Intelligent Fault Diagnosis in Industrial Actuator based on Neuro-Fuzzy Approach

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« Neuro-fuzzy system », « Hybrid learning », « Fault diagnosis ».

Abstract

This paper introduces the application of the hybrid approach Adaptive Neuro-Fuzzy Inference System (ANFIS) for fault classification and diagnosis in industrial actuator. The ANFIS can be viewed either as a fuzzy inference system, a neural network or fuzzy neural network (FNN). This paper integrates the learning capabilities of neural network to the robustness of fuzzy systems in the sense that fuzzy logic concepts are embedded in the network structure. It also provides a natural framework for combining both numerical information in the form of input/output pairs and linguistic information in the form of *if-then* rules in a uniform fashion. The proposed algorithm is achieved by the intelligent scheme ANFIS. This intelligent system is used to model the valve actuator and classify the fault types. Computer simulation results are shown in this paper to demonstrate the effectiveness of this approach for modeling the actuator and for classification of faults for different fault conditions.

I. Introduction

Artificial intelligent techniques, such as artificial neural networks (ANN) fuzzy logic (FL) have been successfully applied to automated detection and fault diagnosis in different conditions [1][2]. They largely increase the reliability of fault detection and diagnosis systems. The adaptive neuro-fuzzy inference system (ANFIS) [3] is a hybrid model which combines the ANNs adaptive capability and the fuzzy logic qualitative approach (Jang, 1993). By using the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way human process information, ANFIS harnesses the power of the two paradigms: ANNs and fuzzy logic, and overcomes their own shortcomings simultaneously [4][5].

Fuzzy system is tolerant to noise and error in the information coming from the sensory system, and most importantly; it is a factual reflection of the behavior of human expertise. A fuzzy controller is commonly defined as a system that emulates a human expert. The knowledge of the operator would be presenting in the form of a set of fuzzy linguistic rules [5]. These rules produce an approximate decision in the same manner as an expert would do. Ever since the fuzzy systems were applied in industrial applications, developers know that the construction of a well performing fuzzy system is not always easy.

The problem of finding appropriate membership functions and fuzzy rules is often a tiring process of trial and error. However, the design of fuzzy logic rules is often reliant on heuristic experience and it lacks systematic methodology, therefore these rules might not be correct and consistent, do not possess a complete domain knowledge, and/or could have a proportion of redundant rules. Furthermore, these fuzzy logic rules cannot be adjusted or tuned on real-time operation, and the off-line adjustment of their parameters is a time consuming process. Another problem could be raised when better precision is needed which is the huge expansion in the fuzzy rule-based system [5].

Techniques based on the use of Artificial Neural Networks (ANN) have a great interest in control and engineering. The fastness of treatment and their capacity of approximating complex nonlinear functions motivate their use for fault diagnosis [1][6][7]. The learning parameters of neural networks made them a prime target for a given task. This kind of behavior learning methods can be used to solve control and diagnosis problems. Artificial neural networks are considered to be simplified mathematical models of brain-like systems. A neural network is a processor of information which can be represented in its simplest form by a set of connected and layered processing elements (*PEs*). Each *PE* is able of receiving an *n*-dimensional input vector from either external sources or *PEs* at previous layers, and processing the data to deliver a scalar output, which is the function of a present input. They are generally trained by means of training-data, and due their property of generalization, they can learn new associations, new functional dependencies and new patterns. Due to these properties, they have been widely used for control. The learning parameters of neural networks made them a prime target for a combination with a fuzzy system in order to automate or support the process of developing a fuzzy system for a given task. Recently the role of neural networks has been found to be very useful and effective when integrated with fuzzy control systems to produce what is called neuro-fuzzy systems [4]. These hybrid systems provide an urgent synergy can be found between the two paradigms, specifically the capability to mimic human experts in fuzzy logic, and learning from previous experience capability in neural networks. Generally, neuro-fuzzy systems can be classified into two categories, adaptive neuro-fuzzy inference system (ANFIS) [3] and hybrid neuro-fuzzy systems [4]. The first category is the most widely used, and they are designed to combine the learning capabilities of neural networks and reasoning properties of fuzzy logic. The main function of neural network is to learn about the fuzzy inference system (FIS) behavior and uses this knowledge to adaptively modify its parameters. The adaptability of the fuzzy inference system can be achieved by either rule base modification and/or membership functions modifications. Rules can be generated, modified, and/or eliminated, while membership functions of the input variables can adjusted and tuned by scaling mechanism [3].

