FAULT DIAGNOSIS USING NEURO-FUZZY SYSTEMS WITH LOCAL RECURRENT STRUCTURE

Letitia Mirea* , Ron J. Patton**

* *"Gh. Asachi" Technical University of Iaşi*
Department of Automatic Control
Blvd. D. Mangeron 53A, RO-700050 Iaşi, Romania
Fax: +40-232-214290, E-mail: lmirea@ac.tuiasi.ro

** *University of Hull*
Department of Engineering
Cottingham Road HU-6 7RX, Hull, United Kingdom
Fax: +44 (0)-1482-466664, *E-mail*: r.j.patton@hull.ac.uk

Abstract: This paper investigates the development of the Adaptive Neuro-Fuzzy Systems with Local Recurrent Structure (ANFS-LRS) and their application to Fault Detection and Isolation (FDI). Hybrid learning, based on a fuzzy clustering algorithm and a gradient-like method, is used to train the ANFS-LRS. The experimental case study refers to an application of fault diagnosis of an electro-pneumatic actuator. A neuro-fuzzy simplified observer scheme is used to generate the residuals (symptoms) in the form of the one-step-ahead prediction errors. These are further analysed by a neural classifier in order to take the appropriate decision regarding the actual behaviour of the process.

Keywords: fault diagnosis, fuzzy multiple-modelling, fuzzy hybrid systems, neural networks, dynamic modelling, neural classifier, actuator systems

1. INTRODUCTION

High performance process control and supervision often require accurate process models. Most processes are non-linear and, therefore, their model should be non-linear (Patton *et al*., 2000). Neural networks have been shown to possess good non-linear function approximation capabilities and have been used in non-linear process modelling. However, the neural model obtained is considered to be a "black-box" model since it is difficult to interpret.

Within a specific operating region, a linear model can approximate the non-linear process behaviour with a reasonable accuracy. An approach to process modelling is therefore to divide the process operation into several regions and determine a locally linear model within each region. Takagi and Sugeno (1985) used a fuzzy modelling approach in which each model input is assigned with several fuzzy sets characterised by a membership function. Through logical combination of these fuzzy inputs, the model-input space is partitioned into several fuzzy regions. A locally linear model is used within each region. The global model output is obtained through the weighted average of the local model outputs.

Fuzzy sets provide an appropriate tool to define operating regions since the definition of the operating regions is often vague in nature and there usually exist overlapping among different regions (Brown & Harris, 1995; Murray-Smith & Johansen, 1997; McGinnity and Irwin, 1997; Babuska & Oosteram, 2001; Uppal & Patton, 2005).

The Sugeno fuzzy model is implemented by an Adaptive Neuro-Fuzzy System (ANFS) that combines the capability of fuzzy reasoning in handling uncertain information and the capability of neural networks in learning from examples (Jang, 1995).

In order to be used to model a non-linear dynamic system, the ANFS should be equipped with dynamic elements. An approach is to use external delay elements, but this increases the dimension of the input space. Another approach is to use internal dynamic elements. This paper proposes a dynamic architecture for the ANFS, namely the adaptive neuro-fuzzy system with local recurrent structure. This is obtained by using Auto-Regressive Moving-Average filters in the consequent part of the fuzzy rules, on the back connection from the output to the input of each local linear model.

Process input-output data are used to train the ANFS-LRS, i.e. to determine the parameters that would minimise a performance index. Firstly, a fuzzy clustering algorithm is used to determine the number of fuzzy operating regions and the initial values for the membership functions. Then, gradient-based learning algorithm is applied in order to refine the parameters of the membership functions and to determine the parameters of the local linear models (Jang, 1995; Zhang and Morris, 1996).

The paper is organised in six sections as follows. In Section 2, the principles of fuzzy and neuro-fuzzy modelling are presented. The architecture and the learning procedure for ANFS-LRS are presented in Section 3. Section 4 refers to the design of an FDI system based on ANFS-LRS (residual generation) and neural networks (residual evaluation). The application of the ANFS-LRS to the fault diagnosis of an actuator located at the Lublin sugar factory in Poland is presented in Section 5. The conclusions are given in Section 6.

