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Identification and fault detection in actuator using NN-NARX

Identificación y detección de fallas en accionamiento utilizando NN-NARX

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ABSTRACT:

In this paper, the use of a Nonlinear Auto Regressive eXogenous Neural Networks model or NN-NARX for identification and fault detection in the actuator of an industrial thermal process is presented. Initially, the techniques of fault detection and diagnosis are exposed; then, emphasis is placed on the models of Artificial Neural Networks for identification and fault detection. Subsequently, the control system of a thermal process used as a case study is described. A monitoring system allows data recording under normal operation conditions for identification using the NN-NARX model. The model is used for residual online generation due to faults that are introduced randomly. Finally, the results of residual generation and evaluation are presented. The designed system is useful for implementation through a hardware device that can be incorporated into the process equipment and support the operator in the presence of failures.

RESUMEN

En este artículo se presenta la utilización de un modelo de Red Neuronal no lineal Auto Regresivo de Variable Exógena o NN-NARX (por sus siglas en inglés), para la identificación y detección de fallas en un accionamiento de un proceso térmico industrial. Inicialmente, se exponen las técnicas de detección y diagnóstico de fallas; luego, se hace énfasis en los modelos de Redes Neuronales Artificiales para identificación y detección de fallas. Posteriormente, se describe el sistema de control de un proceso térmico utilizado como caso de estudio. Un sistema de monitorización permite el registro de datos en condiciones normales de operación para la identificación usando el modelo NN-NARX. El modelo es utilizado para la generación en línea de residuos ante fallas que son introducidas aleatoriamente. Finalmente, se presentan los resultados de la generación y evaluación de residuos. El sistema diseñado es útil para la implementación a través de un dispositivo hardware que puede incorporarse en el equipo del proceso y apoyar al operador ante la presencia de fallas.

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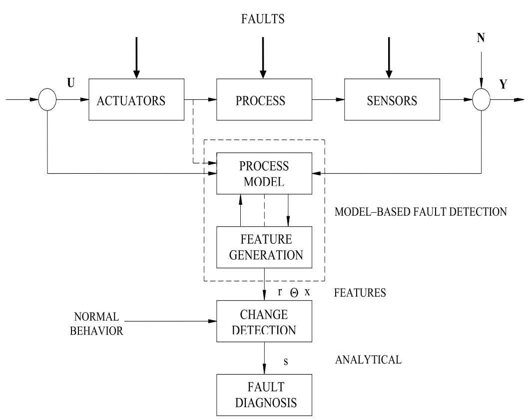
1. Introduction

The process supervision is the set of actions oriented to accomplish the correct operation, even in risk situations. To perform the process supervision, three fundamental phases must be met: fault detection, fault diagnosis and system reconfiguration, in such a way that the process continue operating in accordance with the established specifications [1].
A fault is defined as an impermissible deviation of at least one characteristic of a variable from an acceptable behavior. Therefore, the fault is a state that can lead to malfunction or damage to the system [2].
Fault detection and diagnosis systems allow to identifier the operating status of a system, as well as to identify the nature of the faults presented, their location and severity. Figure 1 illustrates a general scheme of a fault detection and diagnosis system.

Figure 1. General scheme of a fault detection and diagnosis system.



Source: own

The inputs and outputs of the control process block feed the supervision system whose function is to detect the presence of a fault and diagnose its nature. With this information is possible to correct the parameters of the controller in a manual or automated way or to intervene in the process to correct the detected problems.
To perform the fault detection and fault diagnosis, multiple approaches have been proposed, which could be based on the following classification:

1.1. Methods based on process mathematical models

They are strategies that make use of a model formulated from the knowledge of the dynamics involved in the process. Basically, they are based on obtaining a difference between the process outputs and a process model, which show the presence of faults. This approach usually represents a very low computational cost, but it can only be applied to processes where is possible to obtain the model analytically, which limits its application to linear systems or relatively simple non-linearities. Obtaining the parameters also represents a great difficulty, which can be addressed by systems identification techniques [3], [4].

1.2. Methods based on process data

They use process data that seeks to solve a classification problem. For this purpose, the use of fuzzy classifiers, analysis of principal components, artificial neural networks, machines with support vectors, radial base functions, among others, has been proposed. The main disadvantage of these techniques lies in the computational cost and in that they generally operate as a "black box" system, unable to provide additional information about the fault [5].