In this paper, an approach to design neuro-fuzzy systems type ANFIS is described for an intelligent fault diagnosis task. The supervision system can detect and classify the infected fault in the industrial actuator. This paper is organized as follows: section 2 gives the necessary background of ANFIS model. In section 3, we will describe the DAMADICS benchmark. The designed ANFIS models are introduced and explained in section 4. Section 5 shows simulation results for the three steps in this application (modelling, generation of residuals and fault classification). The section 6 concludes this paper.

II. Adaptive Neuro-Fuzzy Inference System (ANFIS)

II.1 ANFIS architecture

In this section we introduce the basic of ANFIS network architecture and its hybrid learning rule. Inspired by the idea of basing the fuzzy inference procedure on a feed forward network structure, Jang [3] proposed a fuzzy neural network model (**A**daptive **N**eural-based **F**uzzy **I**nference **S**ystem) whose architecture is shown in Fig.1. He reported that the ANFIS architecture can be employed to model nonlinear functions, identify nonlinear components on-line in a control system, and predict a chaotic time series. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference system. The learning algorithm tunes the membership functions of a sugeno-type fuzzy inference system using the training input-output data. ANFIS consists of five layers; the adaptive nodes of the neural network are the nodes in layers 1 and 4. The depicted model defines a controller with two inputs and one output. Each input has two membership functions. We assume that the rule base contains two fuzzy if-then rules of a Takagi and Sugeno's type:

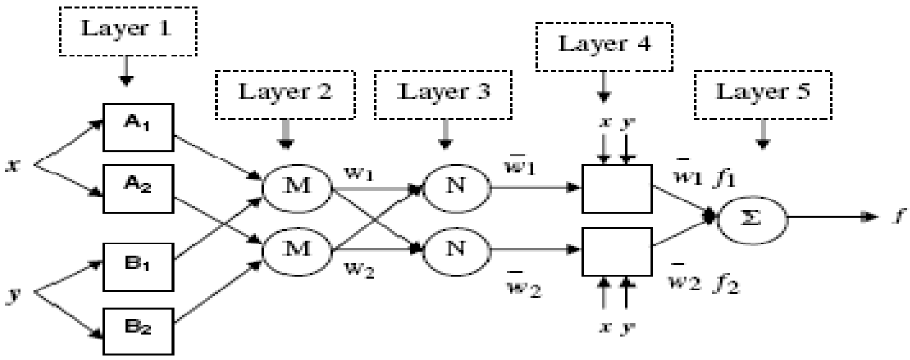

Fig.1: ANFIS structure for TS system with 2 inputs-one output

$$\boldsymbol{R_1} : \textbf{IF } x \; is \; A_1 \; and \; y \; is \; B_2 \; Then \; y_1 = f_1(x,y) = p_1 x + q_1 y + r_1 \quad (1)$$
$$\boldsymbol{R_2} : \textbf{IF } x \; is \; A_2 \; and \; y \; is \; B_2 \; Then \; y_1 = f_2(x,y) = p_2 x + q_2 y + r_2 \quad (2)$$

The output of the nodes in layer 1 is the membership values of the premise part:

$$O_i^1 = \mu_{A_i}(x), i = 1,2 \quad (3)$$

Every node in layer 2 is a fixed node labeled *M*, which multiplies the incoming signals:

$$O_i^2 = w_i = \mu_{A_i}(x1).\mu_{B_i}(x1) \; , \; i = 1,2 \quad (4)$$

Every node in layer 3 is fixed node labeled *N* for normalization. it calculates the ration of the *i-th* rule`s firing strength to the sum of all rules firing strengths:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2} \; , \; i = 1,2 \quad (5)$$

In layer 4, every node is an adaptive node while the node function is*:*

$$O_i^4 = \overline{w_i} \times f_i = \overline{w_i}(p_i \, x + q_i \, y + r_i) \; , \; i = 1,2 \quad (6)$$

Where $\overline{w_i}$ is the output of layer 3 and p_i, q_i, r_i are the parameters for the first order Sugeno rule.

