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NEURO-FUZZY STRUCTURES IN FDI SYSTEM

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Abstract: Fault diagnosis systems have an important role in industrial plants because the early fault detection and isolation (FDI) can minimize damages in the plants. The main aim of this work is to propose a two-stage neuro-fuzzy approach as a fault diagnosis system in dynamic processes. The first stage of the system is responsible for fault detection and is implemented using a neuro-fuzzy (N-F) model. The second stage of the system is responsible for fault isolation and is built using an hierarchical structure of fuzzy neural networks. The FDI system is applied to fault diagnosis in the actuators of one sugar factory. *Copyright ©2002 IFAC*

Keywords: Fault diagnosis, neural network, fuzzy modelling, backpropagation algorithms, hierarchical structure, actuators.

1. INTRODUCTION

Modern industrial systems are liable to numerous faults due to their complexity. In many applications, increased requirements on productivity and performance lead to plants operating near to the design limits and therefore, faults can occur in the components of the process or in the sensors and actuators. So, the early detection and isolation of faults can minimise damages in the plants and reduce the effects of the faults in the industrial environment. Systems that have the capability of detect, isolate and identify faults are called a fault diagnosis systems. These systems are very important for the increase of safety, reliability and availability of processes.

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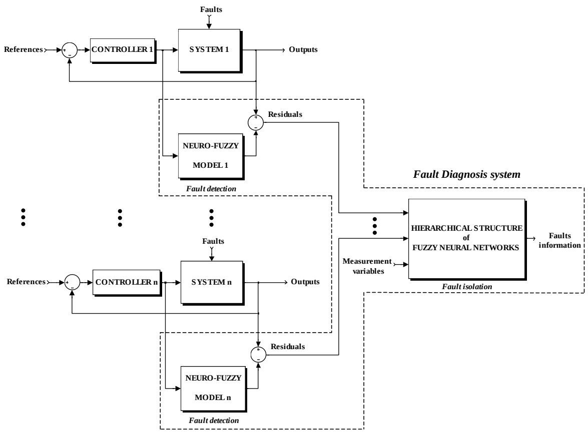

Fig. 1. Fault diagnosis system.

In dynamical processes, faults may be divided into two main classes: abrupt faults and incipient faults. Abrupt faults give rise to jumps in the process parameters, resulting in an appreciable deviation from normal system behaviours. On the other hand, incipient faults affect the process behaviour slowly and may take a long time before being detected. The fault detection and isolation of these faults can be achieved with N-F methods, which have the capability to use simultaneously quantitative and qualitative knowledge and the ability to represent some kind of uncertainty present in real processes (Takagi, 2000; Yager and Filev, 1994).

It has been constructed a fault diagnosis system, as described in the Fig. 1. This system have two stages, the first stage is responsible for fault detection and is based in the N-F models for all subsystems considered for the fault diagnosis and in which the faults will occur. The second stage is responsible for fault isolation, decision making or classification of residuals (with or without more measurement variables depending of the process) to determine the type, location and reasons of the faults. This decision is described by a discrete mapping from continuous symptom space to discrete fault space. Such task is carried out by a classifier, which determines what kind of faults are present in the process. In this approach, the second stage is done with an hierarchical structure of fuzzy neural networks (HSFNN) that combines the advantages of both fuzzy reasoning and neural networks (Mendes *et al.*, 2001; Calado *et al.*, 2001). The proposed fault diagnosis system is applied to fault diagnosis of sugar factory actuators valves.

The paper is organised as follows. Section 2 provides a description of the fault detection system. Section 3 presents the description of the fault isolation system. Section 4 describes the case study. Section 5 presents the simulation of faults and the results of this fault diagnosis system applied to the sugar factory actuators. Finally, in Section 6 some concluding remarks are given.

2. FAULT DETECTION

The first stage of the fault diagnosis system is the N-F model for residuals generation.

