Detection of Single and Dual Incipient Process Faults Using an Improved Artificial Neural Network

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ABSTRACT: *Changes in the physicochemical conditions of process unit, even under control, may lead to what are generically referred to as faults. The cognition of causes is very important, because the system can be diagnosed and fault tolerated. In this article, we discuss and propose an artificial neural network that can detect the incipient and gradual faults either individually or mutually. The main feature of the proposed network is including the fault patterns in the input space. The scheme is examined through a sample unit with five probable occurring faults. The simulation results indicate that the proposed algorithm can detect both single and two simultaneous faults properly.*

KEY WORDS: *Fault Tolerance, Fault Diagnosis, Incipient faults, Dual faults, Artificial Neural Networks.*

INTRODUCTION

Faults in the 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. Further, the gradual and incipient faults can cause the other ones exploring in a cascade manner and eventually lead the process to catastrophes [1]. The inspection task can be carried out using finite and certain numbers of measured noisy quantities as input to the *fault detector* module. The software inherent in the module should report the fault by these data.

There are several quantitative techniques to explore the incipient faults [2-4]. The major parts of the researches include application of various observers - either linear or nonlinear - and henceforth need a great deal of complex and hard modeling tasks. The uncertainties in modeling add another complexity to the problem and the model error may cause a misleading alarm or on the contrary may lead to ignore a real fault.

The expert systems equipped with either binary or multi-valued logics (like fuzzy logic) perform the fault tolerance in a qualitative manner [2,5]. One of their shortcomings is the necessity of relatively exact datum of rules or predicates. The data entries and editing of the large database need the expensive expertise of the plant technicians and engineers, hence it is time consuming and expensive and even more difficult than the rigorous modeling of plant [6, 7].

The artificial neural networks are a convenient alternative of storing and representation of data related to fault tolerance tasks. The data, mapping and relations of

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faults and measured quantities (in steady state) can be learned by the neural net and in practice, we can recall the net by inputting the measured quantities and ask the probable faults occurred. The neural nets have the capability of noise filtering and more important classifying and recognizing the patterns of faults [8,9]. They learn and adapt their parameters easily and can interpolate the multidimensional data elaborately.

In this article we have attempted to evaluate the abilities of feed forward artificial neural networks to detect and classify the incipient process faults. In addition a new structure of these types of neural nets has been proposed. The main issue has been the recognition of simultaneously occurring faults. The proposed scheme detects not only the single fault accurately but also the simultaneous (two faults) ones precisely.

The Artificial Neural Networks

In this section we review the properties and structure of artificial neural networks for recognition of fault patterns.

Artificial Nodes

An artificial node is a computing element in which calculation and mapping of multidimensional inputs to one-dimensional output is carried out. The transfer function is often nonlinear and is represented by a sigmoid function. The mapping of input(s)-output relation for the j-Th node presented in the l-Th layer can be analytically represented by:

$$x_j^{(l)} = \frac{1}{1+\exp(-u_j^{(l)})} \qquad (1)$$

where $u_j^{(l)}$ is usually a linear combiner of weighted inputs and a bias term called threshold value:

$$u_j^{(l)} = \sum_{i=1}^{N-1} w_{ji}^{(l)} x_j^{(l-1)} + \theta_j^{(l)} \qquad (2)$$

in which $x_j^{(l)}$ is the output node, $w_j^{(l)}$ the associating weight of every input and $\theta_j^{(l)}$ is the threshold value of layer (l).

Network Structure

Fig. 1 shows a common structure of a multi-layer feed forward artificial neural network. The connections are one-way and are directed from inputs to outputs. Every link is associated with a weight ($w_j^{(l)}$), to multiply by the input value, taking part in the linear combination with the others. For fault detection purposes, output of the last layer, is the pattern of defect or fault.

