 (probability)
Fault 1	**0.9514**	0.0340	0.0477	0.0563
Fault 2	0.0002	**0.9434**	0.0409	0.0472
Fault 3	0.0243	0.0813	**0.9573**	0.0061
Fault 4	0.0407	0.0843	0.0077	**0.9119**

The results in Table 4 show that the probability of each respective fault can achieve above 0.9 in the fault detection for the given part of chemical plant. The graph in Figure 4 also shows that the network outputs nearly match all targets set. The overall results imply that the artificial neural network is again indeed very effective in the fault detection and diagnosis of this chemical process plant.

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4. Discussions and Conclusions

Artificial neural networks exhibit a number of features that make them attractive for fault detection and diagnosis in complex systems. A network can learn the correct associations between system faults and system data provided. As demonstrated, neural networks are able to acquire diagnostic knowledge from examples of fault scenarios. This knowledge acquisition is an automatic process driven by a learning algorithm called the back-propagation algorithm [7]. Furthermore, a network can generalize so that input patterns not in the training set can be classified. Finally, artificial neural networks can accommodate their diagnosis to noise and uncertainty that exist in all process measurements [6].

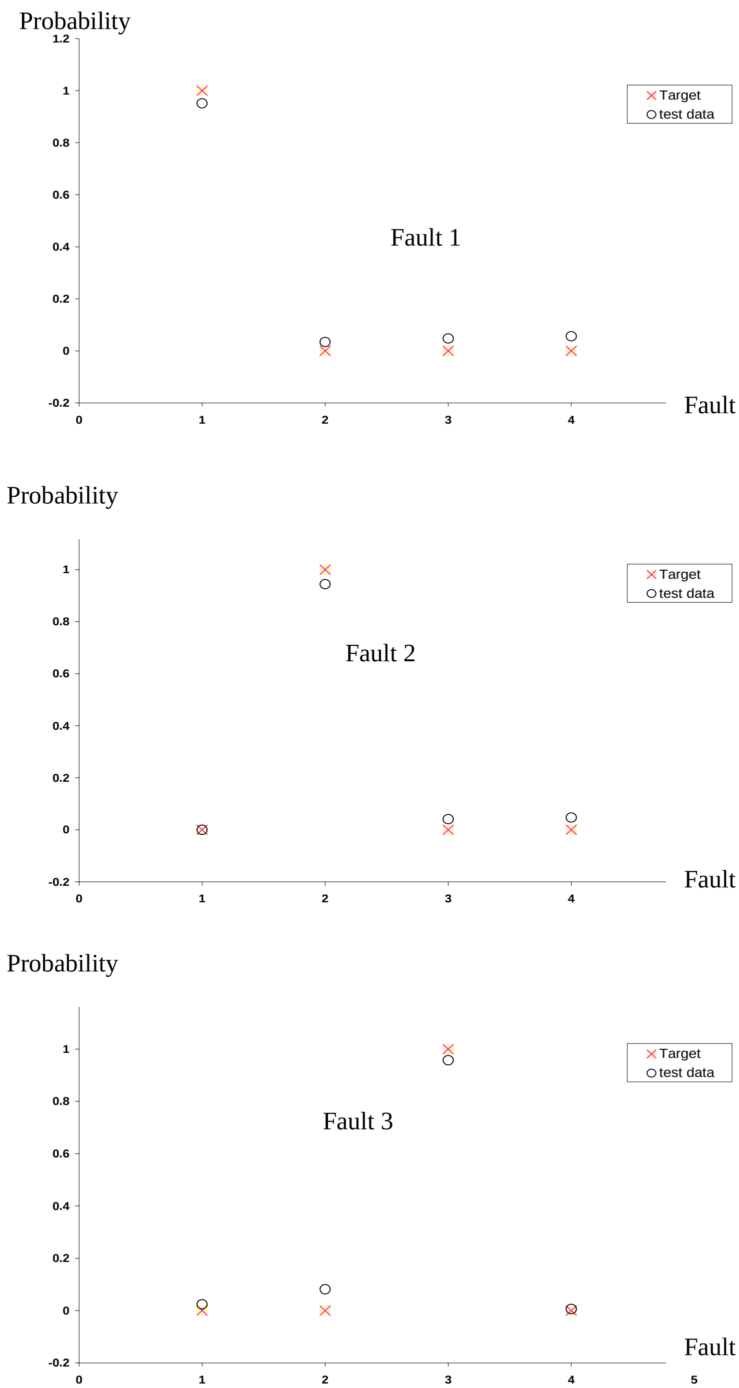

Fig. 4. Faults Diagnosis Results for Case Study 2. **(Continued on next page).**

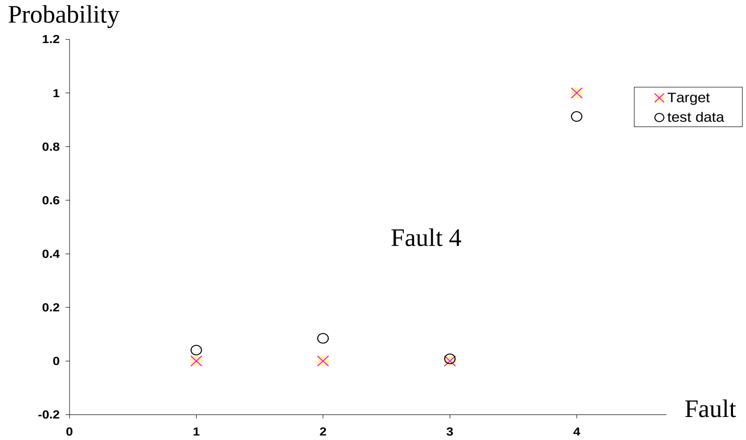

Fig. 4. Faults Diagnosis Results for Case Study 2.