1.3. Methods based on historical data models of the process

For process that allow the collection of data representative of its operation, both in normal and anomalous conditions, it is possible to build a model using techniques such as neural networks or fuzzy models of the Takagi-Sugeno type. These approaches are generally costly from a computational point of view and require large volumes of data, which are sometimes difficult to obtain. However, they are very useful for obtaining models of nonlinear dynamic systems [6].
The objective of this work is to develop a fault detection system of an actuator, based on methods based on historical data models of a thermal process, using a nonlinear autoregressive neural network model of exogenous variable (NN-NARX). The article is organized like this: section 2 makes an approach to the techniques of modeling and fault detection with Neural Networks, section 3 makes a description of the thermal process control system used as a case study, section 4 describes the process monitoring system, in section 5 the design of the NN-NARX model is presented and in section 6 the results obtained with the proposed model for the plant are shown under fault conditions. The conclusions are given in the last section.

2. Modeling and fault detection using neural networks

Control theory and statistics have been investigated mainly by the FDI (Fault Detection and Isolation) community, and techniques based on models that use computer science and artificial intelligence have been treated by the diagnostic community or DX

(Diagnosis). These techniques use qualitative models and logical approaches, such as artificial neural networks, fuzzy and neuro-fuzzy inference systems and immune systems [1], [7].

The Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) have been successfully applied in fault detection and diagnosis automated in different conditions [8], [9], [10]. Additionally, they can be combined into two categories: Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [11] and Neuro-Fuzzy Hybrid Systems [12]. These approaches greatly increase the reliability of fault detection and diagnosis systems [13]. Particularly, ANNs are used in a wide range of problems such as grouping, recognition, pattern classification, optimization, approximation of functions and prediction [14], since they have a powerful ability to learn, store and remember information.

Since the main objective in the modeling of dynamic process behavior is to obtain the functional relationship between the variables that explain its behavior, it is impossible to perfectly capture all the details of the real behavior of the process from the systematic application of the laws of nature. An empirical study, seeks this unknown relationship by some mathematical functions, using the information collected experimentally from the system, especially when the process is too complicated [15]. The ANNs are black box modeling tools that have the capability to perform a nonlinear mapping of input and output spaces, when the relationships between input and output spaces are unknown [16].

The ANNs are development based on mathematical models. The choice of the ANN model depends on a priori knowledge of the system to be modeled. A NARX or NN-NARX neural network is a good predictor of time series [17], [18], the NARX concept is a nonlinear generalization of the Autoregressive Exogenous (ARX), which is a standard instrument in the linear identification of the system of black box [19]. NN-NARX models can be used to model a wide variety of nonlinear dynamic systems. They have been applied in various applications that include time series modeling [20].

In accordance with the above, the following describes the design of an NN-NARX type system as an identification scheme to later be used in the residual generation for an actuator in an industrial thermal plant. The residual is useful for the fault detection and diagnosis, and for the development of fault tolerance mechanisms.

3. Thermal process control system

The plant defined as a case study, is a laboratory industrial thermal plant that has installed equipment, instruments, actuators and devices to control the heat transfer between two fluids [21]. The main components of the thermal plant include an industrial refrigerator to cool the process fluid, a heating device for the hot fluid circuit, temperature sensors, pressure sensors, a diaphragm control valve, among others, and a monitoring system with an operator interface (Fig. 2).

Figure 2. Thermal plant as case of study [21].