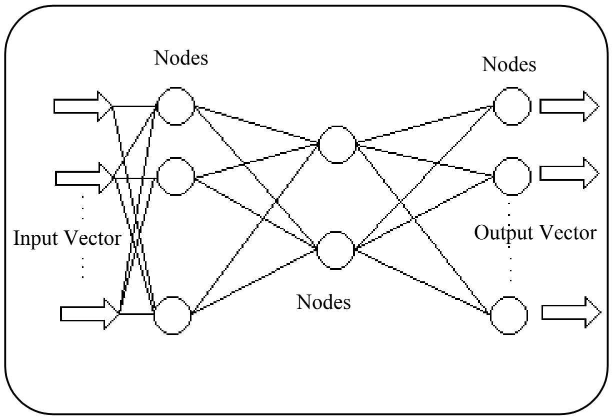

Fig. 1: Structure of a multilayer artificial neural network.

Process of Variables (number crunching)

Every node in the layers receives the measured inputs, such as temperatures or pressures and processes the data through its transfer function and finally produces a local output. The outputs act as inputs to the nodes of next layer. It should be noted that the values of outputs and especially inputs might be regularized and/or normalized to avoid numerical errors such as propagation and truncation errors.

Training

The training of a network is the same as parameters adaptation or a least squares problem in the sense of optimization formulations. In other words the weights and also the threshold values of each layer in the whole structure of neural network are to be exposed by the target or desired outputs (fault types or patterns) corresponding the inputs patterns. In the phase of learning, groups of inputs are fed into the network and the calculated outputs are examined and compared with desired or defined outputs, in which the faults are characte-rized by specific values of network output. The adaptation law is carried out using the error (the difference of desired and calculated outputs) emerging from triggered functions of neural network. The algorithm is generically referred as back-propagation technique.

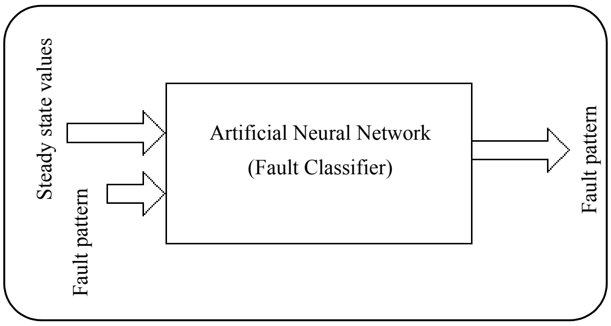

Fig. 2: The proposed neural network fault detector.

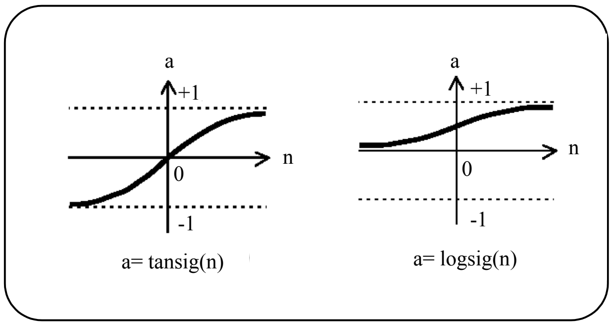

Fig. 3: Two common node functions used in network layers.

Network Test and Fault Detection

After the parameter adjustment, we can test the functionality of network by feeding some inputs other than the ones used in training phase. If the network is trained successfully it can be used to predict the process faults.

Proposed Neural Net Structure

Schematic structure of the proposed neural network has been shown in Fig. 2. The main issue in this structure is including the fault patterns in the network input. This was done to emulate the reasoning and induction of patterns quantitatively. In addition, it improves the network performance for not only detecting individual faults but also for cognition of dual faults.

It should be mentioned that the better performance has been obtained at the expense of more computation efforts.

Training Patterns

As can be seen from Fig.2, the network needs the fault patterns as part of the input. By the fault pattern, we mean a set of system parameter values, which defines a specific faulty condition. The process or its model can be used to produce the fault patterns through experiment or by simulation. Every cycle of training includes the pairs of input-output patterns. The input pattern consists of two major parts, one the pure inputs including the values of steady state quantities as independent variables, and the other, the fault patterns. The output pattern corresponds to index of fault type, but the values represent the level of fault.

