FDI WITH NEURAL AND NEUROFUZZY APPROACHES
Application to Damadics

Y. Kourd, N. Guersi
Department of Control Engineering, Faculty of Science and Engineer, Mohamed Khider Biskra University, Algeria
Department d'Electronique, Université Badji Mokhtar Annaba, Algeria

D. Lefebvre
GREAH – Université Le Havre, 25 rue Philippe Lebon, 76058 Le Havre, France

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Abstract: Fault diagnosis is a major challenge for complex systems as long as it increases the safety and productivity. This work concerns faults diagnosis, based on artificial intelligence, neural networks, and fuzzy logic. Thanks to an associative memory, neural networks have good capacities of organization, approximation and classification. Combined with fuzzy logic, neural networks are an effective tool for system modelling, fault detection and fault diagnosis. This paper illustrates the potential of these tools for the modelling and the diagnosis of an industrial actuator (DAMADICS benchmark).

1 INTRODUCTION

Fault detection and isolation (FDI) is a major issue for complex systems as long as it increases the safety and productivity of these systems. Its first vocation is the detection and the isolation of system failures. The necessity to detect and isolate early the failures calls upon techniques of the artificial intelligence. These techniques have been recently developed and improved by many researchers. The point is that artificial intelligence makes easier the task carried out by the operators as long as the observation of symptoms and the data analysis or information interpretation is carried out by the diagnosis system.

Several methods exist for the diagnosis of dynamical systems. Basically, model-based and data-based methods can be distinguished (Chow, 1980; Patton et al. 1989; Gertler, 1991; Willsky, 1976). Model – based methods compare the measured data with the knowledge provided by the model of theconsidered system in order to detect and isolate the faults that disturb the process. Such techniques require a sufficiently accurate mathematical model of the process.Data-based methods require a lot of process measurements and can be divided into signal processing methods and artificial intelligence approaches. Model and data based methods are used to design residual signals. The fault detection results from the comparison of the residuals with arbitrary thresholds: a fault is detected each time one residual ccross over the threshold. This comparison is calculated on line. To isolate the faults, residuals are structured to be robust and sensitive to some specific sets of faults.

In this context, our study concerns the investigation of model-based FDI methods with artificial intelligence, particularly neural networks and fuzzy logic. Fuzzy logic can be used to describe the system behaviours according to linguistic rules and fuzzy sets. The advantage of fuzzy logic is that it can be used in presence of uncertainties. The drawback is that the number and expression of the rules and also the parameters of the membership functions that define the sets are not easy to be work out. In that case, neural networks are helpful to identify the unknown parameters according to measured data and to learning algorithms.

This paper concerns the application of neural networks, fuzzy logic and neurofuzzy systems (ANFIS) for an industrial actuator from the sugar factory in Lublin, Polen (Damadics, 2004).

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2 FDI METHODS

The proposed approach can be presented with 3 stages (1) the design of a data – based model; (2) the fault detection according to a residual generator; (3) the fault isolation thanks to neural or neurofuzzy classifiers.

2.1 Reference Model Design

In the following we consider dynamic systems with q inputs $u_i(t)$ and n outputs $y_j(t)$ and it is assumed that the state variables are no measurable. Such systems exhibit often complex dynamics, with strong nonlinearities. As a consequence, knowledge –based models are not easy to obtain. Another approach lies in the data–based models. Artificial neural networks (ANN) are often used for that purpose (Juditsky et al. 1995). The goal is to design a model that will be used for the generation of residuals (figure 1).

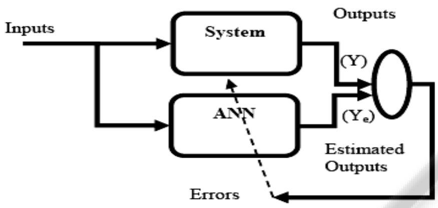

Figure 1: Data-based model design.

In order to get the best ANN architecture, several configurations are tested according to a trial – error processing that uses pruning to eliminate the useless nodes. The learning of the ANN is obtained according to the Levenberg-Marquardt algorithm with early stopping. This algorithm is known for its rapid convergence. During learning stage, the ANN is trained with data collected during the normal functioning of the system. Then the ANN reference model is validated with another set of data.

2.2 Fault Detection

The considered system may be affected by p faults Fi with the assumption that simultaneous faults do not occur. The vector r(t) of n residuals $r_i(t)$ is calculated according to the difference between the outputs vector of the system y(t) and the output vector of the ANN model $y_e(t)$. As long as the system has no fault, the estimated output $y_e(t)$ remains in the neighbourhood of the actual output y(t) and the residual r(t) is near zero. When a fault occurs, at least one estimated output becomes different from and the actual one and the corresponding residual is no longer near zero.