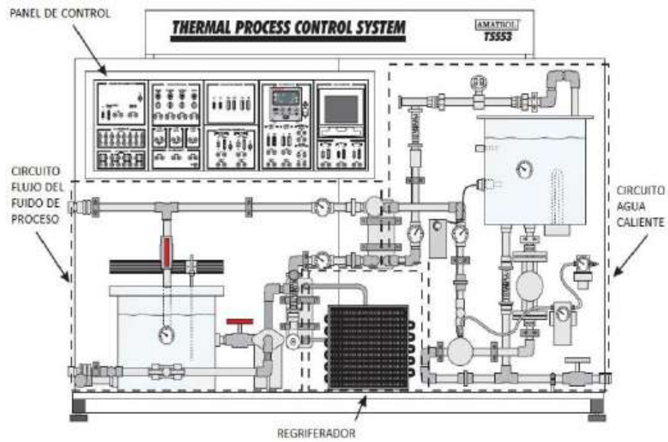
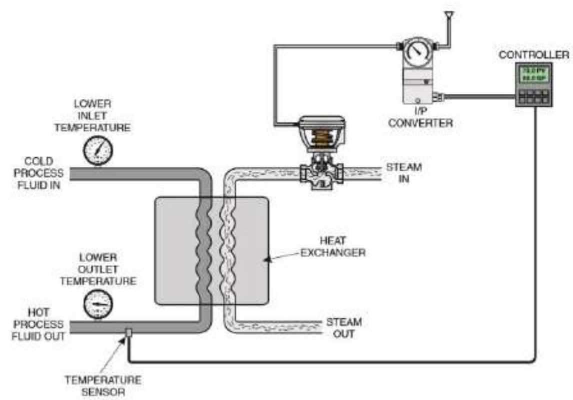


Figure 3. Temperature control system of the thermal process [21].



In the process fluid circuit, water is pumped from a tank and passes through two exchangers to return to the tank. the refrigerator is connected to one of the exchangers to cool the water. In the hot fluid circuit, the water is heated in a tank and pumped through the other exchanger to raise the temperature of the process fluid. The temperature control of the process fluid T is done by regulating the flow of hot water in the exchanger by means of the diaphragm valve, which is pneumatically operated by an electropneumatic I/P converter, which maintains the pressure in the diaphragm of the valve, according to the signal from controller C (Fig. 3).

4. Plant monitoring

The thermal plant has a monitoring system, this consists of a data acquisition module, a program for data management and a user interface for interaction with the equipment operator (see Fig. 4).

Figure 4. Plant monitoring system of the thermal plant. Source: own.

The data acquisition module consists of an electronic card and a software application. The hardware consists of a printed circuit board with a microcontroller from the Arduino® manufacturer, with digital and analog input/output ports, which can be connected to expansion boards, it has a USB connection port for power and communication with the computer, a software allows to program the card to capture the data of C and T.

The user interface for operator interaction runs on the platform and development environment to design systems with a visual programming language from the Labview® package. The interface allows the operator to observe the behavior of the variables in real time and alerts due to faults.

For programming, the monitored signals in the equipment are taken, the 4-20mA control signal C is processed by the Arduino® card, adjusting it to a 1-5V scale to be used in the program as a monitoring signal. Several screens are developed for user monitoring.

5. NN-NARX system design

5.1. NN-NARX architecture

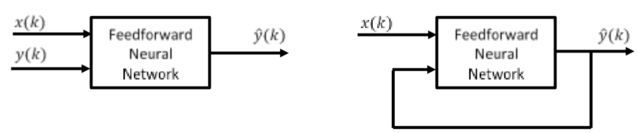
A Nonlinear Auto Regressive eXogenous Neural Networks model or NN-NARX is a recurrent dynamic network, with feedback connections that enclose several layers of the network. The NN-NARX model is based on the ARX linear model, which is commonly used in time series modeling. The NN-NARX models can be used to represent a wide variety of nonlinear dynamic systems and have been extensively implemented in several applications. The formulation of a NARX model is represented by "equation (1)":

$$\hat{y}(k) = f(u(k-1),...,u(k-n_u),(k-1),...,y(k-n_y)) + e(k) \tag{1}$$

Where $u(k)$ and $\hat{y}(k)$ are the inputs and outputs of the model, respectively, n_u and n_y are the respective maximum delays, which establish the order of the model, k represents the discrete time step, $f(.)$ describes the nonlinear correlation between inputs and outputs, and $e(k)$ It is a noise term, generally assumed as gaussian and white. Different internal network architectures are derived, depending on the representation and parameterization of the function $f(.)$.

Based on the representation of the NARX model of equation (1), the previous samples of the input and output data are presented to the neural network during the training phase. In doing so, a notion of memory is incorporated into the network, which results in the model's ability to learn system dynamics. This network configuration is denoted as serial-parallel architecture (Fig. 5a), which can only be used for predicting one step forward. It can be converted to parallel architecture by feeding the predicted output instead of the measured output data (Fig. 5b). The parallel network is often used to model the output prediction on a recurring basis, as is the case in this work.