2.1 *Neuro-fuzzy modelling*

The idea of model based fault detection consider the comparison of the model output with the real values measured from the process, thereby generating the residuals, which are the faults indicators (Korbicz *et al.*, 2001; Patton *et al.*, 2000). The proposed fault detection approach utilises the N-F technique to implement necessary models. Two types of the N-F networks are commonly used for modelling purpose: Mamdani N-F network and Takagi-Sugeno N-F network. Generally Takagi-Sugeno N-F structures have better performance in modelling than other structures due to their possibility to representation of the non-linear systems by several local linear models. For this reason the N-F networks with Takagi-Sugeno topology are used in the proposed approach to build the models. The structure of the Takagi-Sugeno system can be presented in the form of a layered topology similar to the neural networks. Such structure is shown in Fig. 2 where the following notations are used: $x_1, ..., x_{m+n}$ - are the inputs, y - is the output, n - is the number of inputs, N - is the number of rules, N_i - is the number of fuzzy partitions for i-th input and c, w and a are the weights. Presented N-F network consists of five layers. The elements of the first layer are responsible for calculation of membership degrees of input signals. It should be noticed that not all network inputs have to be connected with the nodes in the first and fifth layer. Some input can be connected only with the nodes in the fifth layer. The nodes in the second layer realize algebraic product that is used to do the operation of aggregation in order to achieve the firing levels of the rules. The third layer realizes the inference operation that is commonly defined as the algebraic product. The fifth layer express conclusions described by the linear combinations of the input variables. The fourth layer is responsible for defuzzification of computed results and is realized by two summation nodes and one division node because the most commonly used method of defuzzification is the Height Method. Three types of weights c, w and a are tuned during the learning process in the presented N-F network. The weights c and w are the parameters of the Gaussian functions, which express antecedents and the weights

a are the parameters of the linear functions, which express the consequences.

2.2 *System identification*

Proposed fault detection scheme requires modelling of the non-linear dynamic systems. The identification process of such systems usually is divided into two steps: structure identification and parameters estimation. In this work the first step consists of two phases: input variable selection and rule base self-generation. During the first phase the input variables and the number of input and output lags have been selected and next it has been decided, which input variables should be included in the antecedent of the fuzzy rules. Different structures of the models has been obtained and next compared during tests. The performance criteria for tested structures were defined in the form of the sum of the squared errors. Implemented structures have been tested using validation data and the best has been chosen to build the model. During the second phase clustering algorithm called the Mountain Method has been used to network structure self-generation (Yager and Filev, 1994). The basic idea of such approach is to group the input-output data into the clusters and use one rule for each cluster. The second step of system identification is required to estimate the parameters of the N-F network. At first the Fuzzy C-Mean (FCM) clustering algorithm is used to determine the sizes of discovered clusters and next obtained information is used to estimate the centers and widths of membership functions by projecting the clusters on the input variables. The parameters of the linear consequences are initialized using the ARX method and during the next step all parameters are tuned using the backpropagation algorithm.

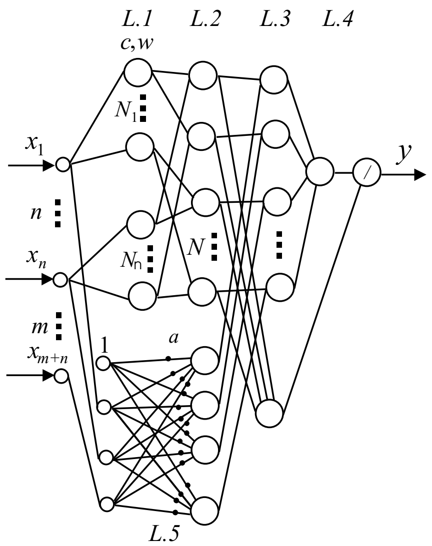

Fig. 2. The structure of Takagi-Sugeno N-F network.

3. FAULT ISOLATION

The second stage of the fault diagnosis system of Fig. 1 is an HSFNN for fault isolation (classification of residuals).

3.1 *Hierarchical structure of fuzzy neural networks*

The HSFNN has been used to isolate (classify) multiple simultaneous faults from only single abrupt fault symptoms (Mendes *et al.*, 2001). The hierarchical structure has three levels where several fuzzy neural networks (FNNs) are used, as shown in Fig. 3. The lower level consists of one FNN where residuals (and also measurement variables, if necessary to diagnose some fault that aren't dependent from the neuro-fuzzy model) are used as inputs. At the medium level a number of FNNs (structurally identical) that is equal to the number of single fault scenarios considered, are used. Each FNN at the medium level is also fed with all the residuals and measurement variables, and each one is associated with an output of the FNN at the lower level, corresponding to a particular single fault. The upper level consists in one fuzzy OR operation between the outputs of the FNNs of the medium level. The elements of the set used in the fuzzy OR operation are determined by the outputs of the FNN at the lower level. Thus, if the ith and jth outputs of the FNN at the lower level is taking values greater than a specified threshold (e.g., 0.5), then the outputs of the ith and jth FNNs at the medium level form the