Training Algorithm

The commonly used algorithm for training of feed-forward artificial networks is variants of back-propagation technique. It is basically an optimization algorithm in which the independent variables (decision variables) are the weights and biases of neural network structure. The objective function is sum of squared deviations of target values from calculated network output, which has to be minimized. In other words, the training algorithm minimizes the distances of desired and predicted values (fault patterns) of network.

For better training and handle the numerical issues, it is common to do some regularization or normalization procedures in prior to training. The regularization type is case dependent, especially depends on the type of node functions used in the early net layers. For instance, if we have selected the function *tansig* (Fig. 3) for all the nodes in the first layer, it is better to maintain the normalized inputs in the range of –1 (minus one) to +1. However, if the function *logsig* is selected, it would better to choose the range of 0 (zero) to +1. We have used the latter function as described later for the case study.

The Matching Algorithm

As mentioned previously, the network input vector has included the output pattern. Due to this implicit relation, we should make the patterns consistent in some way. For this reason, we have used some type of direct search method to minimize the distinction of input elements and output vector and also avoiding iteration and the need for initial values. The details of *recall* algorithm are as follow:

Step 1 - Supply the network inputs by measuring the plant outputs and the first fault pattern.

Step 2 - Recall the network and obtain the fault pattern, generated by the network.

Step 3 - compare the assumed pattern , considered in the input vector with the detected fault pattern by defining an error norm.

Step 4 - Take the second fault pattern and repeat the above steps until all the patterns have been processed.

Step 5 - Search for the least element in the error norm vector. Find the index of the least element and report the corresponding fault.

Simulation of Faults in a Reactor

To evaluate the performance of the proposed scheme, we selected a typical unit, which is frequently used in the open literatures [3,4].

The schematic diagram of the simulated process unit is depicted in Fig. 4. As it is shown the reactor feed consists of heptane, which is delivered via a process pump. The following catalytic and endothermic reaction takes place in the reactor: $C_7H_{16} \rightarrow C_7H_8 + 4H_2$.

The temperature of reactor is controlled via a PI (Proportional-Integral) controller. The operation is carried out as described below. The live steam is passed through a heater and is fed into the jacket of reactor. The effluent of jacket is circulated back to the heater. The controller (regulator) receives the reactor temperature (supplied by sensor) and compares it with set-point value and provides the proper command signal to manipulate the heat input to the exchanger.

If we denote the output concentration of reactants C_7H_{16}, C_7H_8, H_2 by C_{1o}, C_2, C_3, respectively and input concentration of heptane by C_{li}, then the following equations result from component mass balance around the reactor:

$$\frac{dC_{1o}}{dt} = -\frac{q}{V}C_{1o} - kC_{1o} + \frac{q}{V}C_{1i} \quad ,C_{1o}(0) = C_1^{\circ} \tag{3}$$

$$\frac{dC_2}{dt} = -\frac{q}{V}C_2 - kC_{1o} \quad ,C_2(0) = C_2^{\circ} \tag{4}$$

$$\frac{dC_3}{dt} = -\frac{q}{V}C_3 + 4kC_{1o} \quad ,C_3(0) = C_3^{\circ} \tag{5}$$

The reaction rate constant is related to temperature as given below:

$$k = k_{\circ}e^{-E_a/RT}$$

If ΔH is the energy of reaction, a and h, the surface and overall heat transfer coefficient, then the energy balance around the reactor yields:

$$\rho VC_p\frac{dT}{dt} = \rho\, C_p q(T_i - T) - kC_{1o}V\Delta H + ah(T_h - T) \tag{6}$$

or,

$$\frac{dT}{dt} = \frac{q}{V}(T_i - T) - \frac{kC_{1o}\Delta H}{\rho\, C_p} + \frac{ah}{\rho VC_p}(T_h - T) \tag{7}$$

where T_i and T are the feed and product temperature and T_h is the outlet temperature of vapor from the heat exchanger. The set-point value (u_c) of 740 mV is chosen for simulation. The gain of measuring device is $K_{mV/T} = 1$ and hence the feedback error signal is:

$$e = u_c - K_{mV/T}T \tag{8}$$

If the integrator output is denoted by s_i and controller output by s_h, then the dynamic relation of controller is given by:

$$\begin{cases} \dfrac{ds_i}{dt} = \dfrac{K_c}{\tau_I} \quad , \quad s_i(0) = s_i^{\circ} \\ s_h = K_c e + s_i \end{cases} \tag{9}$$

