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AN EXPERT SYSTEM COUPLED WITH A HIERARCHICAL STRUCTURE OF FUZZY NEURAL NETWORKS FOR FAULT DIAGNOSIS

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An on-line fault diagnosis system, designed to be robust to the normal transient behaviour of the process, is described. The overall system consists of an expert system cascade with a hierarchical structure of fuzzy neural networks, corresponding to a multi-stage fault detection and isolation system. The fault detection is performed through the expert system by means of fault detection heuristic rules, generated from deep and shallow knowledge of the process under consideration. If a fault is detected, the hierarchical structure of fuzzy neural networks starts and it performs the fault isolation task. The structure of this diagnosis system was designed to allow for the diagnosis of single and multiple simultaneous abrupt and incipient faults from only single abrupt fault symptoms. Also, it combines the advantages of both fuzzy reasoning and neural networks learning capacity. A continuous binary distillation column has been used as a test bed of the current approach. Single, double and triple simultaneous abrupt faults, as well as incipient faults, have been considered. The preliminary results obtained show a good accuracy, even in the case of multiple faults.

Keywords: fault diagnosis, fault detection, fault isolation, expert system, fuzzy neural network, abrupt faults, incipient faults, shallow knowledge, deep knowledge.

1. Introduction

Fault diagnosis systems play an important role in modern control systems, especially for safety-critical systems such as chemical plants, nuclear reactors, spacecrafts, aircrafts, etc. (Patton *et al.*, 1989). Accurate and timely information enables operators to respond rapidly to plant failures. Also, it minimises the effects of faults on the plant itself, both in the plant production and in the environment. For this reason, there is a growing need for on-line fault diagnosis systems in order to increase the reliability of such safety-critical systems.

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In early stages of process control, skilled operators were used to detect and isolate a process failure in order to prevent a process or production breakdown, by taking appropriate corrective actions. Nowadays, the complexity of modern plants and the availability of inexpensive computer hardware allow us to develop automatic fault diagnosis systems. These fault diagnosis systems, also called Fault Detection and Isolation systems (FDI), usually perform two basic functions, i.e. fault detection and fault isolation, which can be performed sequentially, or parallelly, or even simultaneously in one stage. Fault detection gives a binary indication if all parts of the systems are running fine or if something is wrong, i.e. if a failure occurs. Fault isolation, also called fault localisation, gives an indication of the fault localisation within the system.

Linear models of the process usually support FDI systems based on conventional techniques. For non-linear processes, the usual approach is to linearise the process model around the operating point. This approach is effective for many non-linear processes if the operating range is limited and the FDI system is designed to be robust enough to tolerate small perturbations around the operating point. However, for processes with strong nonlinearity behaviour and a wide dynamic operating range, the linearised approach fails to give satisfactory results. One solution is to use a large number of linearised models, corresponding to a range of operating points, which is not very practical for real-time applications (Chen, 1995). Another possible solution makes use of the so-called *intelligent* techniques based on fuzzy systems, or artificial neural networks, or a combination of both.

Since artificial neural networks (ANNs) can be trained to have the required mapping between inputs and outputs, they can be used to overcome the difficulties of conventional FDI techniques to deal with non-linear behaviour. ANNs are properly aimed at processes that are ill-defined, complex, non-linear and stochastic. However, most studies using ANNs for fault diagnosis only deal with processes under steady-state conditions and do not consider explicitly the dynamic change in the ANN input due to normal transient process behaviour. This change in the ANN inputs can also affect certain features of the ANN outputs, giving rise to incorrect information about a failure in the process in the presence of a normal transient behaviour due to changes in the operational settings.

In order to overcome the previously mentioned problems, in this paper we propose an FDI system using a deep/shallow knowledge-based system coupled with a hierarchical structure of fuzzy neural networks. The on-line FDI system is designed to cope with normal transient behaviour of the process and to be able to diagnose multiple simultaneous faults from only single abrupt fault symptoms. The fault detection is performed by an expert system which encodes fault detection heuristic rules generated from deep and shallow knowledge of the process under consideration, following a systematic methodology. The deep knowledge is obtained from structural decomposition of the overall process into subsystems according to the plant topology (Calado and Roberts, 1996a), while the shallow knowledge is extracted from the operational experience in conducting the plant.

The fault isolation stage is based on a hierarchical structure of several fuzzy neural networks. The use of ANNs for fault diagnosis purposes has received increasing attention in both research and applications. The number of publications on this subject demonstrate the interest and potentiality of this new tool (Kavuri and Venkatasubramanian, 1994; Patton *et al.*, 1994; Sorsa and Koivo, 1993; Tang *et al.*, 1998; Watanabe *et al.*, 1994; Zhang and Roberts, 1992). Here a fuzzy-neural system that combines the advantages of both fuzzy reasoning and neural networks will be used. Fuzzy reasoning is capable of handling uncertainty and imprecise information, while an ANN is capable of learning from examples. In contrast to the conventional multilayer feed-forward neural network, the adopted fuzzy neural network (FNN) system has an additional fuzzy input layer which maps the increment of each on-line measurement into fuzzy sets.

As was previously mentioned, the overall fault diagnosis system is designed to cope with on-line fault detection and isolation in the presence of normal transient behaviour of the process. This is achieved without the FNN outputs being affected by the measured variables transient response to changes in the operational settings of the system. The FDI system has been implemented and successfully applied to a continuous binary distillation column (CBDC). Single and multiple simultaneous abrupt faults, as well as incipient ones have been considered to validate the FDI system developed.

The paper is organised as follows. In Section 2 the overall description of the FDI system architecture is given. Section 3 describes the design of the expert system used at the fault detection stage. Section 4 provides a description of the hierarchical structure of the fuzzy neural networks used for the fault isolation stage, and explains the design of this FNN. Section 5 describes the CBDC process and the results obtained with the developed FDI system for single and multiple faults. Finally, in Section 6 some concluding remarks are given.