2. FUZZY INFERENCE SYSTEM AND FUZZY MODELLING

The Fuzzy Inference System (FIS) is a framework based on the concepts of fuzzy sets, fuzzy rules and fuzzy reasoning. It has been successfully applied in fields such as automatic control, data classification, decision analysis and computer vision. The basic structure of a FIS consists of three main components: (1) a rule base which contains a selection of fuzzy rules, (2) a database which defines the membership functions used in fuzzy rules and (3) a reasoning mechanism which performs the inference upon the rules and a given condition to derive a reasonable conclusion (output).

One of the most applied FIS structures is the Sugeno fuzzy model proposed by Takagi and Sugeno in (Takagi and Sugeno, 1985). A typical fuzzy rule in a Sugeno fuzzy model has the form:

Rule i:

if x_1 is A_1 ***and*** x_2 is A_2 ***and*** ... ***and*** x_n is A_n ***then*** $z_i = f(x_1, x_2, ..., x_n)$,

where A_j, $j = 1,...,n$ are fuzzy sets in the antecedent part of i-th rule, while $z_i = f(x_1, x_2, ..., x_n)$ is a crisp function in the consequent part of i-th rule. Usually, $f(x_1, x_2, ..., x_n)$ is a polynomial in the input variables x_j, $j = 1,...,n$, but it can be any function. If $f(x_1, x_2, ..., x_n)$ is a first-order polynomial, then the resulting FIS is called first-order Sugeno fuzzy model.

Each fuzzy rule can be interpreted within a local modelling framework. The consequence function $f(x_1, x_2, ..., x_n)$ of each rule can be considered to constitute a local model, defined by a set of parameters. The antecedent part of each rule, defined by the fuzzy sets: A_j, $j = 1,...,n$, determines the regime of each local model or a subset of the input space over which this local model applies. The rule firing strengths defined by:

$$w_i = \prod_{j=1}^{n} A_j \, , \tag{1}$$

give the validity function of each local model. Since each rule has a crisp output, the overall output is obtained via weighted average:

$$z = \left(\sum_{i=1}^{M} w_i z_i \right) \Big/ \left(\sum_{i=1}^{M} w_i \right), \tag{2}$$

where w_i are the firing strengths of i-th rule (Jang, 1995) and M is the number of fuzzy rules.

A fuzzy model can be implemented by a special type of neural network called Adaptive Neuro-Fuzzy System (ANFS) (Jang, 1995). The ANFS combines the capability of fuzzy systems to handle uncertain and imprecise information, with the ability of the neural networks to learn from examples. The concept of neuro-fuzzy modelling refers to the way of applying various learning techniques developed in the artificial neural network literature in order to determine the parameters of a fuzzy model.

The identification of dynamic systems requires models with adequate memory. For this reason, the ANFSs have to be provided with dynamic elements and appropriate learning methods (Mirea and Marcu, 2002a). A first approach refers to ANFS with external dynamics (Jang, 1995; Zhang and Morris, 1996), i.e. static ANFSs provided with external cascades of filters. A different approach is achieved by ANFSs with internal dynamics, for which internal local recurrent connections are used. In the sequel, the second approach is considered leading to the so-called ANFS-LRS. This kind of neuro-fuzzy system processes multiple inputs and does not require past values of the process measurements.

3. ADAPTIVE NEURO-FUZZY SYSTEMS WITH LOCAL RECURRENT STRUCTURE

The proposed ANFS-LRS architecture is presented in Fig. 1. In contrast with the ANFS approach, in this case each local model is described by:

$$\begin{aligned} z_i[k] &= \sum_{p=1}^{P} a_{i,p} \cdot u_p[k] + \tilde{z}_i[k] + \theta_i, \\ \tilde{z}_i[k] &= \sum_{j=1}^{n_B} b_{i,j} \cdot z_i[k-j] - \sum_{j=1}^{n_D} d_{i,j} \cdot \tilde{z}_i[k-j], \\ i &= 1, \ldots, M \end{aligned} \tag{3}$$

where M is the number of the fuzzy rules.

