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# Multiple Fault Diagnosis Method Using a Neural Network

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## ABSTRACT

It is well known that neural networks can be used to diagnose multiple faults to some limited extent. In this work we present a *Multiple Fault Diagnosis Method (MFDM)* via neural network which can effectively diagnose multiple faults. To diagnose multiple fault, the proposed method finds the maximum value in the output nodes of the neural network and decreases the node value by changing the hidden node values. This method can find the other faults by computing again with the changed hidden node values. The effectiveness of this method is explored through a neural-network-based fault diagnosis case study of a fluidized catalytic cracking unit (FCCU).

## 1. INTRODUCTION

The sophisticated chemical industries have needed the fault diagnosis expert systems that can detect and diagnose the faults of some processes and give an adviçe to the operator in the event of process faults. A number of knowledge-based expert system (KBES) approaches have been proposed in the literature for automated diagnosis. However, rapid deployment of these systems has been difficult to achieve due to certain inherent limitations associated with current KBES. These limitations include 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 (Venkatasubramanian *et al.*, 1990).

Fault diagnosis for chemical processes via neural networks has elicited notable research interest (Hoskins *et al.*, 1988; Venkatasubramanian *et al.*, 1989), and has been applied to several processes (Venkatasubramanian *et al.*, 1990; Fan *et al.*, 1993; Hoskins *et al.*, 1991, *etc.*). Recently, many researchers in the area of neural networks for process fault diagnosis have investigated the characteristics of varied node transfer functions (Himmelblau, 1992; Kavuri *et al.*, 1992; Leonard *et al.*, 1992a; Leonard *et al.*, 1992b; Kavuri *et al.*, 1993).

Process plants are often very complicated and the number of faults can be very large. While a suitable decomposition of the process could be used, it is still not feasible to consider the combinatorially large number of multiple fault combinations. Unfortunately, multiple faults, including sensor failures and parameter drifts, are commoh in the process industry. It would be very useful if there is a way to generalize the inference to multiple faults from the information on single fault situations (Venkatasubramanian, 1991). With an artificial neural network trained only for typical fault patterns for single fault, investigations have shown that the network can diagnose multiple faults to some limited extent. Typical neural network based fault diagnosis systems frequently diagnoses only one fault correctly concerning multiple faults in a chemical process because one symptom overshadows the others by the interaction on each other and differences in their propagating speed. Thus we propose *Multiple Fault Diagnosis Method (MFDM)* via neural network to effectively detect multiple faults.

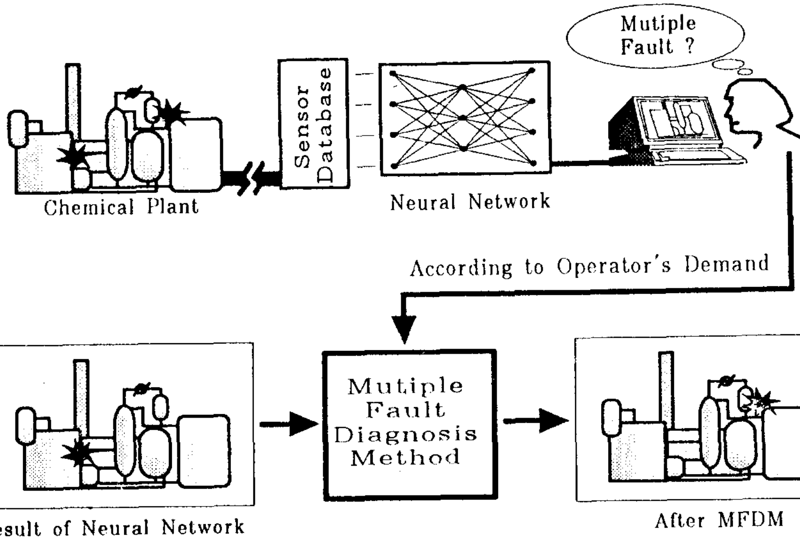


**Figure 1. The function of Multiple Fault Diagnosis Method.**

Using the MFDM, usually, the neural network diagnoses faults in chemical processes. But, if an operator asks for MFDM, it will analyze the result from the neural network for possible multiple faults. Figure 1 shows the function of the method within a fault diagnosis system based on neural network. As shown in lower left-hand corner of the figure, the diagnosis result in the two-fault case indicates only one fault, but the method can find the other fault by decreasing the maximum output value of the network result. We use a fluidized catalytic cracking unit (Venkatasubramanian *et al.*, 1989) to illustrate the proposed method.