2. System Architecture

A knowledge-based system, also called the expert system, performs reasoning using pre-established heuristic rules for a well-defined narrow domain. They combine knowledge bases of rules and domain-specific facts with information about specific instances of problems, provided by a domain expert. Ideally, in these systems, reasoning can be explained and the knowledge bases can be easily modified or updated, independently of the inference engine, as new rules become available. These features made expert systems suitable for building diagnosis systems. However, a major limitation of the knowledge-based approach comes from the fact that domain experts do not always think in terms of heuristic rules. Moreover, domain experts may not be able to explain their ways of reasoning, or they may explain them incorrectly, which makes it difficult or even impossible to build the necessary knowledge bases. Thus, for a well-behaved process with well-defined failure rules, knowledge-based systems can be developed to provide a good performance in the fault detection assessment.

On the other hand, artificial neural networks rely on training data to model the process. Establishing an appropriate training set that allows the neural network to learn and generalise for operation on future input data, permits us to develop a particular application. The inputs that match the training data exactly are recognised and identified, while new data, or incomplete or even noise versions of the training data can be closely matched to patterns recognised by the network. This learning capacity also makes ANNs suitable for designing diagnosis systems. However, in the neural network approach, the knowledge is represented as numeric weights and, hence, the rules and the reasoning process are not readily explainable. An ANN can be preferable to a knowledge-based system when rules are not known either because the topic is too complex or no domain expert is available. As a matter of fact, while in some cases an ANN can perform tasks better or faster than expert systems, in most instances the two technologies are not in competition. In fact, the characteristics of both techniques are so useful that they can complement each other giving better results in some practical applications. This fact leads us to build the FDI system in a multistage way, using an expert system for fault detection and a fuzzy-neural system for fault isolation. As will be explained latter in Section 4, fuzzy-neural systems can be interpreted in terms of a hierarchical topology to make the training task easier and to allow for isolation of multiple abrupt and incipient faults from symptoms of single abrupt faults. Figure 1 shows a diagram of the proposed FDI system.

Once a fault has been detected by the expert system, the fault isolation system is triggered to locate the hypothetical failure in the process under consideration. On-line measurements, after the pre-processing stage, are then fed forward through the FNN system and the corresponding output values processed to make a final decision about the fault localisation.

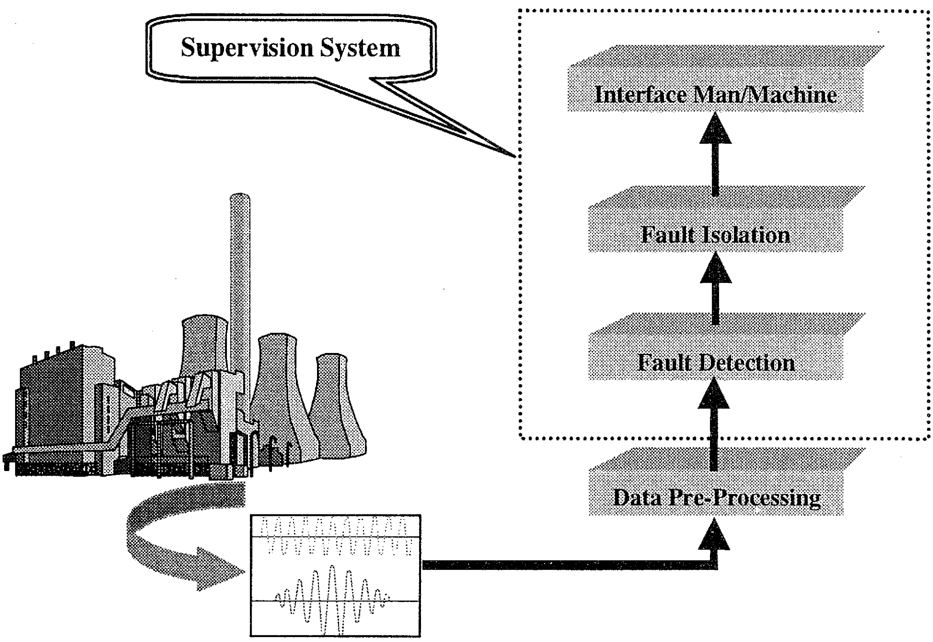

Fig. 1. Architecture of an on-line fault detection and diagnosis system.

The external data handled by the FDI system are the changes that occur in the measured variables of the process, after a pre-processing stage. Besides the usual filtering operation to reduce noise measurements and variable reconstruction, in this pre-processing stage a normalisation operation is performed to obtain all changes in the range $[-1, +1]$, for the sake of numeric simplicity. A man/machine interface keeps the operator informed about all diagnosis (fault detection and isolation) given by the FDI system.

3. Expert System for Fault Detection

A number of expert systems have been reported, which perform fault diagnosis by the method of heuristic classification (Chitarro *et al.*, 1993; Clancey, 1985; Moor and Kramer, 1986; Swartout, 1983). In this methodology, diagnostic knowledge is represented mainly in terms of heuristic rules which perform a mapping between data abstraction (usually called symptoms) and solution abstraction (typically called faults). Such a knowledge representation, usually called 'shallow' knowledge, does not contain much information about the causal mechanisms underlying the relationship between symptoms and faults. The rules typically reflect empirical knowledge derived from an operator's experience, rather than a theory of how the system under diagnosis actually works and how the fault propagates in the system. However, sometimes this latter knowledge, called 'deep' knowledge, is also used in designing expert systems, since it involves the understanding of the structure of the system and the way its components operate (Jackson, 1990).