The overall output of the network can be defined as:

$$O_i^5 = y = \sum_i \overline{w_i} \times f_i \quad (7)$$

II.2 Hybrid learning techniques

Using a given input-output data set, constructs a fuzzy inference system whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone or in combination with a least squares method [3]. This adjustment allows the fuzzy systems to learn from the data they are modeling. Jang proposed that the learning task is done in two passes using a hybrid learning algorithm as shown at table 1. In the forward pass the first set is fixed and S_2 is optimized by the least square estimate (*LSE*). In the backward pass S_1 is tuning by the back-propagation algorithm [3].

Table I: Two passes in the hybrid learning

	Forward Pass	***Backward Pass***
Premise Parameters	Fixed	Back-propagation
Consequent Parameters	Least Squares Estimate	fixed

III. The Damadics Benchmerk

In order to evaluate the proposed schemes, we apply it to fault diagnosis in DAMADICS benchmark. The DAMADICS benchmark (Development and Applications of Methods for Actuator Diagnosis in Industrial Control Systems) is an engineering research case study that can be used to evaluate detection and isolation methods [8]. The industrial actuator data set is collected under various operating loads, and different conditions including different fault categories. It is possible to simulate 19 abnormal events from three actuators, and a fault scenario is characterized by the fault type in conjunction with the failure mode, which can be abrupt (*A*) or incipient (*I*). The detailed description of the fault types is shown in Table 2. The actuator consists of a control valve, a pneumatic servomotor, and a positioner as depicted in Figure 2. *PC* is the positioned processing unit, *E/P* is the electro-pneumatic transducer, V_1, V_2, V_3 are bypass valves, *PP* stands for displacement, P_1,P_2 are pressures, *F* is the flow value of transducer and T_1 for temperature. The output variables of the actuator model (*F* and *X*) are employed to construct the observation sequences ($O = \{o_1,o_2,\ldots,o_t,\ldots,o_T\}$. Were $o_1 = [Ft=1\ Xt=1]$ [8][9]. Different approaches and papers are presented to study the fault diagnosis in DAMADICS benchmark likes [8-11].

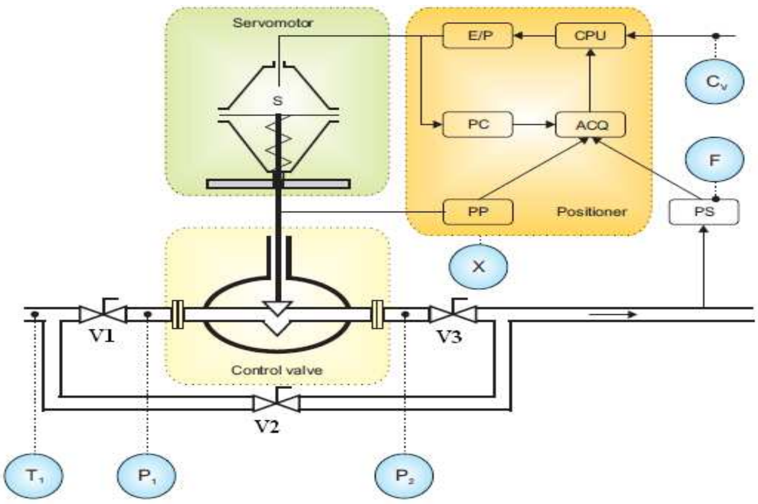

Fig. 2 : DAMADICS actuator

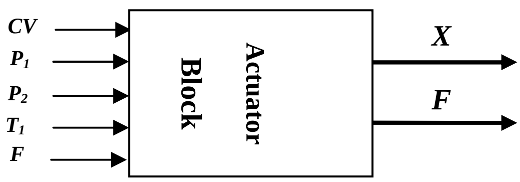

Fig. 3 : The general scheme for the actuator

In the DAMADICS actuator, faults can appear in control valve, servomotor, electro pneumatic transducer, piston rod travel transducer, pressure transmitter or in control unit. Nineteen types of faults are considered as shown in table 2. The faults are emulated under carefully monitored conditions, keeping the process operation within acceptable quality limits. Five available measurements and 1 control value signal have been considered for benchmarking purposes: process control external signal CV, values of liquid pressure on the valve inlet P_1 and outlet P_2, liquid flow rate *F*, liquid temperature T_1, and displacement of the rod *X*. Table 3 summarizes the parameters of input and outputs variables.