Every node in the 1st layer is an adaptive node with the output defined by $\mu_{A_{p,i}}(u_p)$, i=1,...,M, p=1,...,P, where u_p is the input to the node and $A_{p,i}$, $i = 1, \ldots, M$ are the fuzzy sets associated with this node. The outputs of the first layer represent the membership values of the antecedent part of the rules. The membership functions can be any appropriate parameterised membership function, such as the Gaussian function:

$$\mu(x) = e^{-\left(\frac{x-c}{\sigma}\right)^2} . \tag{4}$$

In relation (4), c represents the centre of the membership function and σ determines the membership function's width. Parameters in this layer are referred to as premise parameters.

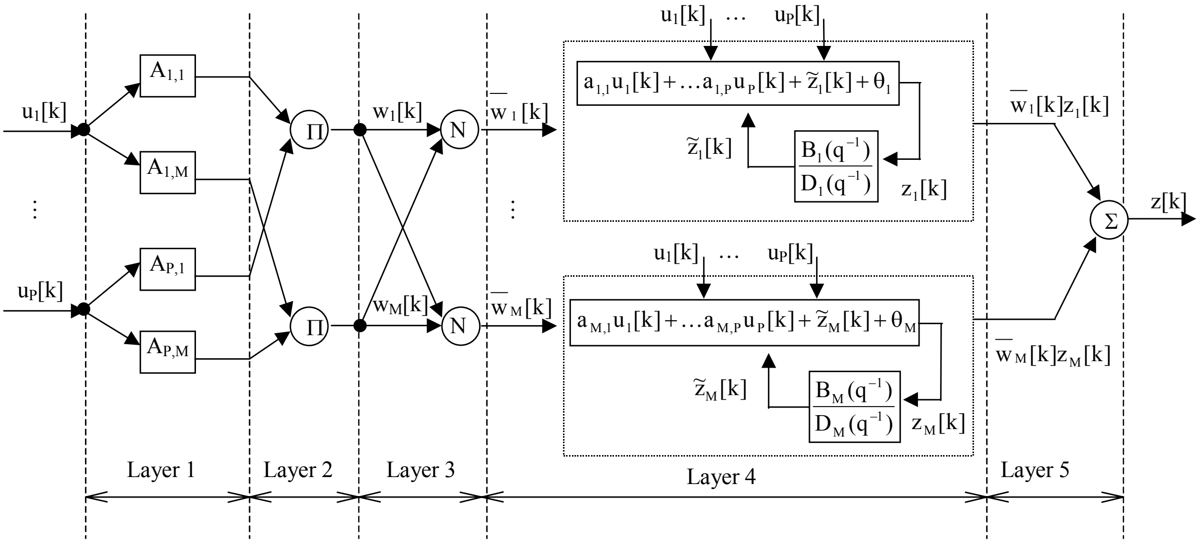


Fig. 1 ANFS with local recurrent structure

The 2nd layer consists of fixed nodes, which multiplies the incoming signals:

$$w_i[k] = \prod_{p=1}^{P} \mu_{A_{p,i}}(u_p[k]), \quad i = 1,\ldots,M\,. \qquad (5)$$

In fact, each node output represents the firing strength of a rule. Instead of the product, any other T-norm operator can be used to perform the fuzzy AND operator.

Every node in the 3rd layer is a fixed node that computes the normalised firing strength of the i-th rule:

$$\overline{w}_i[k] = \frac{w_i[k]}{\sum_{j=1}^{M} w_i[k]}, \quad i = 1,\ldots,M\,. \qquad (6)$$

The 4th layer consists of adaptive nodes with the output given by $\overline{w}_i \cdot z_i[k]$, where $\overline{w}_i$ is the output of the third layer and $z_i[k]$ is given by relation (3). The parameters in this layer, $\{a_{i,p}$, θ_i, $b_{i,j}$, $d_{i,l}\}$ will be referred to as consequent parameters.

