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NEURO AND NEURO-FUZZY HIERARCHICAL STRUCTURES COMPARISON IN FDI: CASE STUDY

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Abstract: In this paper a hierarchical structure of several artificial neural networks has been developed for fault isolation purposes. Two different approaches have been considered. The hierarchical structure is the same for both approaches, but one uses multi-layer feedforward artificial neural networks and the other uses fuzzy neural networks. A result comparison between the two architectures will be presented. It is aimed to isolate multiple simultaneous abrupt and incipient faults from only single abrupt fault symptoms. A continuous binary distillation column has been used as test bed of the current approaches. *Copyright ©2002 IFAC*

Keywords: Fault isolation, neural networks, fuzzy systems, hierarchical structures, fuzzification, white noise.

1. INTRODUCTION

Process failures can potentially result not only on the loss of productivity but also in the loss of expensive equipment and, ultimately, of human lives. For these reasons, there is a growing need for on-line fault detection and isolation approaches in order to increase reliability of such industrial processes.

In dynamical systems, faults may be divided into two main classes: abrupt failures and incipient failures. The incipient failures affect the process behaviour slowly and may take a long time before being detected. Conversely, abrupt failures give rise to jumps in the process parameters, resulting in an appreciable deviation from normal system behaviours.

Recently, the use of artificial neural networks (ANN) for fault detection and isolation purposes has received increasing attention in both research and application (Frank and Koppen-Seliger, 1997; Butler *et al.*, 1997; Calado and Sá da Costa, 1999; Patton, *et al*., 1999; Altug *et al.*, 1999; Aminian *et al.*, 2000). In some of these applications, ANNs are used to examine the possible fault or faults in the process under concern and give a fault classification signal to declare whether or not the process is faulty (Chen, 1995).

ANNs can be used to overcome the difficulties of conventional fault isolation techniques to deal with nonlinear behaviours. Establishing an appropriate training set allows the ANN to learn and generalise for operating with future input data.

However, fault symptoms concerning multiple simultaneous faults are harder to learn than those associated with single faults. Furthermore, the larger the set of faults, the larger the set of fault symptoms will be and, hence, the longer and less certain the training outcome. In order to overcome this problem, the proposed approach has a hierarchical structure of three levels where several neural networks are used. Thus, a large number of patterns are divided into many smaller subsets so that the classification can be carried out more efficiently. The adoption of a hierarchical structure of neural networks approach for fault isolation aims at development of an architecture that can localise abrupt and incipient single and multiple faults correctly, or at least with a minimum misclassification rate and be easily trained, from only single abrupt fault symptoms.

During the current studies a continuous binary distillation column has been used as a test bed of an approach consisting of a hierarchical structure of classical feedforward ANNs and other approach where the feedforward ANNs are replaced by fuzzy neural networks (FNNs). These networks have been achieved by adding a fuzzification layer to the conventional feedforward neural networks (Calado and Sá da Costa, 1999a). Therefore, a result comparison between the two architectures will be presented, showing the fuzzification layer influence in the performance of the fault isolation approach proposed in this paper.

The paper is organised as follows. Section 2 presents an overall description of the fault isolation approach. Section 3 shows some results achieved using the two architectures mentioned above, as well as, a comparison between those results. In Section 4 some concluding remarks will be provided.

2. THE ARCHITECTURE OF THE FAULT ISOLATION SYSTEM

In the current approach a hierarchical structure of several artificial neural networks has been developed for fault isolation purposes (Haykin, 1994; Nauck *et al.*, 1997; Calado and Sá da Costa, 1999). It is aimed to isolate multiple simultaneous abrupt and incipient faults from only single abrupt fault symptoms. The hierarchical structure has three levels configuration where several ANNs are used. Two different approaches have been considered. The hierarchical structure is the same for both approaches, but one uses multi-layer feedforward artificial neural networks and, the other uses fuzzy neural networks (FNN) as depicted in Figure 1. It can be seen that the fuzzy neural networks have been achieved by adding a fuzzification layer to the conventional feedforward neural networks as mentioned above.

The lower level consists of one neural network (NN) where all variations (Δe) of the measured variables are used as inputs. At the medium level a number of NNs (structurally identical or different) that is equal to the number of single fault scenarios considered, are used. Each NN at the medium level is also fed with all the measurement variables and each one is associated with an output of the NN at the lower level, corresponding to a particular single fault. The upper level consists of an OR operation on the NNs outputs at the medium level. The elements of the set used in the OR operation are determined by the outputs of the NN at the lower level. Thus, if the *i*-th and *j*-th outputs of the NN at the lower level is taking values close to 1, then the outputs of the *i*-th and *j*-th NNs at the medium level form the elements used in the OR operation. However, if only one output of the NN at the lower level is taking a value close to 1, then the corresponding NN in the medium level is used to confirm that this fault is a single fault, or to diagnose multiple faults. Obviously, the multiple faults must include the one corresponding to the output of the NN at the lower level.