Figure 5. Architectures of NARX networks.



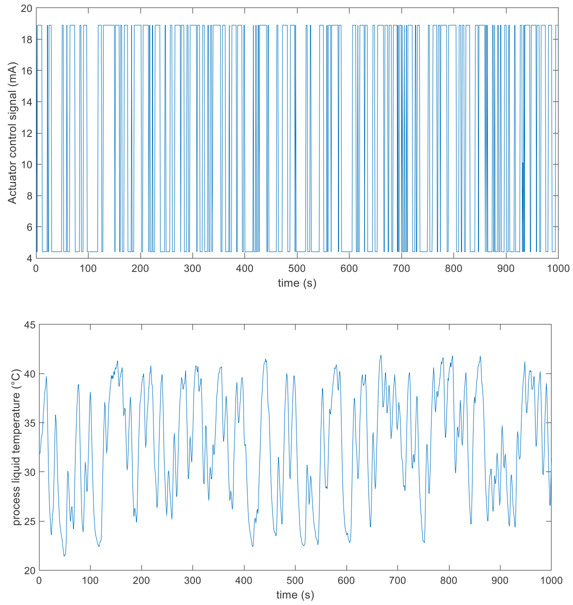
(a) Serial-parallel architecture (b) Parallel architecture
Source: own.

5.2. Training

The conventional NARX network is a two-layer advance network model, the sigmoidal function resolves the hidden layer, while the linear function resolves the output layer. As a dynamic neural network, it contains time delay lines that are used to filter nonlinear data and predictions. For training, the Levenberg-Marquardt (LM) training function was used because it has the capability to converge faster.

For the training of the network two vectors of 1000 data were used corresponding to the input and output variables (C, T), taken during the operation of the equipment under normal conditions (without failures). Figure 6 shows the graphs of the C and T data.

Figure 6. Input and output data during equipment operation. Source: own.



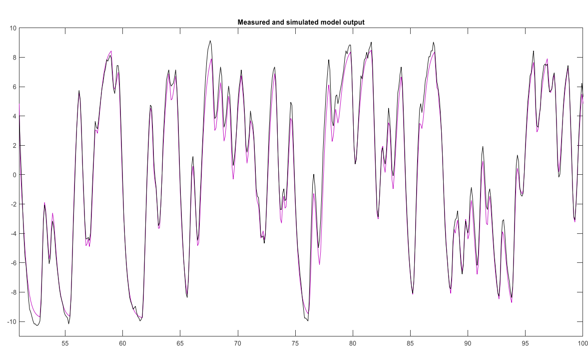
6. Results

6.1. Actuator identification

The selection of the number of neurons in the NN-NARX model is an important step. In the case of a large number of neurons, the complexity of the calculation increases and causes excessive parameterization. Therefore, the number of neurons can be selected by means of the use of mean square error (MSE) curves. 70% of the data was used for training, 15% for testing and 15% for validation.

The training of the network was carried out by calculating the gradients and updating the weights until the network converged to a minimum error value. The Levenberg-Marquardt (LM) algorithm also known as Damped Least Squares (DLS) is commonly used to solve nonlinear least squares problems. Figure 7 shows the adaptation of the NN-NARX network to temperature data after training.

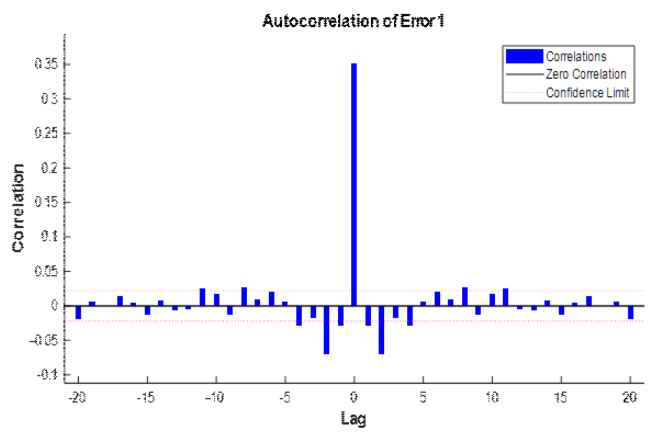
Figure 7. Adaptation of the NN-NARX model to temperature data. Source: own



The best results for the valve operation adaptation were achieved with a recurrent neuronal network of NARX with 10 neurons in the hidden layer and a neuron in the output layer. the histogram of the error was obtained, which shows how many instances of test and training data set belong to the corresponding error value. The error is represented as the difference between the measured temperature and the expected temperature. Due to the serial-parallel configuration, these are errors for only a one-step prediction. Therefore, the network was reorganized in the original parallel form (closed loop) to make an iterated prediction over many time steps.