The 5th layer has a single fixed node that computes the overall output of ANFS-LRS as a summation of all incoming signals:

$$z[k] = \sum_{i=1}^{M} \overline{w}_i \cdot z_i[k]\,. \qquad (7)$$

As a system is usually monitored using sampled data, a discrete time representation of the process is required. The purpose is to identify neuro-fuzzy models for each system output, i.e. Multi-Input Single-Output (MISO) models (Mirea & Marcu, 2002b).

For dynamic system identification, these models require spatial representation of time. Because the structure suggested for the neuro-fuzzy system includes dynamic elements (the local recurrent connections), it has to be fed only with current values of the inputs and the outputs of the process (Mirea & Marcu, 2002a; 2002b). In this way, the order of the input space of the neuro-fuzzy system is decreased in comparison with the approach based on the ANFS with static structure. For the sake of simplicity, a Single-Input Single-Output (SISO) dynamic system is considered.

Thus, the input-output model obtained using an ANFS -LRS is:

$$\hat{y}[k] = f(u_P[k], y_P[k-1])\,, \qquad (8)$$

where u_P denotes the process input, y_P represents the process output, and $\hat{y}$ denotes the approximated output given by the trained ANFS-LRS.

One considers N data pairs collected from the inputs and outputs of the process. In the training stage, the ANFS-LRS parameters, collected in a vector ξ, are adapted in order to minimise a quadratic performance index such as the sum-squared error between the ANFS-LRS output, $\hat{y}[k]$, and the considered process output, $y_P[k]$. The objective is to ascertain an optimal parameter set ξ^* of the ANFS-LRS that minimises the considered performance index:

$$\xi^* = \arg\min_{\xi}\{\frac{1}{2}\sum_{k=1}^{N}(y_P[k] - \hat{y}[k,\xi])^2\}\,. \qquad (9)$$

A method to select the number of fuzzy rules and the initial values for the premise parameters, based on the training data, is to use a fuzzy clustering algorithm (Chiu, 1994; Mirea & Marcu, 2002b). The purpose of the fuzzy clustering algorithm is to distil natural groupings of the ANFS-LRS input data set, producing a concise representation of the system's behaviour. Finally, a number of cluster centres are obtained. For each data point a degree of membership to each cluster is computed (Marcu, 1996; Mirea & Marcu, 2002b). Based on these values, the standard deviations of each Gaussian membership function are obtained. The resulting cluster centres and standard deviations are used as initial values for the premise parameters and are found using the following gradient method:

$$\varsigma_{new} = \varsigma_{old} + \Delta\varsigma; \quad \Delta\varsigma = -\eta \cdot \frac{\partial E}{\partial \varsigma}; \quad E = \frac{1}{2}\cdot\sum_{k=1}^{N}(y_P[k] - \hat{y}[k,\varsigma])^2\,. \qquad (10)$$

Relation (10) is used to adapt the consequent parameters as well. For these parameters, an initialisation with small random values is applied. In relation (10), ς is one of the ANFS-LRS premise or consequent parameters and η is the learning rate.

4. NEURO-FUZZY DESIGN OF FDI SYSTEM

4.1 Residual generation

For the generation of symptoms, the ANFS-LRSs replace the analytical models that describe the process. Instead of a multi-input multi-output structure, an ANFS-LRS model for each system output is identified, i.e. a MISO model. As the control system operates in closed-loop, faults tend to be hidden by feedback action. Thus, both inputs and outputs of the process are used as inputs of the ANFS-LRS.