Table II: Faults to be detected and isolated

Fault	Description
Control valve faults	
F_1	Valve clogging
F_2	Valve plug or valve seat sedimentation
F_3	Valve plug or valve seat erosion
F_4	Increased of valve or bushing friction
F_5	External leakage (leaky bushing, covers)
F_6	Internal leakage (valve tightness)
F_7	Medium evaporation or critical flow
Pneumatic servo-motor faults	
F_8	Twisted servo-motor's piston rod
F_9	Servo-motor's housing tightness
F_{10}	Servo-motor's diaphragm perforation
F_{11}	Servo-motor's spring fault
Positioner faults	
F_{12}	Electro-pneumatic transducer fault
F_{13}	Rod displacement sensor fault
F_{14}	Pressure sensor fault
F_{15}	Positioner feedback fault
General faults / external faults	
F_{16}	Positioner supply pressure drop
F_{17}	Unexpected pressure change across the v
F_{18}	Fully or partly opened bypass valves
F_{19}	Flow rate sensor fault

Table III: Input and outputs variables

Input	Range	Unit	Description
CV	0 − 100	%	control signal from external PI controller
P_1	0 −100	kPa	Inlet liquid pressure
P_2	0 − 1000	kPa	Outlet liquid pressure
T_1	50 − 150	°C	Liquid temperature
Output	**Range**	**Unit**	**Description**
X	0 − 100	%	Position of the rod
F	0 − 500	m^3/h	Average flow

IV. Designing of ANFIS Models

IV.1 Structure of the trained Models

In our work, we used hybrid approaches based on ANFIS models for modelling and fault diagnosis tasks in DAMADICS actuator. The positioner and the control valve are modelled with two hybrid models: $ANFIS_1$ and $ANFIS_2$. Each model has 4 inputs and one output as presented with the two following equations:

$$X = ANFIS_1\,(CV, P_1, P_2, T) \tag{8}$$

$$F = ANFIS_2\,(X, P_1, P_2, T) \tag{9}$$

VI.2 The training task

This task consists to adjust the fuzzy models parameters (premise part and conclusion part) using the training data. This data-base contains 4 vectors of the inputs variables and their appropriate actions (*X* and *F*). The training and the testing data sets for elaborating the models are generated by simulation using the valve model [12]. The training data set has about 3600 samples extracted from measured data without faults. Figure 4 shows the scheme of the data based model used for modeling the valve (training the two neuro-fuzzy systems $ANFIS_1$ for the output *X* and $ANFIS_2$ for the output *F*). The structures of the trained neuro-fuzzy systems are depicted in figure 5. The obtained network structures are similar to that of a neural network, which maps inputs through output membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