By writing the energy balance around the heat exchanger, we have:

$$C_p'V'\rho'\frac{dT_h}{dt} = C_p'\rho'q'(C_T - T_h) + a'h'k_h's_h \tag{10}$$

or:

$$\frac{dT_h}{dt} = \frac{1}{\tau}\left(C_T - T_h\right) + \frac{K}{\tau}s_h \tag{11}$$

In which $K = \dfrac{a'h'k_h'}{\rho' C_p' q'} = 20\, , \tau = \dfrac{V'}{q'} = 0.3h$.

The rest of system parameters are given in Table 1.

It is assumed that no fault occurs in the controller and just five faults with different four levels of change may occur.

Fault 1: reduction in catalyst activity.

Fault 2: fault in reactor heat exchanger.

Fault 3: fault in heater.

Fault 4: reduction in feed flow rate.

Fault 5: reduction in circulation rate.

The steady-state values (normal condition) have been presented in Table 2. Results of simulation have been presented in Table 3. and Table 4., using the normalized variables. Schematic structure of the proposed neural network for the simulated reactor has been shown in Fig.5.

Table 1: Parameters used in simulation studies.

Reaction rate constant, k_o	$5.01\times10^8\ h^{-1}$
Energy of activation, E_a	1.369×10^5 J/mol
Specific heat, C_p	490.7 J/mol.°K
Density, ρ	593 mol/m^3
Heat transfer area, a	10 m^2
Overall heat transfer coefficient, h	6.05×10^5 J/m^{2}h °K
Heat of reaction, ΔH	$2.2026\times10^5+6.2044\times10$ T- $5.536\times10^{-2}\ T^2 - 1.15\times10^{-6}\ T^3 + 3.1496\times10^{-7}\ T^4$ J / mol
Reactor volume, V	30 m^3
Heater time constant, ι_I	0.2 h
Heater gain, k	1 °K / mV

Table 2: Steady-state values or normal condition.

Reactor temperature, T	740 °K
Inlet concentration of C_7H_{16} , C_{1i}	1000 mol / m^3
Outlet concentration of C_7H_{16} , C_{10}	476 mol / m^3
Outlet concentration of C_7H_8 , C_2	524 mol / m^3
Outlet concentration of H_2 , C_3	2097 mol / m^3
Heater temperature, T_h	889 °K
Feed temperature, T_i	300 °K
Inlet temperature of heater,C_T	0.9×740 °K
Feed and product Flow rate, q	3m^3/ h

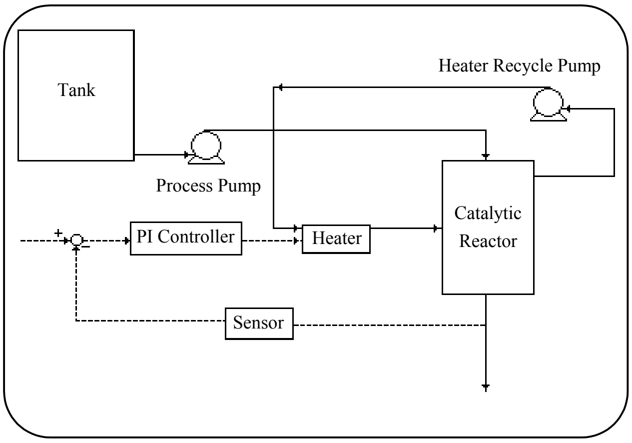

Fig. 4: The schematic diagram of the simulated process.