Knowledge acquisition is a key issue related to the design of expert systems, being very time-consuming since the process operators may know little about knowledge engineering, and therefore the interchange of information between a knowledge engineer and a process operator may not be carried out efficiently. Moreover, in an industrial process, many faults to be detected and isolated may never have been experienced and, for new or recently developed plants, there may be little applicable past experimental knowledge. Furthermore, the heuristic rules used in designing expert systems based on shallow knowledge lack process generality and they tend to fail under new circumstances. On the contrary, deep knowledge can provide reliable behaviour for infrequently occurrences. However, as Clancey (1985) has pointed out, the deep models required for building expert systems are hard to construct, even for relatively simple processes. Therefore, to narrow the diagnosis focus on the process under consideration, as well as to facilitate the analysis of the behaviour of the process variables, several researchers have pointed out some methodologies. Moor and Kramer (1986) report a fault detection and diagnosis system based on a deep knowledge approach which tries to explore the causal path from the observed abnormalities to their causes and, hence, to locate any associated fault. Finch and Kramer (1988) propose a different methodology, where the process is decomposed into several subsystems according to their functions, and then it identifies the subsystem where the fault occurs. A similar approach is pointed out by Steels (1989), but in his approach the function of the system being diagnosed is hierarchically decomposed. Zhang and Roberts (1992) have proposed a fault diagnosis system based on structural decomposition of the process under consideration and component functions.

However, most of these reported fault diagnosis systems only deal with a single failure assumption. Moreover, in most of these approaches, in order to avoid false diagnosis under normal transient process behaviour, the decision of the diagnosis system is based on threshold values, set properly according to previous operational experience, or simply switch off when a set-point change in the process is performed. The use of these threshold values will affect the performance of the diagnosis system.

Due to the above reasons, the expert system approach will only be adopted here for fault detection. This expert system will use a combination of deep and shallow knowledge, but where deep knowledge plays a dominant role. A systematic methodology for generating fault detection heuristic rules with abilities to cope with multiple fault situations and to increase the system reliability under transient behaviour situations will be proposed. The fault detection heuristic rules are generated from the knowledge about the system structures, component functions, and system operation.

To deal with normal process transient behaviour, the process reference signals are explicitly included in the heuristic rules antecedents, being the expert system designed to take into account these operating situations. In this way, if a setting point change occurs in the reference signal, the proposed FDI system is not affected and, therefore, it does not recognise such a situation as a fault.

During the design phase, to make the behaviour analyses of the process variables easy, the process under concern is structurally decomposed into several subsystems. Usually, this structural decomposition corresponds to the plant topology (Calado and Roberts, 1996a). Even though not necessary for design proposes, a graph similar to a directed graph (Oyeleye and Kramer, 1988) can be used as a modelling tool to help the designer to understand the important subsystems of the process and the causal relationships between them. With this tool, the process can be represented by a graph that contains nodes and directed edges. Each node represents a subsystem and the directed edges represent interactions between subsystems, giving an indication about the causality between them. For instance, if a hypothetical system is divided into four subsystems, S_1, S_2, S_3 and S_4 interacting with each other, we can represent such a system by a directed graph that is depicted in Fig. 2.

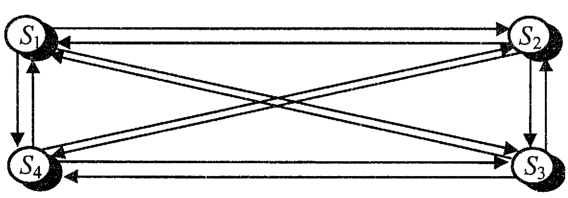

Fig. 2. A directed graph.

As was pointed out by Calado and Roberts (1996a), the system structure is represented by a set of three matrices, namely the connection matrix, the causal matrix, and the self-causal matrix, represented in the following by C, CM and CS respectively. The rows and columns of these matrices represent subsystems or measured variables, as appropriate. If there is a possible interaction between a specific row and a specific column, the corresponding matrix element takes the value 1. Otherwise, that matrix element will take the value 0. Hence, the connection matrix C, will be used to represent the interaction between subsystems. If the process is decomposed into n subsystems S, then the connection matrix for such a system is an $n \times n$ matrix, where each element c_{ij} is given by

$$c_{ij} = \begin{cases} 1, & \text{if subsystem } S_i \text{ can directly affect} \\ & \text{subsystem } S_j, \text{ with } i \neq j \\ 1, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The state of a system is given by its measurements. A subsystem is said abnormal if one of its measurements departs from the normal expected values. As is pointed out in (Zhang and Roberts, 1991), such a situation can be represented by the following equation:

$$\exists k, k \in \overline{1, m_i}, AB(m_{ik}) \Rightarrow AB(S_i) \tag{2}$$

i.e. if in subsystem S_i there exists at least one measurement m_{ik} which is abnormal, then this subsystem is abnormal. In (2) the following notation is used: AB is a predicate meaning abnormal, m_i denotes the total number of measurements in S_i, m_{ik} is the k-th measurement in S_i.

As was previously mentioned, the connection matrix only states if there exists a relationship among subsystems. However, the measurement causal matrix CM_{ij} gives a more refined description about the relationship between subsystems S_i and S_j. If there are n measurements in S_i and m measurements in S_j, then the measurement causal matrix between S_i and S_j is an $n \times m$ matrix, where each element cm_{ij}^{kl} is given by

$$\mathrm{cm}_{ij}^{kl} = \begin{cases} 1, & \text{if the } k\text{-th measured variable in } S_i \text{ can} \\ & \text{directly affect the } l\text{-th measured in } S_j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Causal relationships also exist between measured variables within a subsystem. The self-causal matrix, CS_i, represents these relationships. If there are n measurements in subsystem S_i, then the self-causal matrix for subsystem S_i is an $n \times n$ matrix, where each element cs_i^{kl} is given by

$$\mathrm{cs}_i^{kl} = \begin{cases} 1, & \text{if the } k\text{-th measured variable in } S_i \text{ can} \\ & \text{directly affect the } l\text{-th measured in } S_i \\ 1, & \text{if } k = 1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The reasoning for generating fault detection heuristic rules, corresponding to the single fault scenarios, is based on the predicate stated by (2). If we assume that the j-th measurement in the i-th subsystem presents an abnormal behaviour, which is represented by $\mathrm{AB}(m_{ij})$ according to (2), then a search is conducted to causally look for any measured variable in subsystem S_i that could be responsible for the observed abnormality in m_{ij}. If such a variable exists, then it is retained and a fault detection heuristic rule must be generated. The self-causal matrix of subsystem S_i guides this search. Similar searches are also performed to find further causes in S_i for the retained variable. If there is another variable in S_i which can directly affect the retained variable behaviour, then this one is also retained and another diagnostic rule is generated. If there are no more variables in S_i that could be responsible for the observed abnormality, then the causal search at subsystem S_i is terminated.