The neuro-fuzzy models can be then used in an observer-like arrangement (Marcu *et al*., 2001). Structured sets of symptoms are generated to enable a unique fault diagnosis. This is based on residual signals that are obtained by subtracting the approximations of an observer scheme from the corresponding process measurements. The Neuro-Fuzzy Simplified Observer Scheme (NF-SOS) is described in the sequel. Its design is based on the use of ANFS-LRS introduced previously. It is further applied to the considered case study.

<u>The Neuro-Fuzzy Simplified Observer Scheme</u> (NF-SOS). One considers a process with I inputs $u_{P,i}[k]$, $i=1,...,I$ and O outputs $y_{P,j}[k]$, $j=1,...,O$, all known at sampling time k. The NF-SOS consists of a number of MISO neuro-fuzzy systems with each one driven by all inputs and outputs of the process. Each ANFS-LRS estimates one output of the system:

$$\begin{aligned}&\hat{y}_j[k] = f_{\text{NF-SOSj}}(\mathbf{u}_P[k], \mathbf{y}_P[k-1]);\\ &j = 1,...,O\end{aligned} \tag{11}$$

where $\mathbf{u}_P[k] = [u_{P,i}[k]]_{i=1,...,I}$ is the vector of process inputs and $\mathbf{y}_P[k-1] = [y_{P,j}[k-1]]_{j=1,...,O}$ is the vector of process outputs.

The resulting bank of neuro-fuzzy models approximates all outputs of the process. The training of the ANFS-LRSs is based on the system data corresponding to its normal behaviour. The following residuals are then generated:

$$\varepsilon_j[k] = y_{P,j}[k] - \hat{y}_j[k]; \quad j = 1,...,O \tag{12}$$

These patterns of change are further used to detect and locate the faults.

4.2 Residual evaluation

The Residual evaluation stage is actually a classification task. This means to match each pattern of the residual vector with one of the pre-assigned classes of faulty behaviour, if available, and the fault-free case, respectively (Marcu *et al*., 2001).

The uncertainty in classification of patterns may arise here from the overlapping nature of various classes. For fault diagnosis this is a realistic assumption, especially when incipient faults have to be detected and isolated. Therefore, a robust decision can be achieved by using a neural network as pattern classifier (Marcu *et al*., 2001). The static Multi-Layer Perceptron with sigmoid neurons is considered here.

The neural classifier maps the patterns (12) from the residual space into a decision space. The patterns belonging to a class are made to cluster around pre-selected points, optimally chosen (Marcu *et al*., 2001). A fault is detected and isolated if an unknown input pattern is mapped closest to one of the decision space target vectors. That multi-dimensional point corresponds to the associated learned class that reflects a fault.

A fault is only detected if the input pattern is mapped far from all learned classes. For the latter case, that is a new (faulty) situation, only the synthesis of the classifier must be reconsidered for further fault diagnosis. One simple criterion used in the decision logic is based on the minimum Euclidean distance to the target vectors of the classifier.

5. ELECTRO-PNEUMATIC VALVE APPLICATION

The methodology presented is assessed by using real process data from the Lublin sugar factory in Poland (Syfert *et al*., 2003). The study refers to an electro-pneumatic actuator installed at the steam boiler to control the water level in the 4th boiler station.

The actuator has three main parts: the control valve, the pneumatic linear servo-motor and the positioner. A benchmark problem was developed in the DAMADICS EU FP5 contract (Syfert *et al*., 2003; Syfert 2003). In the benchmark, faulty data are generated based on real measurements, corresponding to the normal behaviour of the process. Table 1 shows the list of the faults that have been considered.

<u>Table 1. Faults considered for the FDI task</u>

Control Valve Faults	
F1	Valve clogging
F2	Valve plug or valve seat sedimentation
Pneumatic Servo-Motor Faults	
F3	Servo-motor's diaphragm perforation
Positioner faults	
F4	Electro-pneumatic transducer fault
F5	Rod displacement sensor fault
F6	Positioner feedback fault
General faults/ External faults	
F7	Fully or partly opened bypass valve
F8	Flow rate sensor fault

Fault-free data stored during one hour, every second, have been used to develop the residual generator and are also used to generate the faulty data based on the

MATLAB/ Simulink actuator model. A testing data set from another hour (same day) of exploitation of the actuator was used to test the developed models (testing data set 1). The ANFS-LRS models have been validated using the data stored for 1 hour from the previous day (testing data set 2).