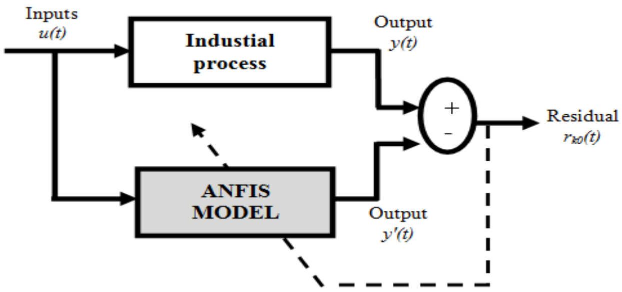

Fig. 4: Data-based model

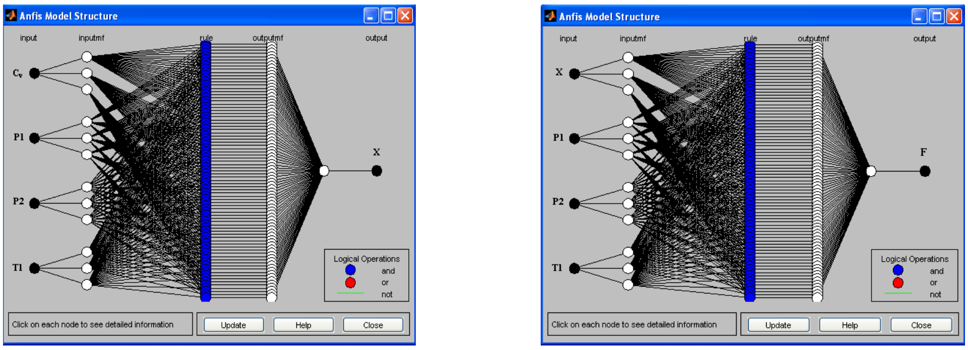

Fig. 5: The structures of the ANFIS models

V. Simulation results

In this section, we present the obtained simulation results for the application of this hybrid approach for modeling and fault diagnosis in the valve actuator.

V.1 Generation of residuals

Residuals are the basic factors for fault detection during monitoring the actuator. The difference between the system outputs $y_k(t)$ and fault-free model outputs $y'_k(t)$ leads to *n* values named residuals $R_{k0}(t)$ (eq.10). These residuals $R_{k0}(t)$ provide a source of information about faults for further processing. Fault detection is based on the evaluation of residuals magnitude. It is assumed that each residual $r_{k0}(t)$, where: $k = 1,\ldots,n$ should normally be close to zeros in the fault-free case, and it should be far from zeros in the case of a fault. Figure 6 shows the method for generating the two types of residuals (R_x, R_f) as shown in figure.5. Where:

$$R_{k0}(t) = y_k(t) - y'_k(t),\ \ k = 1, \ldots, n \tag{10}$$

$$R_{Xfi}(t) = X_{real} - X_{ref} \tag{11}$$

$$R_{Ffi}(t) = F_{real} - F_{ref} \tag{12}$$

Figures 7 and 8 (up) present the results obtained as comparison between the output of the valve model and the measured data of the real actuator (Figure 7 for the output X of $ANFIS_1$ and Figure 7 the output *F* of $ANFIS_2$). As depicted, we observe a big similarity between the two responses. Figures 7-8 (down) show calculated error for the two responses.

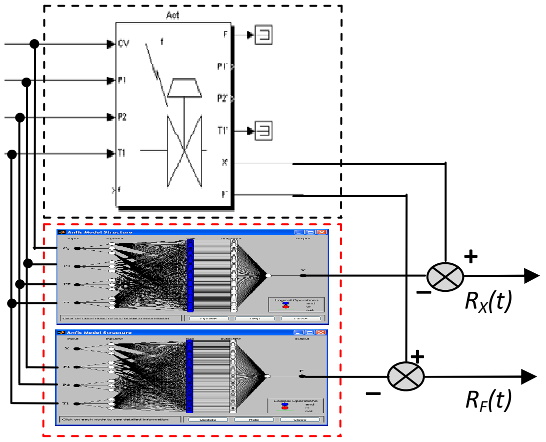

Fig. 6: Comparison of results between the system and the ANFIS model

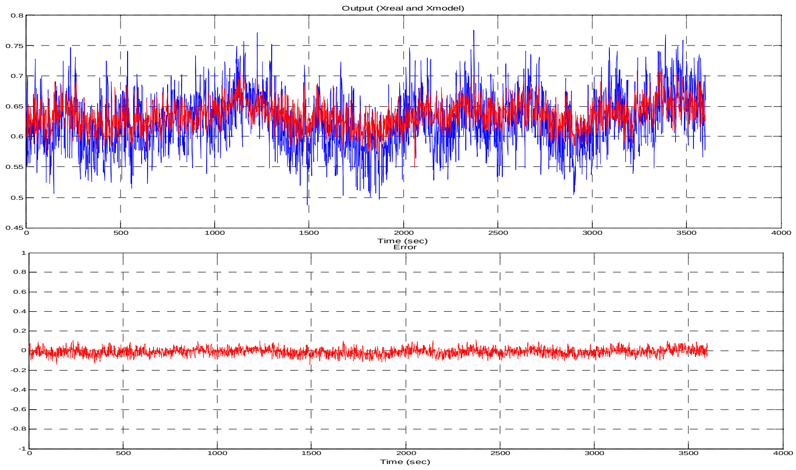

Fig. 7: (up) Actual output X with the estimated X´. (down) Residual RX(t)