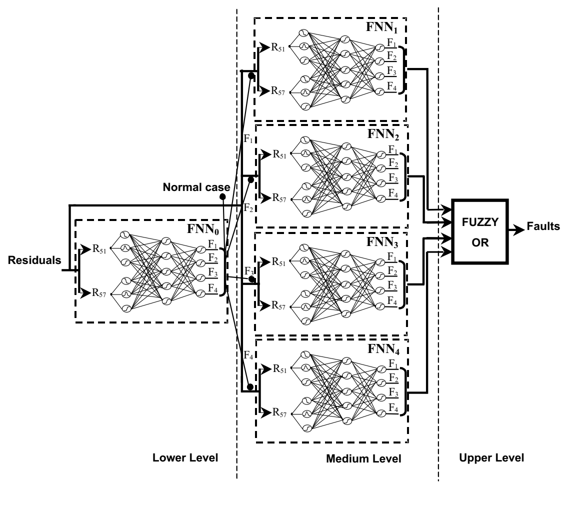

Fig. 3. Hierarchical structure of Fuzzy Neural Networks.

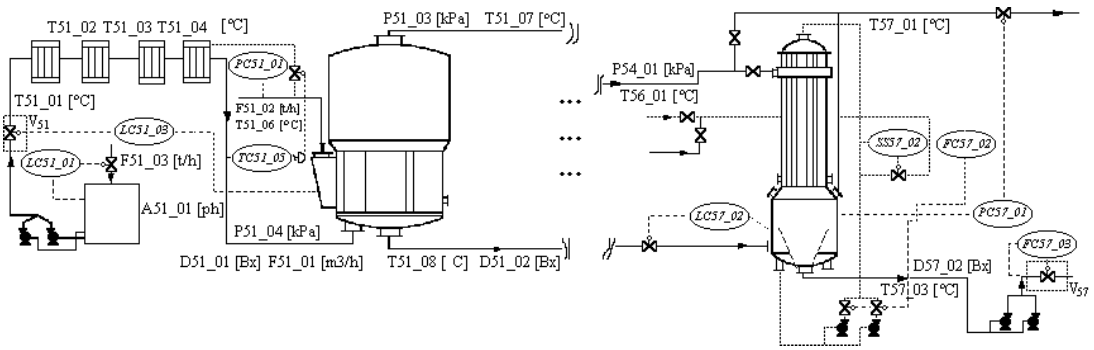

Fig. 4. Evaporation station from Lublin sugar factory.

elements used in the fuzzy OR operation. However, if only one output of the FNN at the lower level is taking a value greater than this specified threshold, then the corresponding FNN 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 FNN at the lower level.

In contrast to the conventional multi-layer feedforward neural network, the adopted FNN has an additional fuzzy input layer that maps the increment of each residuum 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 membership functions used in the input fuzzy layer have been achieved by fuzzy clustering algorithm, the Gustafson-Kessel algorithm (Gustfason and Kessel, 1979), which is implemented in the "*Fuzzy Modeling and Identification Toolbox*" for MATLAB (Babuška, 1998) and have been adjusted with parametric sigmoidal equations. 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: a fuzzification layer, an hidden layer and an output layer. The FNNs have been trained using the resilient backpropagation learning algorithm (Riedmiller and Braun, 1993).

The FNN_0 is trained with single abrupt fault symptoms and with stationary operational conditions symptoms. On the other hand, the FNN_i are trained using the data for one single abrupt fault (the fault associated with the corresponding FNN_i)) and for all possible double abrupt faults that the FNN_i net will be able to diagnose. This training data is obtained by adding the data for the corresponding single abrupt faults considered. This structure is used for fault isolation for all actuators in the industrial plant.

4. CASE STUDY

The evaporation station presented here is a part of Lublin Sugar Factory in Poland. In Fig. 4 the first and last sections of evaporation station are shown. The main technological task of an evaporation station is to thicken the beet juice being just after the filtering and cleaning processes. This station consists of seven evaporators grouped in five sections (sections I, IV and V consist of one evaporator each and sections II and III consists of two evaporators each). The first five evaporators work with natural juice circulation and the last two have another construction and work with juice circulation forced by pumps.

Two valves connected with evaporation station have been chosen for research purposes. First one (valve V_{51}) situated on the inflow of thin juice into the evaporation station and the second one (valve V_{57}) situated on the outlet of thick juice from the V section of evaporation station (see Fig. 4).

5. FAULT DIAGNOSIS RESULTS

This section presents the results achieved with the FDI system proposed.