The learning data used to develop the residual generator are selected from a day the inputs had significant variation, i.e. maximum possible excitation of the process. A training data set of 3600 rows was selected, corresponding to a 1 hour period.

To develop a model, spectral analysis has been performed using the Fast Fourier Transform. Based on this, a low-pass filtering by means of appropriate discrete-time Butterworth filter, with decimation has been applied to reduce the noise. This also allowed for the reduction of the amount of data used in the ANFS-LRS learning.

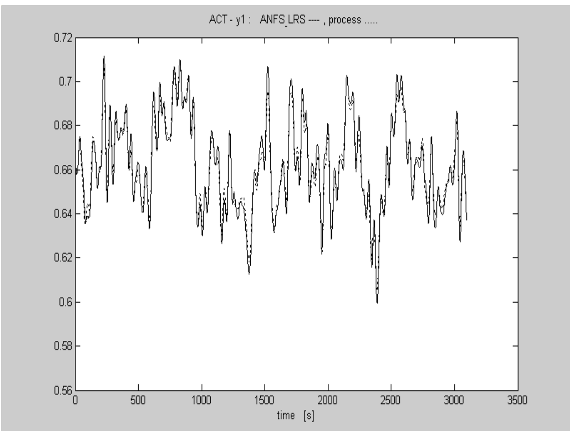
Each identified model was tested by using the complete training data set of 3600 rows and the testing data sets from the next hour (same day) and one hour from the previous day of the plant exploitation.

The actuator has four inputs: the level controller output, valve input water pressure, valve output water pressure and the temperature of the water. The actuator has two outputs represented by the servomotor rod displacement (y_1) and the water flow to the steam boiler inlet (y_2).

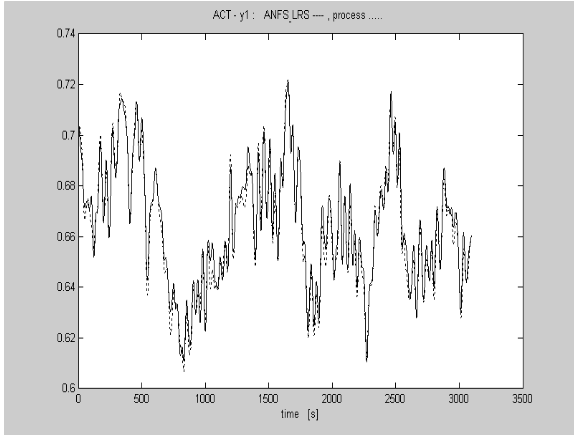
For residual generation, a simplified observer scheme comprising two ANFS-LRS models was developed. The best identification results correspond to ANFS-LRS characterised by 3 rules and $n_B = n_C = 1$ for both actuator outputs.

In Figs. 2 & 3, the outputs of the process (solid line) are compared with the outputs of the corresponding identified ANFS-LRS models (dotted line). Figs. 2(a) and 3(a) refer to the testing data set 1, whilst Figs. 2(b) and 3(b) refer to the testing data set 2.

One observes that the developed ANFS-LRS models have good generalisation properties, i.e. are able to approximate with very good precision, data different than the training data, corresponding to the normal behaviour of the process.