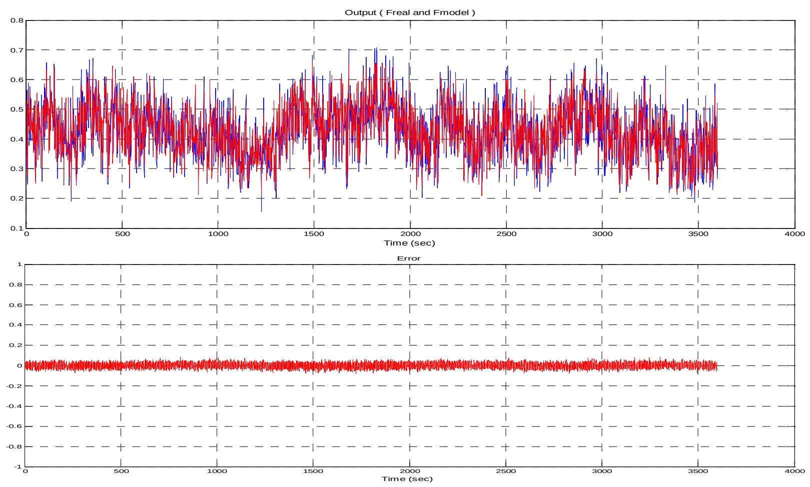

Fig. 8: (up) Actual output F with the estimated F´. (down) Residual RF(t)

V.2 Fault diagnosis using ANFIS models

The DAMADICS valve is infected with 19 faults as mentioned above (table.3) and each fault can be either ***abrupt*** or ***incipient*** fault. In our study, we choose 4 faults to demonstrate the effectiveness of the studied approach: F_1, F_{10}, F_{13} and F_{19}. The parameters of these faults are summarized in table 4. For each fault, we calculate the residual using the equation 8 based on the structure depicted in Fig 6 when we replace the actuator bloc by the bloc presented in figure 9 infected by the 4 studied faults.

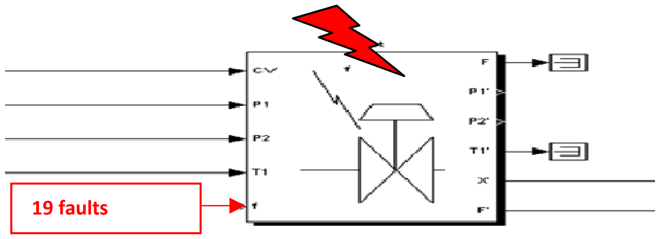

Fig. 9: The symbol of infected valve by faults

Table IV: Parameters of faults for Detection and Isolation

Faults	***Fs***	t_{form}	t_{t0}	***Fd***	***Type***
F_1	1	1000	2000	1	Incipient long
F_{10}	1	1000	1500	1	Abrupt big
F_{13}	1	2700	3600	1	Abrupt big
F_{19}	0.5	0	1200	1	Abrupt medium

V.3 Generation of residuals (with faults)

We generated the faults based on the measurements of the system and the model. The figures 10 to 13 (a-b) present the generated residuals of the two outputs (position of the rod and average flow) for each fault.

1. **Fault F_1 (Valve clogging):** this fault is simulated within time interval [1000s, 2000s].

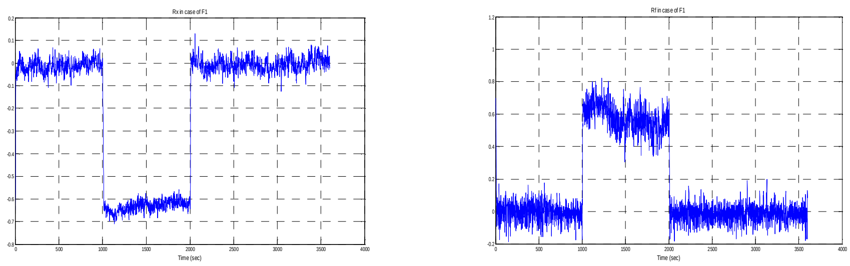

Fig. 10: Residuals R_{Xf1} , R_{Ff1}

2. **Fault F_{10} (Servomotor's diaphragm perforation)**: this fault is simulated within time interval [1000s,1500s].