This search procedure continues, driven by the connection matrix, in order to find all the subsystems that are connected with subsystem S_i that can directly affect any measurement variable in S_i. The goal is to identify all the subsystems whose measurement variables can directly affect the measurement variables in the subsystem where such an abnormal behaviour is observed. Following this reasoning, all subsystems satisfying the condition

$$\forall\, S_j, \mathrm{c}_{ij} = 1, \quad j \neq i \tag{5}$$

form a set of subsystems that can directly affect the subsystem presenting an abnormal behaviour.

Next, a search is conducted through all the subsystems that form the above set in order to find all the measured variables in other subsystems which could directly affect the retained variables. At this stage the measurement causal matrix plays the main role and, hence, if such variables exist, then other heuristic rules are generated. Once this search procedure is terminated, important shallow knowledge about the process in the form of heuristic rules can be added to the previously generated heuristic rules. In this way, the reliability of the fault detection system can be enhanced by including operators' experience about the process.

The heuristic rules based on the deep knowledge of the process have an output in the form 'enable fault detection flag.' However, as shallow knowledge does not contain much information about the causal mechanisms underlying the relationship between symptoms and faults, the heuristic rules based on shallow knowledge are here used to fire the rules based on deep knowledge about the process.

When multiple faults occur at the same time, it is assumed in our design that fault effects on the measurement variables are of additive type. In this way, fault detection heuristic rules for multiple fault scenarios are also generated at the design stage.

The knowledge base of the fault detection system will be built up with the fault detection heuristic rules achieved following the procedure described above. An inference engine makes the reasoning in the expert system. The fault detection heuristic rules will be searched in a forward manner and then, when the data acquired match the antecedent parts of a heuristic rule, a fault detection flag will be enabled. This flag will be used to trigger the fault diagnosis system and to locate a fault or faults in the process.

The main advantage of the present approach is that the fault detection task is based on heuristic evaluation of the time variation of the process variables (input, output and state). In this way, normal transient behaviours of the process can be considered, as well as incipient faults whose development occurs gradually, instead of suddenly as for the abrupt fault case.

4. Hierarchical Structure of Fuzzy Neural Networks

The adoption of a hierarchical fuzzy neural network approach for fault isolation aims at the development of an architecture that can localise abrupt and incipient single and multiple faults correctly, or at least with a minimum misclassification rate, from only single abrupt fault symptoms, and be easily trained. In such a architecture, measurements and/or faults act as antecedents from which we can infer a classification of the pattern input, which means to localise the failure. For each expected single fault scenario there exists a corresponding FNN at the medium level of the hierarchical structure of the FNN.

The number of single faults considered determines the number of fuzzy neural networks used in the hierarchical structure. Other authors (Watanabe *et al.*, 1994) using feed-forward artificial neural networks have already followed the procedure.

The topology of each FNN has been achieved through a trial-and-error procedure until the expected fault diagnosis performance has been achieved. Two degrees of freedom have been considered in this design. The first is related to the number of processing elements in the fuzzification layer. The other is related to the number of neurons of the hidden layer of the neural network.

The number of processing elements in the fuzzification layer depends on the number of measurement variables used for fault diagnosis purposes and on the number of fuzzy qualitative values used to describe the behaviour of the process variables. However, once the number of measurement variables has been fixed, the number of fuzzy sets used depends essentially on the following aspects:

- The number of considered faulty scenarios. It has been observed that the number of faults that can be diagnosed increases with the number of fuzzy sets used to discretise the fuzzy quantity space. Thus, by increasing the number of fuzzy sets, the number of possible patterns to recognise can be increased.

- The ratio of expected data compression. By using fuzzy sets to describe the process variables' behaviour, due to the fact that similar training patterns are transformed into the same fault symptoms, training data will be compressed and the training effort can be lightened.

- The noise level in the measurement variables. The fuzzy approach makes the system less sensitive to the measurement noise (Zhang and Morris, 1994).

A similar topology for an FNN applied for fault diagnosis has already been reported, as well as a comparison between the performance achieved with such an FNN and the classical multilayer feedforward neural network (Zhang and Morris, 1994). Some results are presented which demonstrate that a fault diagnosis system based on a fuzzy neural network performs much better than the one based upon a conventional neural network.

A trade-off between all the above-mentioned aspects, which are very problem dependent and sometimes difficult to evaluate, determines the number of processing elements in the fuzzification layer that allows us to achieve the desired performance.

The second degree of freedom in the design concerns the number of processing elements in the hidden layer. In order to achieve the desired performance, the complexity of the relationships between faults and fault symptoms determines the number of processing elements in the hidden layer. Once again a trial-and-error procedure has been followed, due to the inherent ambiguity associated with most above-mentioned aspects. If the complexity of the relationships between faults and symptoms increases, the number of processing elements in the hidden layer has to be increased to achieve the performance desired. Furthermore, it has also been observed that the number of processing elements in the hidden layer could determine how early an incipient scenario could be isolated, especially when the fault development speed is quite low.

The outputs of each network take values in the range $[0, 1]$. A fault is diagnosed when the corresponding FNN output is close to 1. If all FNN outputs take values close to 0, this corresponds to the normal operation case. Hence, in training an FNN to diagnose single faults by using deterministic data, which is concerned with abrupt fault symptoms, the input matrix has the number of columns equal to the number of measurement variables used for fault diagnosis purposes and for each fault the number of rows which depends on the number of operating regions that can be defined for a specific process. Obviously, the input matrix has also the number of rows corresponding to the input patterns associated with the normal process behaviour, each one concerning each operating region. However, by using an FNN with a fuzzification layer consisting of three fuzzy sets, the fault symptoms, as well as the input patterns associated with the normal process behaviour, are compressed. Thus, independently of the operation state of the process only one row for each single fault considered is achieved.