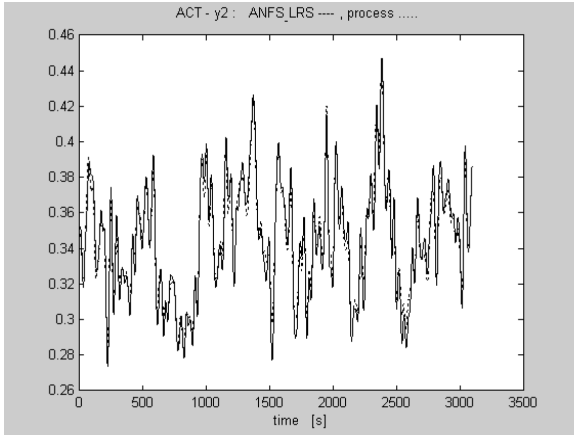


(a)

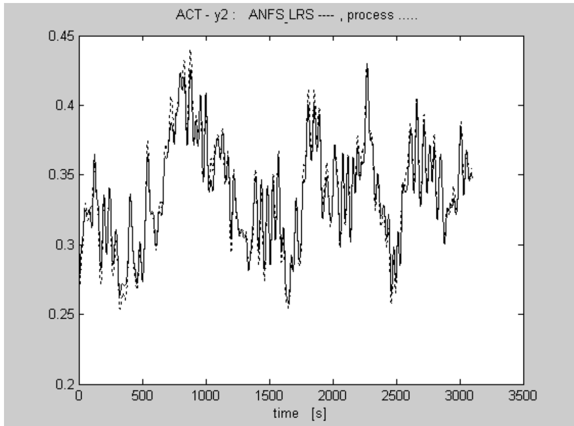


(b)

Fig. 2 Servo-motor rod displacement (metres): process output (solid line) vs. ANFS-LRS model output (dotted line) corresponding to the testing data set 1 (a) and the testing data set 2 (b).



(a)



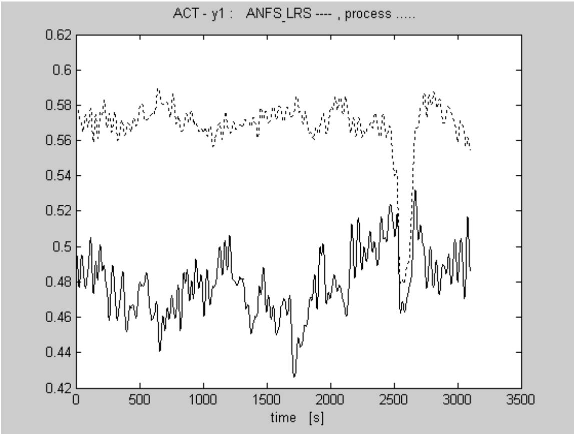
(b)

Fig. 3 Water flow: process output (solid line) vs. ANFS-LRS model output (dotted line) corresponding to the testing data set 1 (a) and the testing data set 2 (b)

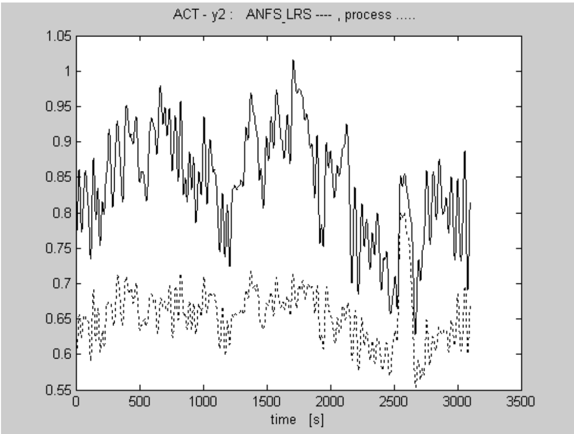
To generate the entire set of residuals, the identified neuro-fuzzy models were also fed with data from the considered faulty behaviours of the process. Fig. 4 illustrates the process outputs (solid line) versus the output of the corresponding identified neuro-fuzzy models (dotted line) in the case of fault F3.

The generated residuals (12) corresponding to the normal and considered faulty behaviours of the process have been evaluated using a static Multi-

Layer Perceptron with two layers of sigmoid neurons. The resulting neural classifier has 12 neurons in the hidden layer. The achieved recognition rate is 93.67 %.