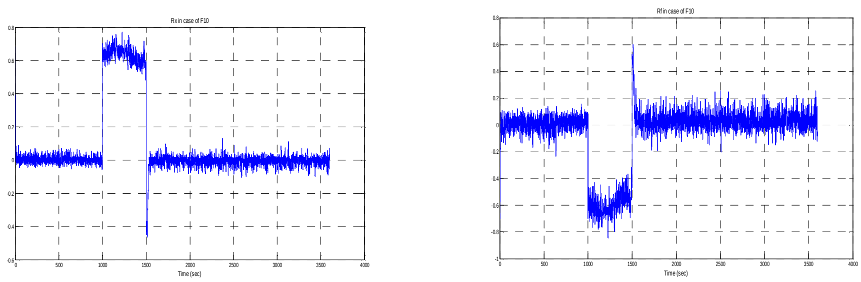

Fig.11: Residuals R_{Xf10} , R_{Ff10}

3. **Fault F_{13} (Rod Displacement)**: this fault is simulated within time interval [2700s, 3600s].

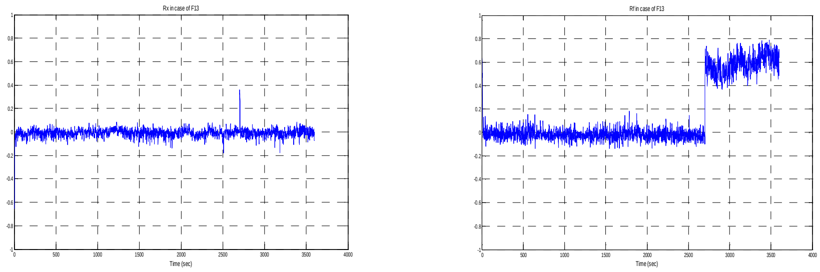

Fig. 12 : Residuals R_{Xf13} , R_{Ff13}

4. **Fault F_{19} (Flow rate sensor fault)**: This fault is simulated within time interval [0 s, 1200s].

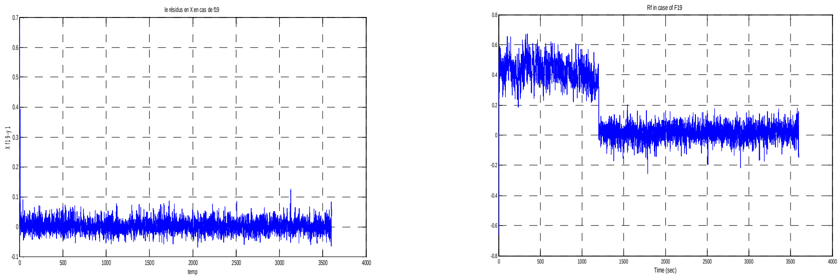

Fig. 13 : Residuals R_{Xf19} , R_{Ff19}

V.5 Evaluation of residuals (Faults classification)

After generating the residuals of each fault; the next step is the evaluation of these computed values in order to classify the detected fault. We used neuro-fuzzy classifiers type ANFIS based on training procedures. Each ANFIS classifier has two inputs which are the residual of *X* and *F* for calculating one output of detected. The structure is shown in figure 14. The overall diagnosis system has as inputs the residuals (R_{Xf1}, R_{Ff1}, R_{Xf10}, R_{Ff10}, R_{Xf13}, R_{Ff13}, R_{Xf19} and R_{Ff19}) and the outputs are the faults (F_1, F_{10}, F_{19} F_{13}). The bloc diagram of the faults diagnosis system is defined in figure 15. Figures 16 to 19 present the detected fault (F_1, F_{10}, F_{19} and F_{13}).