The output decision matrix would have only 0's in the row corresponding to the normal case, one 1 in each row corresponding to a single fault, two 1's in each row corresponding to the double faults, and so on if more than two faults are considered. However, previous research work (Calado and Roberts, 1996b) has shown that the 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 current approach has a hierarchical structure of three levels where several FNNs are used, as shown in Fig. 3. The lower level consists of one FNN where all variations of the measured variables are used as inputs. At the medium level a number of FNNs (structurally identical or different) which is equal to the number of single fault scenarios considered, are used. Each FNN at the medium level is also fed with all the measurement variables and each one is associated

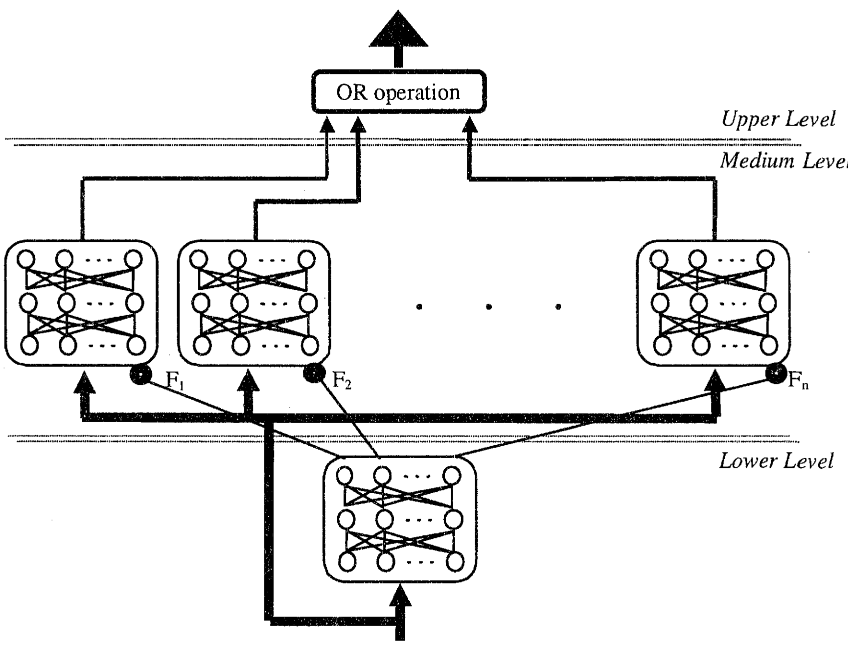

Fig. 3. The hierarchical structure of FNNs.

with an output of the FNN at the lower level, corresponding to a particular single fault. The upper level consists of an OR operation of the outputs of the FNNs of the medium level.

The elements of the set used in the OR operation are determined by the outputs of the FNN at the lower level. Thus, if the i-th and j-th outputs of the FNN at the lower level are taking values close to 1, then the outputs of the i-th and j-th FNNs at the medium level form the elements used in the OR operation. However, if only one output of the FNN at the lower level is taking a value close to 1, then the diagnosis is deemed to be the single fault corresponding to that output. Following this procedure the hierarchical structure can cope with situations involving multiple simultaneous faults (Calado and Sá da Costa, 1998).

Both the lower level and the medium level networks are made up of three layers: a fuzzification layer, a hidden layer, and an output layer. The FNN is trained using an extension of the backpropagation learning algorithm (Calado and Roberts, 1996b).

The fuzzification layer converts each input into the quantity space, $q_f = \{\text{decrease, steady, increase}\}$ by association with three types of neurons in the fuzzification layer. 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. The other processing elements of the fuzzification layer related to the fuzzy set 'steady,' as well as the processing elements in the hidden and output layers use the Gaussian function as their activation function.

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 used include only abrupt fault symptoms. A description of some achieved results is given in the next section.

5. A Case Study

A continuous binary distillation column (CBDC) is used as the test bed to evaluate the performance of the proposed FDI system. Distillation is a process in which a liquid or vapour mixture of two or more substances is separated into its component fractions of desired purity by the application and removal of heat. Figure 4 shows a diagram of the CBDC under consideration, with eight trays, reboiler and condenser, reflux accumulator, and level control in place. The primary controlled variables are distillate and bottom-product compositions, liquid level in the column base and accumulator, and column pressure. The manipulated variables are the product flow rates, reflux ratio, heat input (steam rate), and heat removal (cooling-water flow rate). The feed rate is fed continuously as a saturated liquid into Feed Tray 5. This feed stream is not normally manipulated, since it is a product from the upstream operation.

A mathematical model, based on a material balance, a molar balance and the liquid-vapor equilibrium equation is used to simulate the CBDC (Ingham *et al.*, 1994). We assume a pure binary system with constant relative volatility throughout the column and perfect, 100 per-cent efficient trays, i.e. the vapour leaving the tray is in equilibrium with the liquid on the tray. The feed rate is F (moles/s) and composition is X (mole fraction more-volatile component). The overhead vapor is totally condensed in a condenser and flows into the reflux drum, whose hold up of liquid is M_D (moles). We assume that the content of the reflux drum is perfectly mixed with composition X_D. The reflux is pumped back to the top tray (1) of the column at a rate L (moles/s). The overhead distillate product is removed at a rate D (moles/s). At the base of the column, the liquids bottom product is removed at a rate W (moles/s) and with a composition X_9. Vapor boil-up is generated in a thermosiphon reboiler at a rate V_1 (moles/s). It is assumed that the liquids in the reboiler and in the base of the column are perfectly mixed together and have the same composition X_9 and a total hold up of M_B (moles). The composition of the vapor boil-up is then Y_9 and the vapor composition is in equilibrium with the liquid at X_9.

It is clear that changes in any of the five input variables will affect all output variables. The same is also true when a fault occurs within the process.