It can be seen in Fig. 8 that the correlation between the input and the error in all delays is within the confidence limit. This leads to the fact that the inputs and outputs are accurately modeled, and the model has captured all the characteristics of the system behavior.

Figure 8. Correlation between input and error during training. Source: own.



6.2. Residual generation

The residual are key factors for fault detection during actuator monitoring. The difference between the outputs of the system and the outputs of the fault model generate n values called residual R. These residuals provide a source of information about faults for further processing. The fault detection is based on the evaluation of the magnitude of the residuals. This means that for each residual Rk, where $k = 1\ldots, n$ they will be close to zero for cases of system operation fault-free and will be greater than zero for the cases of equipment operation under fault conditions. Fig. 9 represents the scheme for the actuator fault detection, using the NN-NARX model.

Figure 9. Scheme for the actuator fault detection. Source: own

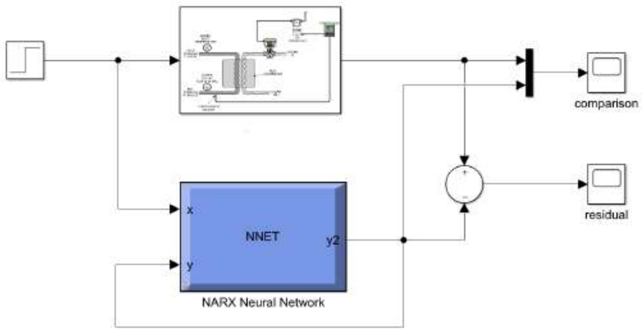
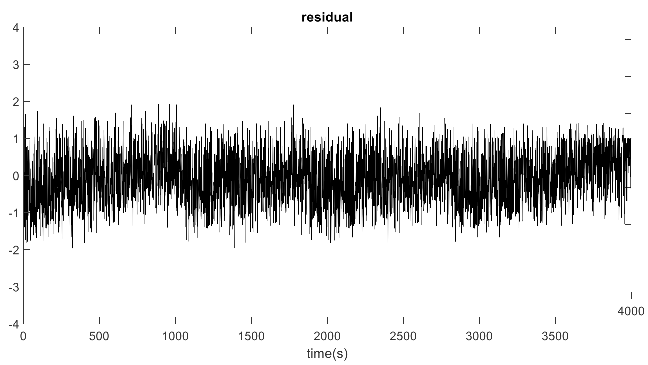


Fig. 10 shows the results obtained for the residual between the output of the modeled valve (T mod) and the measured data of the real drive (real T) in an interval [0s, 4000s] for the fault-free system.

Figure 10. Residue generated from the fault-free NN-NARX mode Source: own.



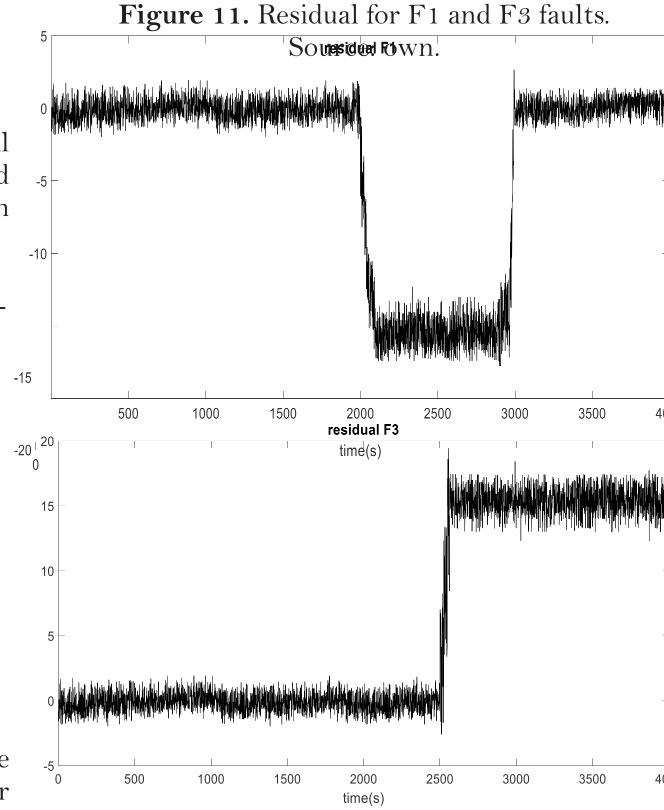
For this work, 4 types of abnormal events in the valve were represented, including abrupt, incipient or intermittent. The description of the types of faults is shown in Table 1. The faults are emulated under carefully controlled conditions, keeping the operation of the process within acceptable safety limits.