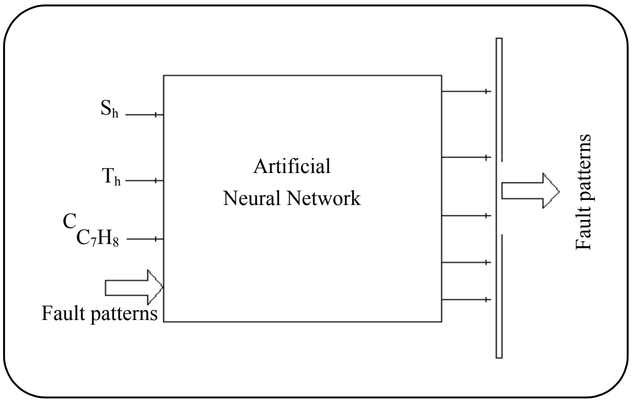

Fig. 5: The proposed neural network fault detector.

Table 3: Single faults in a reactor by input-like regularization.

Number/Level	Control command	Heater temperature	Concentration
1/1	0.9807	0.9952	0.9498
1/2	0.9703	0.9925	0.9225
1/3	0.9592	0.9898	0.8937
1/4	0.9474	0.9868	0.8631
2/1	1.0743	1.0186	1.0000
2/2	1.1180	1.0296	1.0000
2/3	1.1671	1.0419	1.0000
2/4	1.2228	1.0559	1.0000
3/1	0.9504	0.9876	1.0500
3/2	0.9248	0.9811	1.0769
3/3	0.8986	0.9746	1.1052
3/4	0.8718	0.9678	1.1350
4/1	1.1111	1.0000	1.0000
4/2	1.1765	1.0000	1.0000
4/3	1.2500	1.0000	1.0000
4/4	1.3333	1.0000	1.0000
5/1	0.9000	1.0000	1.0000
5/2	0.8500	1.0000	1.0000
5/3	0.8000	1.0000	1.0000
5/4	0.7500	1.0000	1.0000
Normal	1.0000	1.0000	1.0000

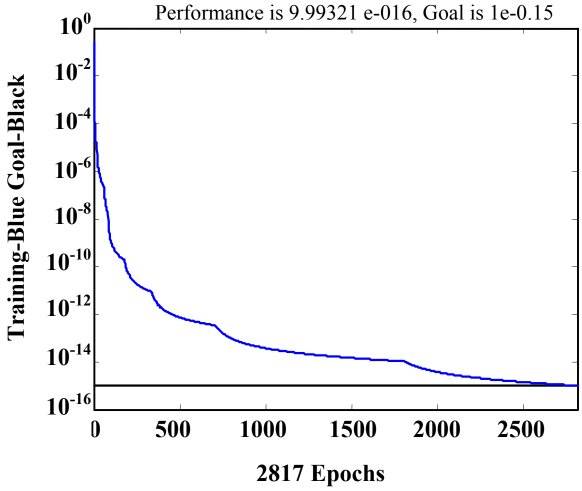

Fig. 6: The training error convergence of single faults.

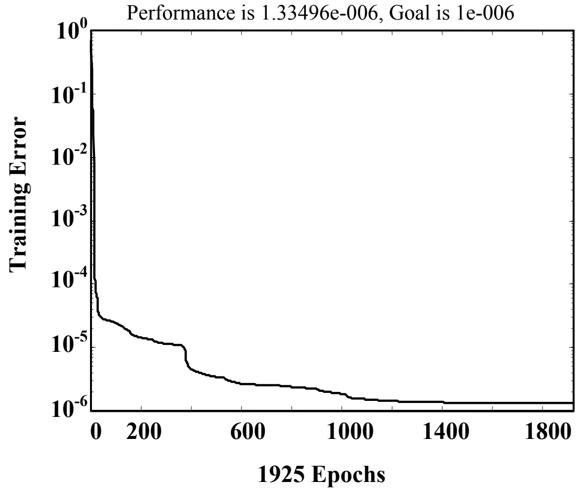

Fig. 7: The training error convergence of dual faults.