2.3 Fault Isolation with ANN

A neural classifier has been developed to isolate the faults after detection (Kourd et al., 2008). This classifier is a multilayer Perceptron ANN (figure 2). The inputs are the n residuals $r_i(t)$ and the outputs are the p signatures f_i of the faults F_i that are under consideration.

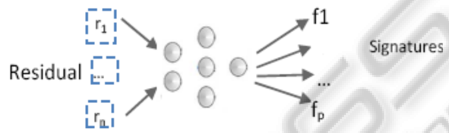

Figure 2: Neural classifier.

The neural classifier is trained and validated with a learning algorithm similar to the one used for reference model design.

2.4 Fault Isolation with ANFIS

In order to deal with improve the isolation, a neurofuzzy classifier has also been developed (figure 3). Such a classifier has an hybrid architecture that takes advantages from fuzzy logic and neural networks (Nauck et al. 1995). This classifier is design as a double Takagi- Sugeno ANFIS networks. The inputs are the n residuals $r_i(t)$ and the outputs are the p signatures f_i of the faults F_i that are under consideration.

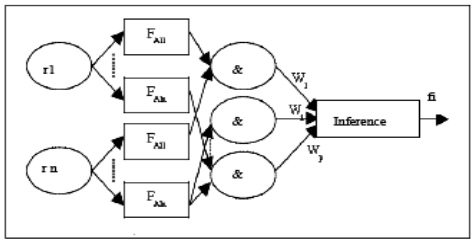

Figure 3: Double neurofuzzy ANFIS classifiers.

3 APPLICATION TO DAMADICS

3.1 System Description

The system under consideration is the DAMADICS valve (figure 4). It is composed of a pneumatic servomotor and a controller that drives the valve.

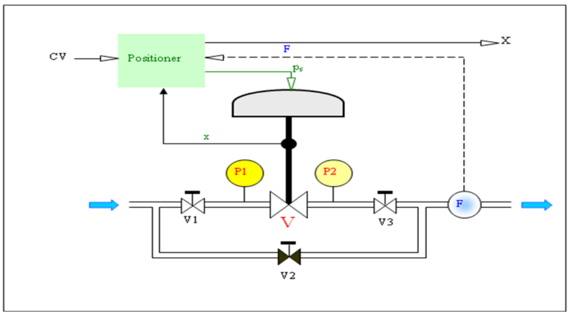

Figure 4: Actuator shema.

This system has four input variables (CV, P1, P2, T1) and 2 outputs variables (X, F) that are described in table 1 (DAMADICS 2004). The other variables are not considered in our application.

Table 1: Input and output variables.

Input	Range	Unit	Description
CV	[0,1]	-	control signal from external PI controller
P1	[2000, 4e+6]	Pa	Inlet liquid pressure
P2	[2000, 4e+6]	Pa	Outlet liquid pressure
T1	[30, 110]	C °	Liquid temperature
Output	**Range**	**Unit**	**Description**
X	[0,1]	-	Position of the rod
F	[0,1]	-	Average flow

There exist 20 possible faults that may affect the functioning of the actuator (DAMADICS 2004). Some faults may be abrupt or incipient ones.

3.2 Model Design

The actuator is modeled with two multilayer perceptrons ANN that represent the interaction between the inputs and the outputs according to (1):

$$\begin{aligned} netX &= netX\,(CV, P1, P2, T1) \\ netF &= netF(X, P1, P2, T1) \end{aligned} \qquad (1)$$

To select the structure of the neural networks netX and netF, numerous tests have been carried out to obtain the best architectures (i.e. number of hidden layers and number of neurons by layer) in order to model the operation of the actuator. The training and test data were generated by the simulation of the Matlab-Simulink actuator model (Kourd et al. 2008).

From table 2, we notice that netX(6,3,1) and netF(6,3,1) give the best results. When the training is over, the ANN netF provides estimated outputs that are not far from the actual ones. Validation is done with the measured data provided by the 'Lublin Sugar Factory in 2001 (DAMADICS, 2004). Validation is illustrated on figure 5.

Table 2: netX and netF neural networks structure.

netX	Layer 1	Layer 2	Output layer	MSE
Operation 1	6	3	1	0.00033
Operation 2	10	8	1	0.00149
Operation 3	21	12	1	0.00491
netF	Layer 1	Layer 2	Output layer	MSE
Operation 1	6	3	1	0.000199
Operation 2	10	8	1	0.000849
Operation 3	21	12	1	0.00949

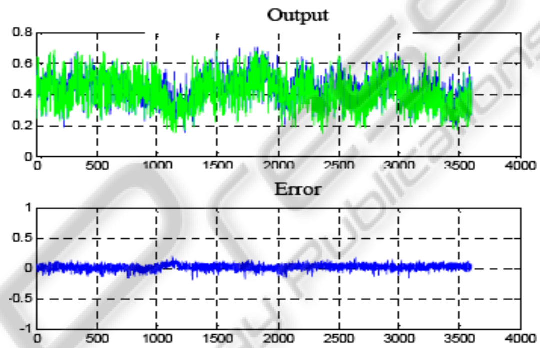

Figure 5: Actual output F and estimated output netF (up); Instantaneous error (down).