(a)



(b)

Fig. 4 Process output (solid line) vs. ANFS-LRS output (dotted line) in the case of fault F3: (a) output y_1 and (b) output y_2

6. CONCLUSIONS

This paper investigates the development of a new neuro-fuzzy system with local recurrent structure and its application to fault diagnosis (fault detection and fault isolation) of an electro-pneumatic actuator valve. The experimental results obtained by using the suggested neuro-fuzzy system reveal its good performances of approximation and generalisation, being characterised by reduced training and evaluation time. This application of fault diagnosis leads to good results, as reflected in a recognition rate greater than 90%.

Further research will investigate the development of a new class of neuro-fuzzy systems with feedback connections between the local linear models and their application to fault detection and isolation.

ACKNOWLEDGEMENTS

The authors acknowledge funding support at Hull University under the EC RTN contract (HPRTN-CT-2000-00110) *DAMADICS*. Thanks are expressed to the management and staff of the Lublin sugar factory, Cukrownia Lublin SA, Poland for their collaboration and provision of manpower and access to their sugar plant.

REFERENCES

Babuska, R. & M. Oosteram (2001), Fuzzy-clustering for Multiple-Model Approached in *System Identification and Control*, Physica-Verlag.

Brown, M. & C.J. Harris (1995), *Neuro-fuzzy Adaptive Modelling and Control*, Prentice Hall.

Chiu, S.L. (1994), A Cluster Estimation Method with Extension to Fuzzy Model Identification, *Proc. of the 3rd IEEE Int.Conf. on Fuzzy Systems*, Orlando, Florida, USA, 1240-1245.

Jang, J.-S. R. (1995), Neuro-Fuzzy Modelling and Control, *Proceedings of IEEE*, **83**, *3*, 378 – 405.

Marcu, T. (1996), Pattern recognition techniques using fuzzily labeled data for process fault diagnosis, *Int. Journ. of Appl. Math. & Comp. Science*, **6**, (4), 815 – 840.

Marcu, T., L. Mirea, P.M. Frank & H.D. Kochs (2001), System identification and fault diagnosis using dynamic functional-link neural networks, *European Control Conference ECC'2001*, Porto, Portugal, CD-ROM Proceedings.

McGinnity, S. & G. W. Irwin (1997), Non-linear state estimation using fuzzy local linear models, *Int. Journ. of Syst. Science*, **28**, 7, 643-656.

Mirea, L. & T. Marcu (2002a), System identification using functional-link neural networks with dynamic structure", *IFAC Congress b'02*, Barcelona, Spain, CD-ROM Proceedings.

Mirea, L. & T. Marcu (2002b), System identification using a neuro-fuzzy technique, *2nd European Conference on Intelligent Systems and Technologies ECIT'2002*, Iaşi, Romania, CD-ROM Proceedings.

Murray-Smith R & Johansen (1997), *Multiple-Model Approaches to Non-linear Modelling and Control*, Taylor & Francis.

Patton, R.J., R.Clark & P.M.Frank (2000), *Issues of Fault Diagnosis for Dynamic Systems*, Springer-Verlag New York, Inc.

Syfert, M., R. Patton, M. Bartys & J. Quevedo (2003), Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems (DAMADICS): a benchmark study, *IFAC Symposium SAFEPROCES' 03*, Washington DC, USA, CD-ROM Proceedings.

Syfert, M, http://diag.mchtr.pw.edu.pl/damadics/

Uppal, F. J. & R.J. Patton (2005), Neuro-fuzzy Uncertainty De-coupling: A multiple-model paradigm for fault detection and isolation, To appear in: *Int. J. Adaptive Control & Signal Processing*.

Takagi, S. & M. Sugeno (1985), Fuzzy identification of systems and its application to modelling and control, *IEEE Trans. Systems, Man & Cybernetics*, **15**, pp. 116-132.

Zhang, J. & J. Morris (1996). Process modelling and fault diagnosis using fuzzy neural networks, *Fuzzy Sets and Systems*, **79**, 127-140.