The network consists of three layers with input layer of dimension 8, hidden layer with 8 nodes and output layer with dimension 5 (faults), respectively. The transfer functions used for both hidden and output layers were selected as log sigmoid function. The number of nodes and layers has been obtained by trial and error, leading 8 nodes for hidden layer and 5 nodes for output layer.

Training Patterns

The process model has been used to produce the training data by simulation. Every cycle of training includes the pairs of input-output patterns, like the records depicted in Table 3 and 4.

The output pattern corresponds to index of fault type, and the values represent the level of fault. For instance, consider the first row of entries in Table 4. This record has been introduced to the artificial neural net classifier by input in the form of [0.9807, 0.9952, 0.9498, 0.9, 1, 1, 1, 1] and output in the form of [0.9, 1, 1, 1, 1].

The first three elements of input vector are the normalized quantities of measured variables (the control command, temperature of heater outflow and concentration of toluene) which supply the arguments and characterization of fault(s).

The elements of output vector demonstrate the fault type and its level. For a typical record like this, the first element is not 1 (one), but the others are 1 (one); so, it means the 1st fault (fault no. 1) has occurred and additionally the fault has happened in level 1, because the value is 0.9 or 90% of normalized variable span.

Training Algorithm

The algorithm minimizes the distances of desired and functional values (fault patterns) of the network. The training set should globally covers the variables span. Hence for single fault detection we need at least 21 training records, while for two-fault detection we need at least 200 plus 21 (i.e. 221) records. Further, to improve the interpolation capability of network, we can inject some noisy records into the trainig set. In Figures 6. and 7, the convergence of training objective function have been shown. In Fig. 6 (single faults) the error tolerance is 1e-15 and in the Fig. 7 , it is 1e-6. It is worth-mentioning that if we use the networks as presented in literature [10], consisting the 3 input and 5 output, the tolerance would be greater than 0.01. The reduction of error about 1e13 order of magnitude indicates the superiority of the proposed structure (with feedback of fault pattern) over the classical ones.

SIMULATION RESULTS

The results of simulation for both single-fault and dual-fault are given in Tables 5. to 8. The procedure is described as follows. First, the performance of plant has been simulated for a typical deviation of parameters (i.e. produing synthetic fault) to get the corresponding measured variables. Afterwards, a level of noise with zero mean and specified variance has been added to (soft) measurements. The level of noise for three measured variables are given below: control command by 7.3%, heater outflow temperature by 4.5 % and reactor outlet

Table 4: Levels of single faults (Table 3) and their patterns.

Number/Level	Cause	Fault pattern
1/1	0.90 k_0	[0.90,1,1,1,1]
1/2	0.85 k_0	[0.85,1,1,1,1]
1/3	0.80 k_0	[0.80,1,1,1,1]
1/4	0.75 k_0	[0.75,1,1,1,1]
2/1	0.90 h	[1,0.90,1,1,1]
2/2	0.85 h	[1,0.85,1,1,1]
2/3	0.80 h	[1,0.80,1,1,1]
2/4	0.75 h	[1,0.75,1,1,1]
3 /1	0.90 h'	[1,1,0.90,1,1]
3/2	0.85 h'	[1,1,0.85,1,1]
3/3	0.80 h'	[1,1,0.80,1,1]
3/4	0.75 h'	[1,1,0.75,1,1]
4/1	0.90 q	[1,1,1,0.90,1]
4/2	0.85 q	[1,1,1,0.85,1]
4/3	0.80 q	[1,1,1,0.80,1]
4/4	0.75 q	[1,1,1,0.75,1]
5/1	0.90 q'	[1,1,1,1,0.90]
5/2	0.85 q'	[1,1,1,1,0.85]
5/3	0.80 q'	[1,1,1,1,0.80]
5/4	0.75 q'	[1,1,1,1,0.75]
Normal	k_0, h, h', q, q'	[1,1,1,1,1]

Table 5: the simulated inputs for single fault detection.