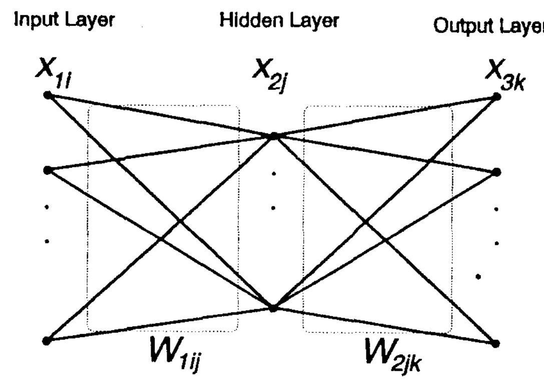


**Figure 2. Multi-layer neural network.**

## 2. NEURAL NETWORK AND MULTIPLE FAULT DIAGNOSIS METHOD

We use a typical multi-layer perceptron neural network with 3 layers, and sigmoid function is employed in the network.

Figure 2 depicts the typical 3-layer perceptron neural network. The output values ($x_{3k}$) of the network are determined as follows:

$$n_{3k} = \sum_j W_{2jk}\, x_{2j} \tag{1a}$$

$$x_{3k} = f(n_{3k} + b_{3k}) \tag{1b}$$

Where $n_{3k}$ is the net sum of the $k$th node in the output layer (the inner product of the weight vector for $k$th node in the output layer and the node vector for the hidden layer), $f(\cdot)$ is a sigmoid function, and

$b_{3k}$ is the bias of the $k$th node in the output layer. For the MFDM, we need an inverse sigmoid function at the output nodes.

$$f^{-1}(x_{3k}) = -\ln\left(\frac{1-x_{3k}}{x_{3k}}\right) \qquad (2)$$

After fault diagnosis for a chemical process in which a multiple fault occurred, a winner node, the maximum value in the output layer, can be selected. The net sums of the winner node, $n_{3M}$, and $n'_{3M}$ changed via MFDM are expressed as follows:

$$\begin{aligned} &\textit{winner node}: \; n_{3M} = \sum_j W_{2jM}\, x_{2j} = f^{-1}(x_{3M}) - b_{3M} \\ &\textit{after MFDM}: \; n'_{3M} = \sum_j W_{2jM}\, x'_{2j} = f^{-1}(x'_{3M}) - b_{3M} \end{aligned} \qquad (3)$$

$$x'_{2j} = x_{2j} - \lambda_{2j} \qquad (4)$$

Where $x'_{3M}$ is a fault certainty that is considered as nonfaulty state (in this investigation, $x'_{3M} = 0.01$), $x'_{2j}$ is the changed value of $j$th node in the hidden layer, and $\lambda_{2j}$ is the change in the same node. The output value of the neural network is determined by its weights connected to hidden nodes and their values. Thus $\lambda_{2j}$ may be determined linearly with its weight connected to the winner node as follows:

$$\lambda_{2j} = \lambda W_{2jM} \qquad (5)$$

Solving for $\lambda$ gives:

$$\lambda = \frac{n_{3M} - n'_{3M}}{\sum_j (W_{2jM})^2} \qquad (6)$$

Given $\lambda$, we determine $\lambda_{2j}$ and $x'_{2j}$ by equations (5) and (4), then new output values are calculated. Therefore we can obtain new diagnosis result from which winner node has vanished.

## 3. OUTPUT COMPENSATION IN MULTIPLE FAULT DIAGNOSIS METHOD

Inherently the proposed method brings on the biases in output values of diagnosis result. When the method is used for a single fault, wrong diagnostic results sometimes happen. These *biases* do not only obscure the diagnostic results but also cause wrong results. Therefore we should compensate for these biases. After the MFDM was applied to winner node $M$, the changed value of the node is $x'_{3M}$ and $n'_{3M} = f^{-1}(x'_{3M})$. But, the other outputs show unacceptable values. Thus we have to adjust these values to acceptable values, $adj\_n_3$ (in this investigation, $f(adj\_n_3) = 0.05$). This can be accomplished by employing compensation values, $adj_k^M$, on MFDM:

$$adj_k^M = n_{3k}^M - adj\_n_3 \qquad (7)$$

Where $adj_k^M$ and $n_{3k}^M$ denote the compensation value and the net sum of the $k$th output node, respectively, concerning the winner node $M$.

Therefore, the MFDM with output compensation can be expressed as follows:

$$n'_{3k} = \sum_j W_{2jk}\, x'_{2j} - \beta\, adj_k^M \qquad (8)$$

$$\beta = \frac{n_{3M} - n'_{3M}}{n_{3M}^S - n'_{3M}} \qquad (9)$$

Where $n_{3M}^S$ is the net sum of the winner node associated with a single fault $M$, $n'_{3M}$ is the changed value after MFDM (this value is specified by user), and $n_{3M}$ is the actual value obtained when fault(s) occurs. Thus $\beta$ is the multiple factor of the compensation method according to the magnitude of the fault. In the following case study, we used the MFDM with output compensation.