Following the methodology proposed in Section 3, fault detection heuristic rules, based on deep and shallow knowledge of the CBDC, have been used to build up the expert system knowledge base. To assure a good reliability of the fault detection system, in some pre-condition of the heuristic rules the linguistic statement 'continuously' is used. Therefore, for implementation purposes, the last two changes in the measurement variables should be retained to give an indication of this linguistic statement.

According to the system architecture described in Section 2, the 'data pre-processing' module performs this task, besides the pre-processing and data normalisation.

Following the methodology proposed in Section 3 for generating fault detection heuristic rules, the CBDC process represented in Fig. 4 was decomposed into three subsystems. The first subsystem, S_1, consists of external feed elements and associated sensors. The second subsystem, S_2, includes the following components: distillation column, Pipe 1, Pipe 5, reboiler level control valve, Pipe 6, reboiler heat exchanger and associated sensors. The remaining components form the third subsystem, S_3, which are all the components related to the surge drum part of the process. The directed graph corresponding to this decomposition is shown in Fig. 5.

Taking into account this decomposition, the corresponding three matrices describing the process structure are obtained as described previously. According to (1), the connection matrix for the CBDC process is as follows:

$$\mathrm{C} = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \end{array} \begin{array}{c} \begin{array}{ccc} S_1 & S_2 & S_3 \end{array} \\ \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \end{array} \tag{6}$$

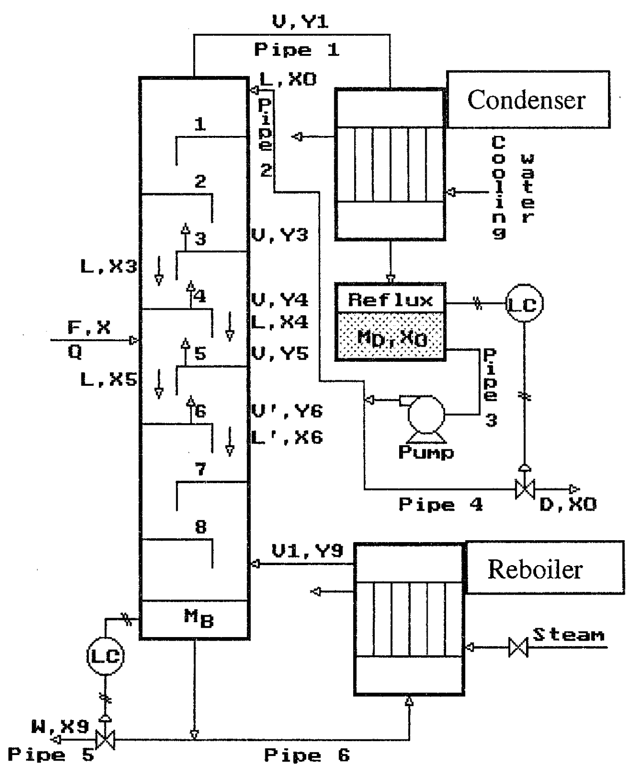

Fig. 4. The continuous binary distillation column.

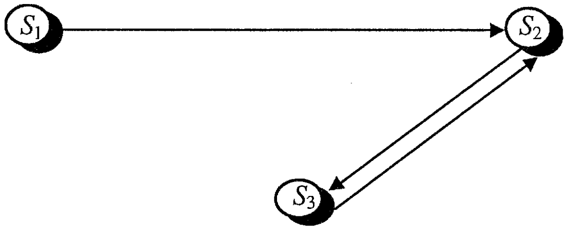

Fig. 5. The directed graph for the continuous binary distillation column.

To perform the process behaviour analysis, nine measurement variables are considered. For the first subsystem, S_1, two measurements F and x are considered which are the column feedrate and the feed composition, respectively. From (4) the self-causal matrix for the first sub-system is given by

$$\mathrm{CS}_1 = \begin{array}{c} \\ F \\ x \end{array} \begin{array}{c} \begin{array}{cc} F & x \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array} \tag{7}$$

Following an analogous procedure, the self-causal matrix for the second subsystem, S_2, is

$$\mathrm{CS}_2 = \begin{array}{c} \\ M_B \\ W \\ V_1 \\ V \end{array} \begin{array}{c} \begin{array}{cccc} M_B & W & V_1 & V \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix} \end{array} \tag{8}$$

where M_B stands for the hold-up in the reboiler, W is the bottoms flow rate, V_1 denotes the vapour boil-up rate and V stands for the vapour flow rate.

For subsystem S_3 the following measurement variables are considered: L – the liquid flow rate, M_D – the hold-up in the surge drum and D – the distillate rate, which determines the self-causal matrix

$$\mathrm{CS}_3 = \begin{array}{c} \\ M_D \\ L \\ D \end{array} \begin{array}{c} \begin{array}{ccc} M_D & L & D \end{array} \\ \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \end{array} \tag{9}$$

From (3) the measurement causal matrix from subsystem S_1 to subsystem S_2 is given by

$$\mathrm{CM}_{12} = \begin{array}{c} \\ F \\ x \end{array} \begin{array}{c} \begin{array}{cccc} M_B & W & V_1 & V \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \tag{10}$$

The measurement causal matrix from subsystem S_2 to subsystem S_3 is

$$\mathrm{CM}_{23} = \begin{array}{c} \\ M_B \\ W \\ V_1 \\ V \end{array} \begin{array}{c} \begin{array}{ccc} M_D & L & D \end{array} \\ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix} \end{array} \tag{11}$$

The measurement causal matrix from subsystem S_3 to subsystem S_2 is given by

$$\mathrm{CM}_{32} = \begin{array}{c} \\ M_D \\ L \\ D \end{array} \begin{array}{c} \begin{array}{cccc} M_B & W & V_1 & V \end{array} \\ \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{array} \tag{12}$$