In the first approach all the neurons use the sigmoid function as their activation functions. In the second fault isolation approach considered, as previously mentioned, the adopted FNNs have an additional fuzzy input layer that maps the increment of each measurement into fuzzy sets. Therefore, the fuzzification layer converts each input into the quantity space, q_f={*decrease*, *steady*, *increase*}, by association with three types of neurons. The processing elements of the fuzzification layer related to the fuzzy sets *decrease* and *increase* use the complement sigmoid function and the sigmoid function, respectively, as their activation functions.

On the other hand, the other processing elements of the fuzzification layer related to the fuzzy set *steady* use the Gaussian function. The hidden and output layers processing elements use the sigmoid function as their activation functions.

Both the lower level and the medium level networks are made up of three layers. In the first approach the

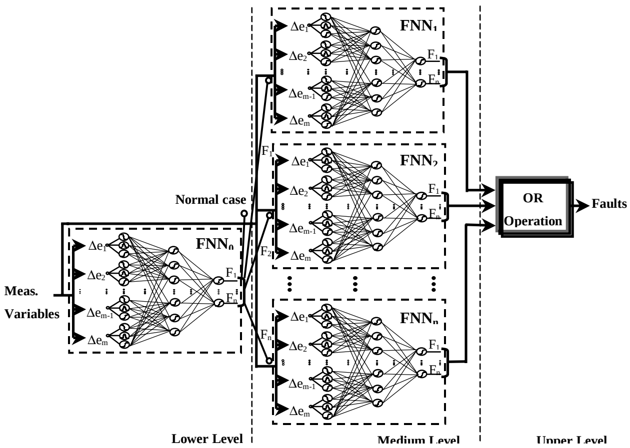

Fig. 1. Hierarchical Structure of Fuzzy Neural Networks.

ANNs have an input layer, a hidden layer and an output layer. The FNNs used in the second approach have a fuzzification layer, a hidden layer, and an output layer. All neural networks are trained using the *resilient backpropagation-learning algorithm* (Riedmiller and Braun, 1993).

The NN_0 (lower level) training data is obtained from the process single abrupt fault simulation, where all abrupt faulty scenarios and the stationary operational conditions are being considered. On the other hand, the NN_i (medium level) is trained using the data for one single abrupt fault (the fault associated with the corresponding NN_i) and for all possible double abrupt faults that the NN_i will be able to diagnose. This training data is obtained by adding the data for the corresponding single abrupt faults considered.

In order to cope with process transient behaviours due to normal set point regulator, the current fault isolation approach should be coupled with a fault detection system, as for instance in Mendes et al. (2002).

In the next section a continuous binary distillation column is used as test bed of the fault isolation approaches described above. Furthermore, a result comparison between both approaches is made.

3. CASE STUDY

A Continuous Binary Distillation Column, which is described by (Ingham *et al.*, 1994), has been used as a test bed of the fault isolation systems proposed in this paper. This process is shown in Figure 2, where a column containing a total of eight theoretical plates plus a reboiler is assumed, with feed entering on plate 5. Surge drum and reboiler levels are controlled by feedback control loops.

The fault isolation systems are based on a hierarchical structure of several artificial neural networks with the characteristics previously presented. Hence, four measurement variables have been used as input data to the fault isolation system. These variables are the following: *MD*, hold-up in surge drum; *D*, distillate flow rate; *MB*, hold-up in reboiler; *W*, bottom flow rate. In order to achieve a diagnosis of a fault or faults in the process, an analysis of the output values from the neural network at the lower level of the hierarchical structure, is necessary.

If the number of nonzero outputs (output ≥ 0,5) in NN_0 is equal to 0, then it is assumed that no fault occurred in the process under consideration. Otherwise, the result of the fault isolation system is considered to be the result of an OR operation (upper level) on several NN_i outputs in medium level, as previously describe.