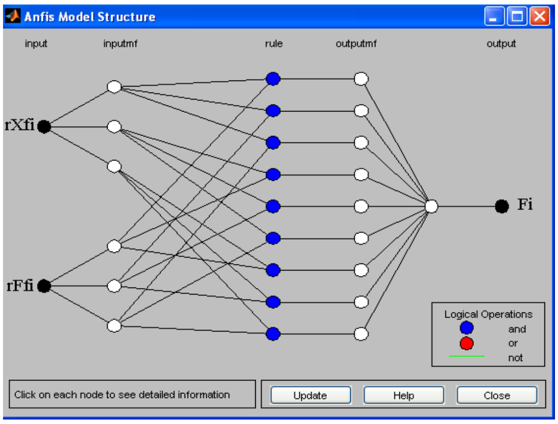

Fig. 14 : The structure of fault classifier

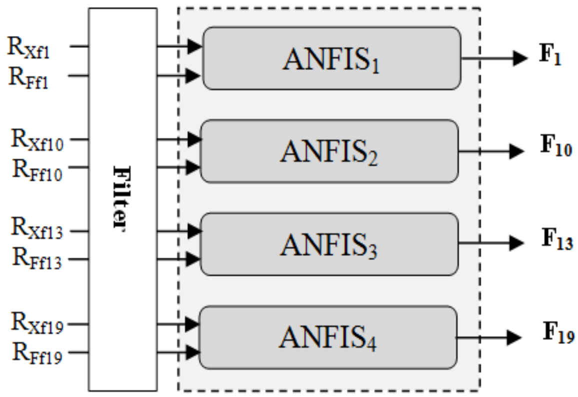

Fig.15 : Diagram bloc of the faults diagnosis system

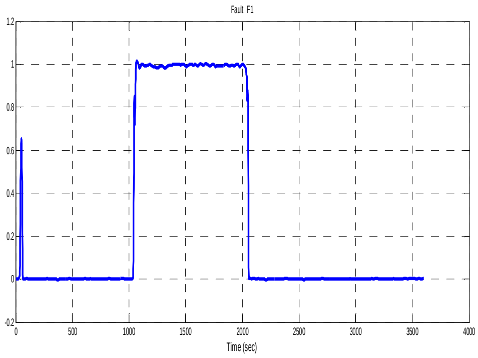

Fig. 16 : The detected fault F1 using hybrid approach

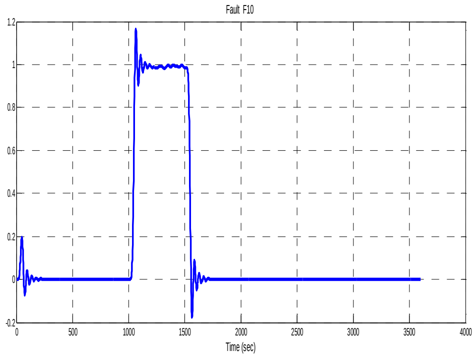

Fig. 17 : The detected fault F10

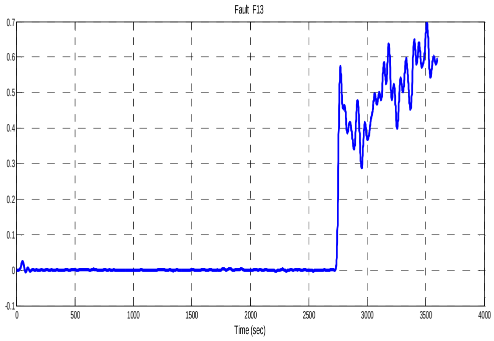

Fig. 18 : The detected fault F13

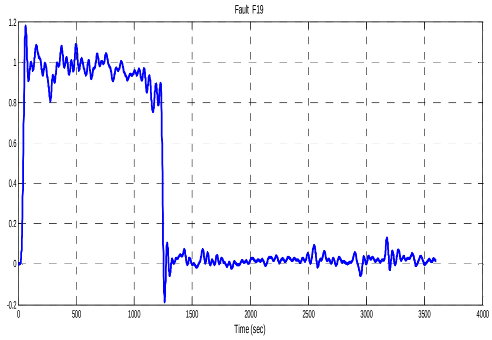

Fig. 19 : The detected fault F19

VI. Conclusion

In this paper, a hybrid approach based on ANFIS models is presented for intelligent fault diagnosis. The proposed diagnosis system is used for detecting faults in DAMADICS actuator. We used these models for three steps (modeling the valve actuator, generation of residuals and fault classification). ANFIS system is well suited for designing intelligent controllers because it is capable of making inference ever uncertainty with a learning capacity of neural networks. The simulation results show the efficiency of the proposed scheme for automatic fault diagnosis. The advantage of the proposed approach is the simplicity and the efficiency for industrial applications.

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