Number/Level	Control command	Heater temperature	concentration
1 / 1	0.9375	0.9951	0.9456
1 / 2	0.9825	0.9954	0.9213
2 / 3	1.1599	1.0453	1.0026
2 / 4	1.2137	1.0530	1.0021
3 / 1	0.9537	0.9863	1.0515
4 / 2	1.1644	0.9969	1.0017
5 / 3	0.8057	0.9998	1.0011
Normal	1.0102	0.9966	0.9924

Table 6: The result of fault detection for single faults.

	Node number				
Number/Level	1	2	3	4	5
1 / 1	0.8999	1	1	1	1
1 / 2	0.8585	1	1	1	1
2 / 3	1	0.7845	1	1	1
2 / 4	1	0.7303	1	1	1
3 / 1	1	1	0.9272	1	1
4 / 2	1	1	1	0.8563	1
5 / 3	1	1	1	1	0.8211
Normal	1	1	1	1	1

Table 7: the simulated inputs for dual fault detection.

Number/Level	Control command	Heater temperature	concentration
1 / 1	0.9699	0.9928	0.9523
2 / 2	1.1295	1.0304	1.0093
3 / 3	0.8882	0.9702	1.1104
4 / 4	1.3401	1.0013	1.0047
1 / 1 & 3 / 2	0.8994	0.9768	1.0365
1 / 4 & 4 / 1	1.0578	0.9886	0.8622
1 / 2 & 2 / 1	1.0386	1.0121	0.9222

Table 8: The result of fault detection for dual faults.

	Node number				
Number/Level	1	2	3	4	5
1 / 1	0.8767	0.9999	1	1	0.9991
2 / 2	0.9898	0.8504	1	1	0.9998
3 / 3	1	1	0.8255	1	0.9994
4 / 4	1	1	1	0.7516	0.9998
1 / 1 & 3 / 2	1	1	0.8470	1	0.9981
1 / 4 & 4 / 1	0.7563	1	1	0.8930	0.9998
1 / 2 & 2 / 1	0.8766	0.9062	1	1	0.9998

concentration by 2.6%. The matching algorithm is described typically for the single fault detection. Consider the first record of Table 5. The data is noisy and the level of the fault is near the the normal situation.

To consider the power of detection, we recall the trained network by training set of single faults. In matching phase, the first three elements of steady-state data (i.e., 0.9375, 0.9951, 0.9456) are coupled by fault patterns to establish the input of ANN for detecting or browsing the fault pattern. For instance, assume that the first patter in database is the normal situation or [1,1,1, 1,1]. For the first trial, we prepare the input as [0.9375, 0.9951, 0.9456, 1,1,1,1,1] and then recall the network. The obtained pattern is matched (compared with) against estimated pattern via making an error norm. This process is done for whole records of the database. Finally the error norms are sorted in a vector and the least element is selected and the corresponding fault is reported.

The results for typical fault 1/1 (first entry of Table 5) are shown in Table 6. As it is clear the single fault detector has detected the fault and its level successfully, by realizing the least error norm. The simulation run is again repeated but the database consist both single and dual fault records. In other words the detector net used in this run has been trained by 221 records (sum of single and dual fault patterns). The simulated typical inputs are depicted in Table 7., and its results are shown in Table 8.

The detector reports all the faults correctly except for the ones when the level is close to normal situation (for example, see the result for faults 1/1 & 3.2). This point confirms the point that the presense of noise may deteriorate the detection process

CONCLUSION

In this article the problem of incipient and also dual faults detection using neural networks was studied and evaluated. A new structure for the neural network was proposed. The main novelty embedded in the architecture is using the fault patterns in the input space of the net during the recalling or detection of faults. The performance of the scheme was examined through a typical reactor model. The results revealed the superior performance of the proposed scheme over the convetional schemes. It should be mentioned that this improvement is obtained at the expense of more computational efforts. In the future work the scheme will be extended to more than two simultaneous faults and examined for various sturucture of networks, both number of nodes and number of layers to detect the faults more precisely.

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