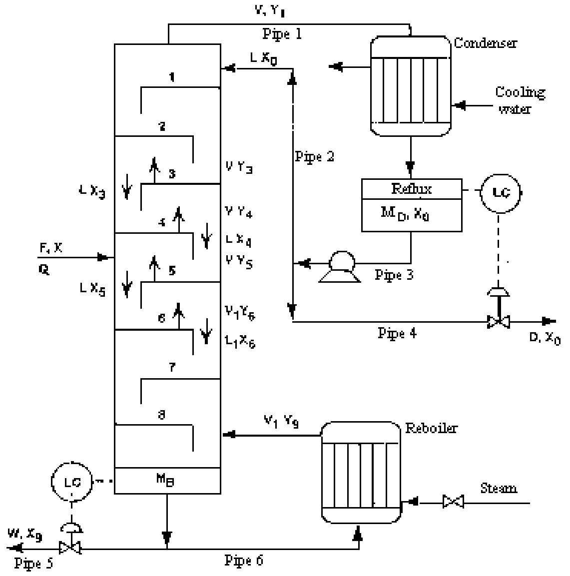

Fig. 2. Continuous Binary Distillation Column.

In the neuro fault isolation system considered all ANNs are equal, with an input layer consisting of 4 neurons corresponding to the 4 measurement variables. Furthermore, in the neuro-fuzzy fault isolation system implemented all the FNNs are equal too, with a fuzzification layer consisting of 12 processing elements arranged in 4 groups, corresponding to the 4 measurement variables, with each group contains 3 neurons corresponding to the respective fuzzy sets. The number of neurons in the hidden layer is determined by the complexities of the relationships between the faults and the fault symptoms. During the current study, following a trial and error procedure, it was found that 10 hidden processing elements could give good performance for the both fault isolation system architectures under concerned. However, further research will be conducted in order to optimise the NN topology by using neural networks pruning algorithms.

Moreover, since 4 single faults have been considered (F_{1v}, valve on pipe 4 blocked fully open; F_{2v}, valve on pipe 4 blocked fully closed; F_{3v}, valve on pipe 5 blocked fully open; F_{4v}, valve on pipe 5 blocked fully closed) the output layer of each network is up of 4 neurons, each one corresponding to a fault. It was also considered all possible double fault scenarios corresponding to an AND operation in the single fault space.

The training data used during the current studies was obtained through simulation with the aim of covering nine different process-operating points (10% to 90% of controlled variables). Then, 45 learning patterns (4 single faults x 9 operating points + 9 stationary operational conditions) are involved during the training procedure of the neural network in the lower level of the hierarchical structure and 27 learning patterns ((1 single faults + 2 double faults) x 9 operating points) are involved in training each neural network in the medium level.

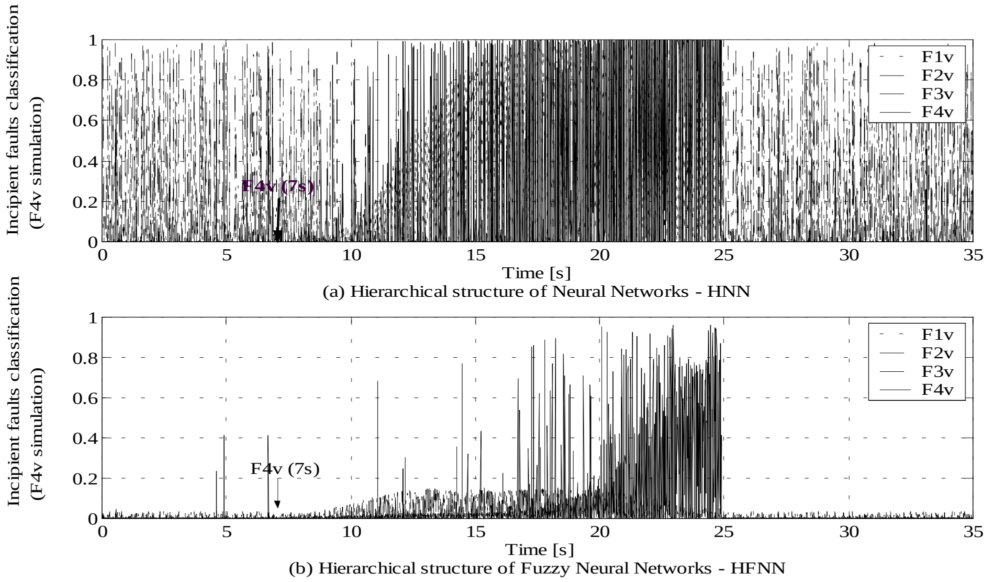

Fig. 3. Incipient F_{4v} fault isolation (M_D=M_B=10%) – with noise (K=0,001).

Several studies have been conducted considering the changes in the measurement variables free of noise. It has been observed that under incipient and multiple simultaneous faulty scenarios the performance of the hierarchical structure of fuzzy neural networks (HSFNN) is better than the similar approach using multi-layer feedforward neural networks. Furthermore, according to the results achieved so far, the HSFNN provides better generalisation capabilities to the fault isolation system. That is a very important aspect as far as the performance of the fault isolation system is concerned, since only single abrupt fault symptoms are considered during the training task.