The neural networks recalled the faults nearly perfectly in the above 2 case studies. Even if the degree of fault differed, the network accurately discriminated among the faults. It implies that the neural networks can accurately classify the correct faults, unlike traditional fault tree analysis, which requires very exact knowledge about the process in fault diagnosis and it takes a longer time to diagnosis the faults out. With such knowledge, the trained network can achieve higher accuracy because the combination of working experience with this neural-network-based computerised system give a more specific identification of the real fault that can happen.

Finally, we can conclude that the artificial neural network is a fast and reliable tool to be implemented in the fault diagnosis and early detection of faults in chemical processes and is highly useful for trouble-shooting such chemical plants.

References

1. Fan, J.Y., Nikolaou, M. & White, R. E. (1993). An approach to fault diagnosis of chemical processes via neural networks. *AIChE Journal*, 39, 82-88.
2. Himmelblau, D. M. (1978). *Fault Detection and Diagnosis in Chemical and Petrochemical Processes*, Amsterdam: Elsevier.
3. Watanabe, K., Matsuura, L., Abe M. & Kubota M. (1989). Incipient Fault Diagnosis of Chemical Processes via Artificial Neural Networks. *AIChE Journal*, 35, 1803-1812.
4. Watanabe, K., & Himmelblau, D. M. (1984). Incipient Fault Diagnosis in Nonlinear Chemical Processes with Multiple Causes of Faults. *Chemical Enineering. Science*, 39, 491-508.

5. Hoskins, J. C., & Himmelblau, D. M. (1988). Artificial Neural Network Models of Knowledge Representation in Process Engineering *Computers and Chemical Engineering*, 12, 881-890.
6. Pao,Y. (1989). *Adaptive Pattern Recognition and Neural Network.* New York: Addison-Wesley.
7. Hussain, M.A & Kershenbaum, L.S. (2000). Implementation of inverse-model-based control strategy using neural networks on a partially simulated exothermic reactor. *Transactions of Chemical Engineers* (Part A), 78, 299-311.