Based on these matrices, heuristic rules are automatically generated as explained previously in Section 3. For illustration, let us consider the situation where the hold-up in the reboiler is subjected to an abnormal behaviour taking a value higher than its set point. It can be seen from (8) that the hold-up in the reboiler can be directly affected by itself and by the bottoms flow rate W. Furthermore, from matrices (6), (10) and (12), we conclude that there are no variables in other subsystems which could be directly responsible for the observed abnormality. From (12) it is possible to conclude that the process variables L and D can directly affect the process variable W. However, M_B is not directly affected by such variables. From this search, the following fault detection heuristic rules are generated:

IF (M_B is higher than its set-point AND W is continuously decreasing)
THEN enable fault detection flag

IF (M_B is higher than its set-point AND M_B is continuously increasing)
THEN enable fault detection flag

From the point of view of the knowledge base implementation, the two heuristic rules presented above, which have been generated from deep process knowledge, can be integrated with heuristic rules generated from shallow process knowledge and the result is as follows:

```
IF (Pipe 5 valve is not saturated AND no M_B set-point change takes place)
THEN
{
    IF (M_B is higher than its set-point) THEN
    {
        IF (W is continuously decreasing OR M_B is continuously increasing)
        THEN enable fault detection flag
    }
    ELSE
    {
                    ...
    }
}
```

The fault isolation system is based on a hierarchical structure of fuzzy neural networks with the characteristics presented in Section 4. Six measurement variables were used as input data to the all FNNs. These are M_D, the hold-up in the surge drum; D_a, the distillate flow rate; M_B, the hold-up in the reboiler; W, the bottoms flow rate; F, the column feed rate; V, the vapour flow rate. Thus, the fault isolation task is performed by presenting changes in the measurement variables to the FNNs, which are propagated in a feed-forward manner through the FNNs. Then, to locate a fault or faults in the process, an analysis of the fuzzy neural networks' output values is carried out as described previously.

All FNNs used in the hierarchical fault diagnosis structure have the same topology. The FNN fuzzification layers have 18 processing elements arranged in 6 groups corresponding to the 6 information sources, where each group contains 3 neurons. 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 studies, it was found that 13 hidden processing elements assure a good performance.

As there are six single faults considered, six FNN output neurons exist, each one corresponding to a single fault. Each FNN at the medium level contains seven inputs corresponding to six measurement variables plus an input corresponding to a particular single fault, which is an output of the FNN at the lower level.

Training and test data were obtained from simulation of the model of the CBDC, taking into account all the faulty scenarios being considered and the nominal operational conditions. The six single faults considered are: F_1 – Pipe 2 blocked, F_2 – Pipe 4 blocked, F_3 – Pipe 5 blocked, F_4 – Pipe 6 partially blocked, F_5 – the external feed rate too high, and F_6 – the external feed rate too low. Also, a selected set of 10 double simultaneous faults achieved through an AND operation in the single fault space, and a selected set of 5 triple simultaneous faults also achieved through an AND operation in the single fault space, were considered.

All FNNs were trained by using an extension of the classical backpropagation learning algorithm already reported by the authors (Calado and Roberts, 1996b).

According to that algorithm, the learning task was performed through the following equations

$$\Delta W_{ji}^{[s]}(k+1) = \text{lcoef} * e_j^{[s]} * x_i^{[s-1]} + \text{momentum} * \Delta w_{ji}^{[s]}(k)$$

$$e_j^{[s]} = \left[f'\left(I_j^{[s]}\right) + f'_{\text{offset}}\right] * \sum_k \left(e_k^{[s+1]} * w_{kj}^{[s+1]}\right) \tag{13}$$

$$e_k^{[0]} = (d_k - o_k) * \left[f'(I_k) + f'_{\text{offset}}\right]$$

where $w_{ji}^{[s]}$ is the weight of the connection joining the i-th neuron in layer $s-1$ to the j-th neuron in layer s, $e_j^{[s]}$ stands for the current error of the j-th neuron in layer s, $x_i^{[s-1]}$ denotes the current output state of the i-th neuron in layer $s-1$, 'lcoef' signifies the learning coefficient, k is the adaptation step, $I_j^{[s]}$ is a weighted sum of the inputs to the j-th neuron in layer s, $f'(I_j^{[s]})$ denotes the derivative of the transfer function associated with the j-th neuron in layer s, d_k is the desired output, o_k stands for the actual output produced by the network with its current set of weights.

It was observed that with 5000 iterations on average, a learning coefficient equal to 0.9, a momentum term equal to 0.6 and a derivative offset equal to 0.2, a LSE error smaller than 0.015 was achieved. Although the training was based on single and double abrupt faults, the testing was carried out on single, double and triple faults considered as abrupt or incipient.

Several simulation studies were performed and it was considered that a fault existed in the test set when the output of a neuron in the output layer was greater than 0.65. During the studies conducted with the CBDC process, under abrupt faulty scenarios a very accurate diagnosis was obtained. Note that all single abrupt faults considered were successfully detected and localised in less than one second. Under incipient faulty scenarios, it was observed that the results achieved are dependent on the fault development speed.

However, all single faults were simulated and successfully diagnosed with different fault development speed values. It is worth noticing that the networks were trained with stronger faults (abrupt fault symptoms) and the tests were performed with small degrees of faults. A number of tests were also performed with double and triple simultaneous faults. The results achieved under these faulty scenarios are quite good but further research is needed to obtain exhaustive conclusions.

In the simulation of incipient faults, it was assumed that the component degradation follows a linear law. Therefore, incipient faults are simulated through the equation

$$M_f = M_n (1 + \gamma t) \tag{14}$$

where M_f is the value of a process variable when there is a fault, M_n is the nominal value of a process variable when there is no fault, γ stands for a constant which determines the speed of the fault development (s^{-1}), and t denotes time (s). In order to test the performance and reliability of the FDI system, the softest incipient fault behaviour was assessed. Note that the common situation is a component degradation following an exponential law. Thus, in this case, the behaviour of the process variable affected by that fault will be closer to a behaviour under an abrupt fault scenario. Therefore, since in our design the FNN training patterns used include only abrupt fault symptoms, the diagnosis of an incipient fault can be achieved with less effort, where the component degradation follows an exponential law.