However, the results presented in this paper are achieved considering that the changes in the measurement variables are affected by white noise, with null mean, variance one and gain proportional to a parameter K. Furthermore, the incipient faults have been simulated considering that the component degradation follows a linear law. In order to find the minimum slope to the component degradation law allowing that the fault isolation system is still able to isolate the correct fault or faults, several studies have been conducted. Since that depends on the operational conditions of the process, several experiments have been performed in order to achieve the minimum slopes to the component degradation law according to the minimum and maximum values that the controlled variables can take, for the four single faults considered.

Figure 3 shows a result comparison between the two fault isolation approaches previously described, considering the incipient fault scenario (F_{4v}). The fault has been simulated with the minimum possible slope to the component degradation law as described in the last paragraph. Furthermore, it has been considered the process measurement variables affected by noise. It can be observed from the figure quoted, that the hierarchical structure consisting of several fuzzy neural networks has a better performance. It is shown in the Figure that the fault isolation system based on that approach is less sensitive to the noise in the measurement variables values than the hierarchical structure using conventional multi-layer feedforward neural networks. Thus, the fault isolation system using fuzzy neural networks can correctly isolate all the faults simulated, for noise levels raised (K=0,001, corresponding to ±1 *mol* or *kmol/h* in the process measurement variables). However, the hierarchical structure using multi-layer feedforward neural networks only begin to provide results with some sense for much lower noise levels, (K=0,00001, corresponding to ±0,1 *mol* or *kmol/h* in the process measurement variables).

Anyway, even under that faulty scenario, it has been observed that the hierarchical structure of multi-layer feedforward neural networks (HSMFNN) isolates the fault F_{1v} before isolate the correct fault F_{4v}. Since the same situation has occurred during simulation studies conducted with the values of the measurement variables noise free, this suggests that the wrong diagnosis could be related with overlearning problems or process dynamics having nothing to do with the noise level. It has been observed that the fuzzification layer works as a filter to the existing noise and improves the generalisation capability of the fault isolation approach proposed in this paper.

Table 1 presents the results achieved with the HSMFNN, under double simultaneous abrupt faults. These tables have a first column with the faults simulated. A second column, where the classification values (F_{4v}=0,9922, for example) are presented, corresponding to the results achieved with the lower level (FNN_0 network). Furthermore, they have also four columns associated with the four fuzzy neural networks at the medium level and finally, a column

Table 1 Results achieved with HSMFNN (M_D=10%, M_B=50%) – with noise (K=0,001)

Double abrupt faults	**Lower level**	**Medium level**				**Upper level**	**Classification**
	NN_0	NN_1	NN_2	NN_3	NN_4	OR operation	
$\mathbf{F_{1v}F_{3v}}$	F_{3v}=0,9928 F_{4v}	-	-	$F_{1v}F_{3v}$	F_{4v}	$F_{1v}F_{3v}F_{4v}$	3 / 2
$\mathbf{F_{1v}F_{4v}}$	F_{3v} F_{4v}=1	-	-	$F_{1v}F_{3v}$	$F_{1v}F_{4v}$	$F_{1v}F_{3v}F_{4v}$	3 / 2
$\mathbf{F_{2v}F_{3v}}$	F_{2v}=0,9985 F_{3v} F_{4v}	-	$F_{2v}F_{3v}$	$F_{1v}F_{3v}$	F_{4v}	$F_{1v}F_{2v}F_{3v}F_{4v}$	4 / 2
$\mathbf{F_{2v}F_{4v}}$	F_{3v} F_{4v}=1	-	-	$F_{1v}F_{3v}$	$F_{2v}F_{4v}$	$F_{1v}F_{2v}F_{3v}F_{4v}$	4 / 2

with the final isolation results of the HFNN structure (achieved after the OR operation).

Table 2 shows the corresponding results under the same test conditions using the HSFNN. A very high misclassification rate can be see in the results presented in the first Table, while very accurate results are presented in Table 2. Thus, the results achieved demonstrate the robustness associated with the HSFNN.

Table 3 shows the results achieved with the first approach under single incipient fault scenarios, while Table 4 presents the results of the neuro-fuzzy fault isolation approach using the same test conditions. It can be seen in Table 3 that there is a misclassification in all results achieved, while Table 4 shows that under the same test conditions the HSFNN gives the correct diagnosis to all fault scenarios considered.