5.1 *Neuro-fuzzy models for sugar factory actuators*

Two models of the valves have been implemented using described N-F technique. Both models have the similar structure (Table 1). They have three inputs but only first two inputs are included in the

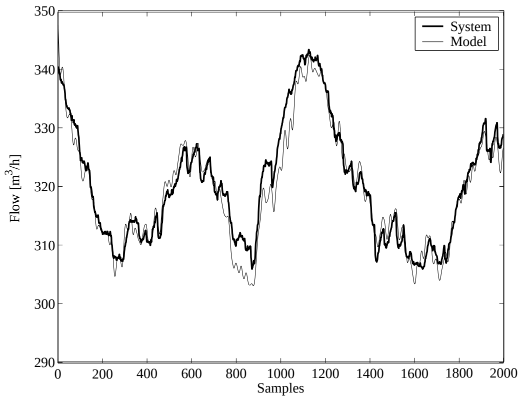

Fig. 5. Performance of Takagi-Sugeno N-F model for valve V_{51} (SSE / $N.^o$ of samples = 6.774).

antecedents of the fuzzy rules. The performances of designed models have been tested using the validation data (the performance index has been defined in the form of the sum of the squared errors divided by the number of samples). The performance indexes for models of valve V_{51} and V_{57} corresponding to the values 6.774 and 8.461. Sample results obtained for the model of valve V_{51} are shown in the Fig. 5. The residuals are generated as a difference between the output of the real system and the model. The normal operation is indicated by the residuals, which values are zero or oscillates around zero.

Table 1. The structures of the N-F models (C_V - control value, F - juice flow.)

Model	Inputs	$N.^o$ of rules	Output
valve V_{51}	$[C_V(k-1), F(k-1), F(k-2)]$	7	$F(k)$
valve V_{57}	$[C_V(k-1), F(k-1), F(k-2)]$	9	$F(k)$

5.2 *HSFNN for sugar factory actuators*

The fault isolation subsystem is based on an HSFNN with the characteristics previously presented (see Fig. 3). But, to construct this structure is necessary to define the fault set and the variables used in the input layer. Thus, two residuals have been used as input data to all the fuzzy neural networks. These residuals are the following: R_{51}, residuum from the valve V_{51}; R_{57}, residuum from the valve V_{57}. It has been considered 4 single abrupt faults: F_1, valve V_{51} blocked fully open; F_2, valve V_{51} blocked fully closed; F_3, valve V_{57} blocked fully open and F_4, valve V_{57} blocked fully closed. The Fig. 6 show how this set of faults has been simulated for training and test data construction because the files from the sugar factory (2000

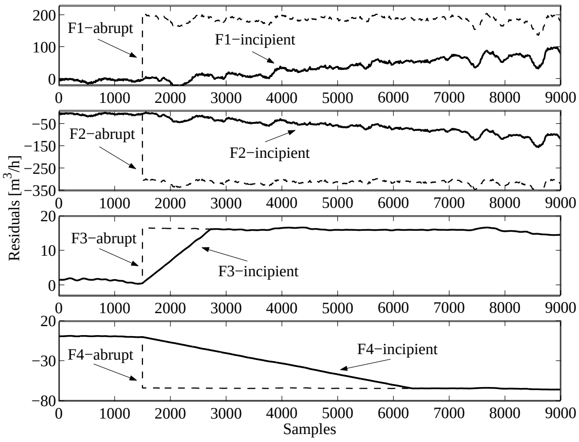

Fig. 6. Simulation of faults for both valves.

campaign) have only steady state data. Therefore, this set of faults (abrupt faults) and also the normal operation residuals have been used to construct the HSFNN training data. The training set for the FNN_0 network has 4200 vectors since it has been chosen, after some tests, that 300 vectors for each fault set point (3 different set points) was sufficient to represent the residuum behaviour under faulty situation. The training set for the FNN_i network has 2700 vectors, and has been achieved as explained before, considering that the fault symptoms are additive.

The HSFNN implemented for fault isolation on the sugar factory actuators is one structure where all the FNNs are equal, with a fuzzification layer consisting of 6 processing elements arranged in 2 groups, corresponding to the 2 residuals, with each group containing 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, it has been found that 5 hidden processing elements could give good performance. The output layer of each fuzzy neural network is up of 4 neurons, each one corresponding to a fault (see Fig. 3).

5.3 *Results of fault diagnosis*

The results achieved with the fault diagnosis system are presented in tables 2-4. The results achieved so far have shown that the system proposed in this paper is a potential tool for fault diagnosis system of single/multiple abrupt (Table 2) and incipient faults (Table 3 and 4).

In the case of single abrupt faults (Table 2), it has been observed 100 % of correct diagnosis. In the case of double abrupt faults the same results can be achieved.

Table 2. Results with single abrupt faults.