Several simulation studies were performed under incipient fault scenarios. For instance, Fig. 6 illustrates the diagnosis achieved after the single fault F_1 was simulated with a speed development value equal to $0.006\ h^{-1}$. It is worth pointing out that since the surge drum level control loop masks the fault effect, the incipient faulty scenario which has a speed development value very low is particularly difficult to diagnose. Under this faulty situation, the change in the liquid flow rate, L, which is directly affected by that fault, is depicted in Fig. 6(a). However, as is shown in Figs. 6(b) and 6(c), since the surge drum level control loop compensates the decrease in the liquid flow rate L by an increase in the distillate flow rate D, only a small perturbation in the surge drum level M_D is observed. Even in this case, the proposed FDI system is still able to diagnose the correct fault after the control valve saturation has been reached. If such a situation takes place, the fault detection flag is enabled and in less than half a second the output of the FNN at the lower level corresponding to F_1 takes the value 0.78 and the fault is thus diagnosed. All the other outputs of such a network take values close to zero.

As was previously described, the diagnosis achieved under multiple fault scenarios is a result of an OR operation on the outputs of the FNN at the medium level. Furthermore, the elements used in the OR operation are determined by the outputs of the FNN at the lower level. For example, when abrupt faults F_1 and F_5 occur simultaneously, the outputs of the FNN at the lower level corresponding to such faults take the values 0.995 and 0.998, respectively. Therefore, as we consider an FNN output which takes a value greater than 0.65 as active, the outputs of the first and fifth FNNs at the medium level form the set used in the OR operation at the upper level. During the studies conducted under the above-mentioned faulty scenario, it was observed that the outputs of the first FNN taking values greater than 0.65 correspond to faults F_1 and F_5. The output of the fifth FNN corresponding to fault F_1 takes the value 0.996 while the output corresponding to fault F_5 takes the value 0.999. Thus, the OR operation was carried out between the sets $\{F_1 F_5\}$ and $\{F_1 F_5\}$ and hence the result was the diagnosis of the double simultaneous faults F_1 and F_5.

6. Conclusions

An on-line fault detection and isolation system, consisting of an expert system cascaded with a hierarchical structure of fuzzy neural networks, has been proposed. Successful results have been achieved during simulation studies conducted with a continuous binary distillation column plant. Because the fault detection task is performed through an expert system containing deep and shallow knowledge, the overall

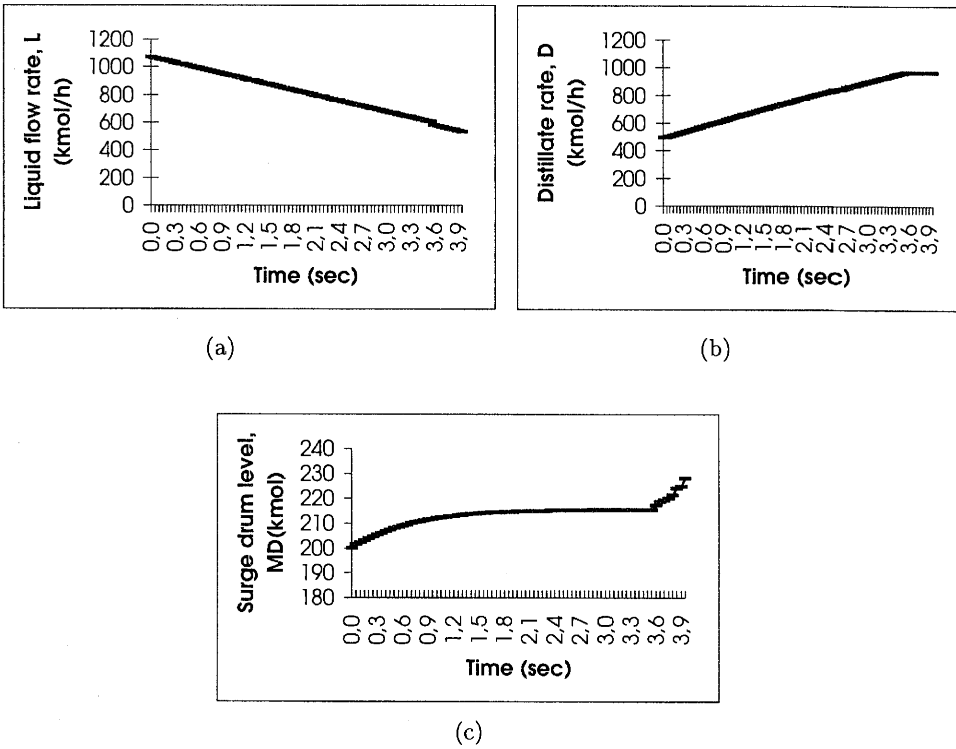

Fig. 6. The process variables under a faulty scenario.

computational fault detection and isolation system has an ability to cope with transient behaviours of the process variables avoiding false fault detection and isolation under such situations. Furthermore, the system is able to diagnose multiple simultaneous faults from only single fault symptoms.

Following a systematic methodology described here, fault detection heuristic rules, based on deep and shallow knowledge of the process under consideration, have been used to build up an expert system knowledge base. The advantage of such an approach is that the fault detection task does not depend on quantitative threshold values and, hence, the performance and reliability of the fault detection and diagnosis system is increased.

The fault isolation system is based on a hierarchical structure of FNNs, which combines the advantages of both fuzzy reasoning and neural networks learning capabilities. Thus, the approach described here compresses the on-line measurement data into qualitative values whose semantics are represented by fuzzy sets and, hence, the training of the FNNs and the diagnosis of the faults can be carried out more efficiently.

Since in the current approach the relationships between fault and faults symptoms are distributed through several FNNs, one can conclude that the training of a hierarchical structure of fuzzy neural networks can be done more easily than that of a non-hierarchical neural network for the same purpose.

The successful results achieved so far during simulation studies with the continuous binary distillation column plant indicate a great potential for the use of the fault detection and isolation system proposed in this paper.

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