The modelling error is acceptable. Similar conclusions are obtained with ANN netX. Let notice that the output of netX is an input for netF and the sensitivity of the estimation depends strongly on the error on netX. As a conclusion, both ANNs provide a good approximation of the actuator dynamics.

3.3 Fault Detection

In the following four faults will be considered: F7 (medium cavity or critical flow) F10 (servo-motor's diaphragm perforation) F15 (positioner spring fault) and F17 (positioner supply pressure drop) in order to illustrate the efficiency of the proposed approach. Two residual are designed according to (2):

$$\begin{aligned} rF &= F - netF \\ rX &= X - netX \end{aligned} \qquad (2)$$

During normal functioning the residuals remain near zero: their magnitude is in range [-0,2; 0,2]. The value 0.2 will be used as detection threshold (Emami-Naeini, 1988; Ding and Frank, 1991). Let us notice that a low pass filter is used to remove high frequency noises. In figure 6, the residuals are worked out when the fault F7 is simulated during interval [500 1000] time units (times units are in seconds).

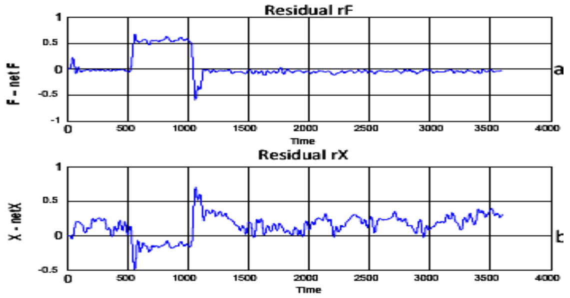

Figure 6: Residual in presence of fault F7; Residual rF (up); Residual rX (down).

3.4 Fault Isolation

The classifiers presented in section 2 are trained with a set of simulated faults. Then they are validated according to the real data collected on the Sugar factory:

- During period [500, 1100], the fault F7 occurs.
- During period [4100, 4600], the fault F10 occurs.
- During period [7700, 9000], the fault F15 occurs.
- At times 11300 and 11850 the fault F17 occurs.

The ANN classifier presented in section 2.3 receives two inputs: the residuals rX and rF and delivers four outputs that are the signatures f7, f10, f15, f17 of the faults F7, F10, F15, F17. The signature f7 is given in figure 7. The neural classifier gives acceptable results in the sense that the signature of each fault is far from zero when the considered faults occur. But misclassifications may occur.

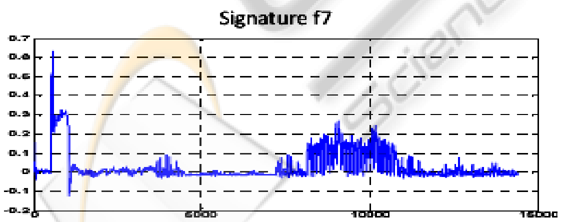

Figure 7: Magnitude of the fault signatures f7 in function of time for ANN classifier.

The ANFIS classifier presented in section 2.4 has also two inputs and four outputs. The resulting signature f7 is given in figure 8.

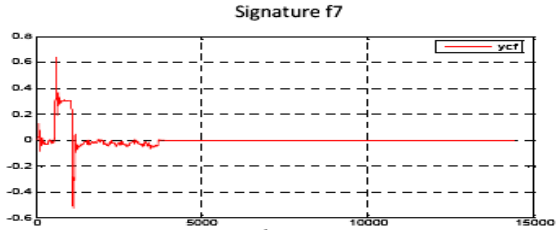

Figure 8: Magnitude of the fault signature f7 in function of time for ANFIS classifier.

The use of ANFIS classifier improves the classification results. The number of misclassifications decreases and the quadratic mean square on error of the residuals decreases (table 3).

Table 3: Quadratic mean square error.

	F7	F10	F15	F17
Neural classifier (x 10^{-3})	3.8	10.0	43.9	23.2
Fuzzy Neural classifier (x 10^{-3})	2.5	4.6	30.6	3.3

4 CONCLUSIONS

This paper uses neural networks and fuzzy logic for the fault diagnosis. The neural networks are good tools for the modelling and diagnosis of non linear processes, but some problems remain in the selection of the optimal architecture as well as the number of layers, and the numbers of neurons in each layer. The uses of neurofuzzy networks improve the classification of faults.

In our further works we will consider numerical criteria to compare both classifiers, we will also compare our results with the existing results and we will improve the neurofuzzy diagnosis system.

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