Faults	Lower level FNN$_0$	Medium level FNN$_1$	FNN$_2$	FNN$_3$	FNN$_4$	Upper level OR
F_1	F_1=1	F_1	-	-	-	F_1=1
F_2	F_2=1	-	F_2	-	-	F_2=1
F_3	F_3=0.63	-	-	F_3	-	F_3=1
F_4	F_4=0.99	-	-	-	F_4	F_4=1

Tables 3 and 4 show the diagnosis results for single and double incipient faults when the process is under the incipient fault scenarios shown in the Fig. 6. The slope used in the incipient fault simulation was $slope = \frac{Residuum}{Time} = 0.013\ [\frac{m^3}{h \cdot samples}]$.

Table 3. Results with single incipient faults.

Faults	Lower level FNN$_0$	Medium level FNN$_1$	FNN$_2$	FNN$_3$	FNN$_4$	Upper level OR
F_1	F_1=0.99	F_1	-	-	-	F_1=1
F_2	F_2=0.99	-	F_2	-	-	F_2=1
F_3	F_3=0.99	-	-	F_3	-	F_3=1
F_4	F_4=0.99	-	-	-	F_4	F_4=1

Table 4. Results with double incipient faults.

Faults	Lower level FNN$_0$	Medium level FNN$_1$	FNN$_2$	FNN$_3$	FNN$_4$	Upper level OR
F_1F_3	F_1=0.98 F_3=1	F_1F_3	-	F_1F_3	-	F_1=1 F_3=1
F_1F_4	F_1=0.85 F_4=0.98	F_1F_4	-	-	F_1F_4	F_1=1 F_4=1
F_2F_3	F_2=1 F_3=0.99	-	F_2	F_2F_3	-	F_2=1 F_3=1
F_2F_4	F_2=0.99 F_4=0.98	-	F_2F_4	-	F_4	F_2=1 F_4=1

In the case of single and double incipient faults (Table 3 and 4), it has been observed 100 % of correct diagnosis, with this slope. As can be seen from the Tables 3 and 4, the fault diagnosis system can diagnose incipient fault with a smaller slope because the diagnosis values are around 1 (F_2=0.99 for example) and the threshold value in the FNN$_0$ network is 0.5. With different slopes for the two valves it is possible to see some false alarms. It has also 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 single abrupt fault symptoms for a limited number of process operating points.

6. CONCLUSIONS

This paper deals with the soft computing methods in fault diagnosis. N-F networks and an HSFNN were used to design and implement the two-stage FDI system. The N-F models of actuators carry out the detection task and the HSFNN isolate the faults. The main advantage of the proposed approach is that no mathematical model of the process is required and the construction task of the FDI system can be realized using quantitative and qualitative knowledge. The developed system has been successfully applied to fault diagnosis in sugar factory actuators. It has been demonstrate that the current fault isolation approach is able to diagnose multiple simultaneous abrupt and incipient faults from only single fault symptoms. As it has been demonstrated this two-stage FDI system is a suitable approach for this kind of fault diagnosis systems.

7. REFERENCES

Babuška, R. (1998). *Fuzzy Modeling for Control.* Kluwer Academic Publishers. London.

Calado, J.M.F., J. Korbicz, K. Patan, R.J. Patton and J.M.G. Sá da Costa (2001). Soft computing approaches to fault diagnosis for dynamic systems. *European Journal of Control* **7**(2-3), 169–208.

Gustfason, D.E. and W.C. Kessel (1979). Fuzzy clustering with a fuzzy covariance matrix. *In Proceeding IEEE CDC* pp. 761–766.

Korbicz, J.K., K. Patan and A. Obuchowicz (2001). Neural network fault detection system for dynamic processes. *Biulletin of the Polish Academy of Sciences. Technical Sciences* **49**(2), 301–321.

Mendes, M.J.G.C., J.M.F.Calado, J.M.C.Sousa and J.M.G.Sá da Costa (2001). Industrial actuator diagnosis using hierarhical fuzzy neural networks. *European control conference ECC 2001* pp. 2723–2728.

Patton, R.J., F.J. Uppal and C.J. Lopez-Toribio (2000). Soft computing approaches to fault diagnosis for dynamic systems: A survey. *Proc. 4th IFAC Symp. Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS'2000* **1**, 298–311.

Riedmiller, M. and H. Braun (1993). A direct adaptive method for faster backpropagation learning: The RPROP algorithm. *Proc. of the IEEE Intl. Conf. on Neural Networks* pp. 586–591.

Takagi, H. (2000). Fusion technology of neural networks and fuzzy systems: a chronicled progression from the laboratory to our daily lives. *Int. J. Appl. Math. and Comp. Sci.* **10**(4), 647–673.

Yager, R.R. and D.P. Filev (1994). *Essentials of Fuzzy Modelling and Control.* John Wiley & Sons, Inc.. New York.