## 4. THE FCCU CASE STUDY

The process considered is the fluidized catalytic cracking unit, which has been investigated as an example for a fault diagnosis system via neural network by Venkatasubramanian *et al.* (1989). The network used in this case study has input patterns encoded in binary values. In this study, the network has 18 input nodes and 13 output nodes which represent the symptoms and their immediate faults, respectively. Table 1 lists the training data for the 13 faults involved. Process schematic and detailed discussion about the process model can be found in Venkatasubramanian *et al.* (1989).

Table 1. Songle-Fault Training Data for the FCCU Case Study

*i* – Input Pattern Symptoms (18 PE's)
*d* – Output Pattern Single Fault Occurrence (13 PE's)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *i* | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | | | | | |
| *i* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| *d* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | | | | | |

(Venkatasubramanian *et al.*, 1989)

Various numbers of hidden nodes (10, 15, 18, 20, 25, 30, 35, and 40) and the different tolerances of r.m.s. recall error (0.001, 0.0025, 0.005, 0.0075, and 0.01) were explored to observe the two-fault generalization performances of the neural networks and the MFDM. Thus we had prepared 40 types of networks and ten trials were done at each network type. Namely, we had prepared total 400 networks for statistical investigation. While the networks were being trained on 13 single faults, 73 symptoms for two-faults be presented by Boolean combinations of 13 symptoms for single faults.

Figure 3 illustrates the diagnostic performance curves for two-fault generalization as a function of hidden nodes. In the figure, successful diagnosis of two-faults is the case when the fault certainties (output node values) of the faults are greater than 0.3 and the other output values are smaller than those certainties. As seen from the figure, the MFDM

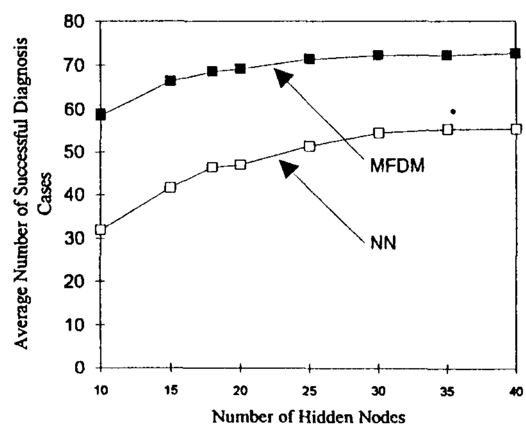


Figure 3. Diagnostic performance curves for two-fault generalization in FCCU case study.

considerably extends the network's capability for diagnosing multiple faults. If the winner node of the diagnostic result via the neural network, indicating the major causal source of the symptom, does not belong to the output nodes concerning the multiple fault, the MFDM which was applied to this winner node suggests meaningless result. In this case study, except these cases which were wrongly diagnosed via the neural networks, the average diagnostic accuracy of the MFDM for two-fault generalization was 98.8% concerning 400 neural networks.

Figure 4 shows the diagnostic performance curves for three-fault generalization with three certainties > 0.2. As seen in two-fault and three-fault generalizations, these results show potential of multiple fault diagnosis of chemical processes via the MFDM.

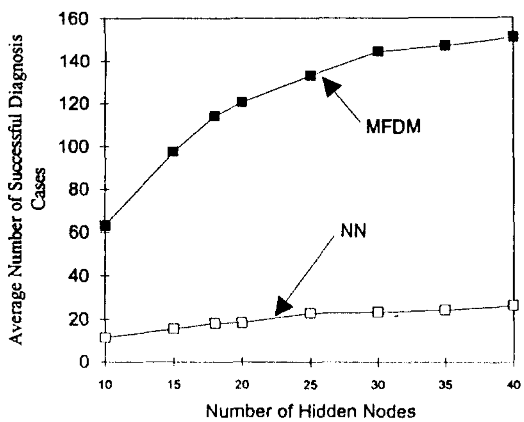


Figure 4. Diagnostic performance curves for three-fault generalization in FCCU case study.

## 5. CONCLUSIONS

In this paper we have presented a *Multiple Fault Diagnosis Method (MFDM)* to correctly diagnose multiple faults using the neural network based fault diagnosis system. Typically fault diagnosis systems diagnose only one fault correctly when multiple faults exist in a chemical process because one symptom overshadows the others due to interactions and differences in their propagating speed. Meanwhile, as demonstrated, the proposed method can recover the overshadowed symptoms and correctly diagnose multiple faults. The results of the FCCU case study show good diagnostic performance for multiple faults.

With small modifications in the existing fault diagnosis system based on neural network(s), the proposed method can give more information about process operability to the operators.

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