4. CONCLUSIONS

It has been demonstrated that the fault isolation task based on a hierarchical structure of artificial neural networks is able to isolate multiple simultaneous faults from only single abrupt fault symptoms.

Two approaches have been considered. The first one uses the conventional multi-layer feedforward neural networks, while the second approach uses fuzzy

Table 2 Results achieved with HSFNN (M_D=10%, M_B=50%) – with noise (K=0,001)

Double abrupt faults	**Lower level**	**Medium level**				**Upper level**	**Classification**
	FNN_0	FNN_1	FNN_2	FNN_3	FNN_4	OR operation	
$\mathbf{F_{1v}F_{3v}}$	$F_{1v}F_{3v}$	$F_{1v}F_{3v}$	-	$F_{1v}F_{3v}$	-	$F_{1v}F_{3v}$	2 / 2
$\mathbf{F_{1v}F_{4v}}$	F_{4v}=0,9922	-	-	-	$F_{1v}F_{4v}$	$F_{1v}F_{4v}$	2 / 2
$\mathbf{F_{2v}F_{3v}}$	F_{2v} F_{3v}	-	$F_{2v}F_{3v}$	$F_{2v}F_{3v}$	-	$F_{2v}F_{3v}$	2 / 2
$\mathbf{F_{2v}F_{4v}}$	F_{4v}=0,9851	-	-	-	$F_{2v}F_{4v}$	$F_{2v}F_{4v}$	2 / 2

Table 3 Results achieved with HSMFNN (M_D=M_B=10%) – with noise (K=0,001)

Single incipient fault	**Lower level**	**Medium level**				**Upper level**	**Classification**
	NN_0	NN_1	NN_2	NN_3	NN_4	OR operation	
$\mathbf{F_{1v}}$	F_{1v}=0,5 F_{3v} F_{4v}	F_{1v}	-	$F_{1v}F_{3v}$	F_{4v}	$F_{1v}F_{3v}F_{4v}$	3 / 1
$\mathbf{F_{2v}}$	F_{2v}=0,5035 F_{3v} F_{4v}	-	$F_{2v}F_{3v}$	F_{3v}	F_{4v}	$F_{2v}F_{3v}F_{4v}$	3 / 1
$\mathbf{F_{3v}}$	F_{3v}=0,5012 F_{2v} F_{4v}	-	$F_{2v}F_{3v}$	F_{3v}	F_{4v}	$F_{2v}F_{3v}F_{4v}$	3 / 1
$\mathbf{F_{4v}}$	F_{1v} F_{3v} F_{4v}=0,5005	F_{1v}	-	F_{3v}	F_{4v}	$F_{1v}F_{3v}F_{4v}$	3 / 1

Table 4 Results achieved with HSFNN (M_D=M_B=10%) – with noise (K=0,001)

Single incipient fault	**Lower level**	**Medium level**				**Upper level**	**Classification**
	FNN_0	FNN_1	FNN_2	FNN_3	FNN_4	OR operation	
$\mathbf{F_{1v}}$	F_{1v}=0,5030	F_{1v}	-	-	-	F_{1v}	1 / 1
$\mathbf{F_{2v}}$	F_{2v}=0,5460	-	F_{2v}	-	-	F_{2v}	1 / 1
$\mathbf{F_{3v}}$	F_{3v}=0,5195	-	-	F_{3v}	-	F_{3v}	1 / 1
$\mathbf{F_{4v}}$	F_{4v}=0,7358	-	-	-	F_{4v}	F_{4v}	1 / 1

neural networks. The artificial neural networks used in the second approach have been achieved by adding a fuzzification layer to the conventional feedforward neural networks.

The results achieved demonstrate the robustness of the HSFNN even when the values of the measurement variables are affected by white noise. Under the same test conditions a quite bad performance has been observed to the neuro fault isolation approach considered. Thus, it has been demonstrated that the fuzzification layer works as filter avoiding a performance degradation of the neuro-fuzzy fault isolation system when the noise is considered. It is worth note that even under incipient fault situations a good performance has been observed to the neuro-fuzzy approach. Of course, since a component degradation linear law has been used to simulate the incipient faults, the fault isolation system performance is affected by the component degradation speed. Thus, it has also been observed that for a component degradation speed below a certain value the fault isolation approach is not able to isolate the corresponding fault.

During the current studies, it has been observed that the neural network's generalisation ability has a great importance in the diagnosis of incipient faults since the training patterns only include symptoms of abrupt faults. The successful results achieved with the on-line fault isolation system using fuzzy neural networks suggest that the approach proposed in this paper could be a powerful methodology for practical implementations.

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