Table 1. Faults in valve
Source: own.

Fault	Description	Type
F1	Valve clogging	Intermittent
F2	Spring crash	Abrupt
F3	Air supply cut the I/P electropneumatic converter	Abrupt
F4	Supply pressure drop to the positioner	Incipient

For the case study of this work, two faults are chosen for the generation of their residuals. The temperature of the process fluid in the system is measured when it separately presents the faults *F1* and *F3*, and it is compared with the temperature of the NN-NARX model when the equipment is fault-free operation. Fig. 11 shows the residual generated by *F1* (intermittent) when it extends from 2000 s to 3000 s and the residual of F3 (abrupt) when it is presented in 2500 s.

Figure 11. Residual for F1 and F3 faults. Source: own.

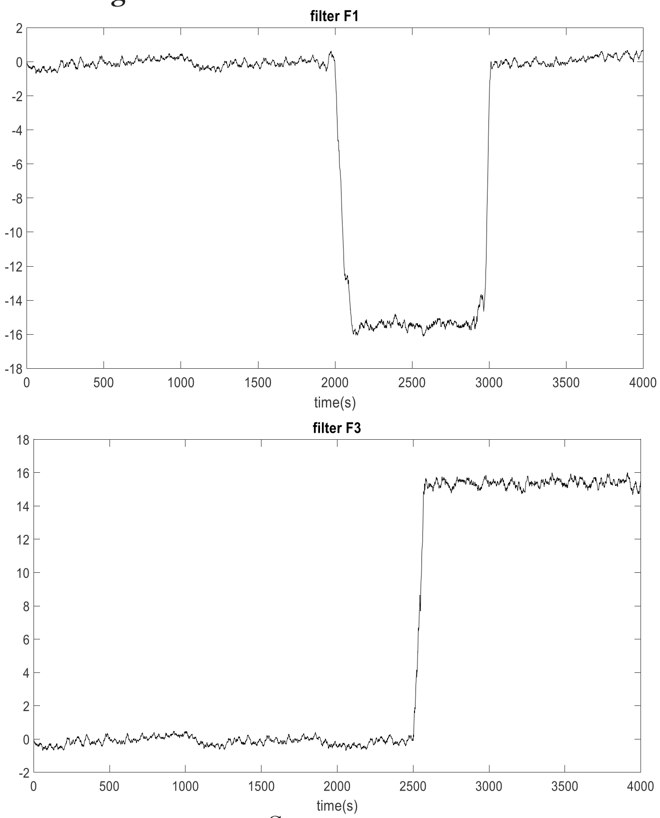


6.3. Residual evaluation

To perform the fault diagnosis and generate alerts for the operator that monitoring the process through the graphical interface, once the detection is made, a signal filtering algorithm is used. The algorithm is an additional program that runs on the processor that has the monitoring system installed and performs the NN-NARX training. The output signals, that is, the residuals, are monitored by the algorithm each sampling period, and depending on the signal change, it sends an alert to the operator interface about the type of fault that occurs during the operation of the process.
The algorithm for the residual evaluation is a version of the filter function of the Matlab® program, which has the functionality to detect the variation of the signal from the defined threshold under normal operating conditions. In this case, each fault signal has a different

value and is defined in the function. Fig. 12 shows the diagnosis of the standard *F1* and *F3* faults. The function, once incorporated, uses the residuals and depending on the fault, sends an alert signal to the operator interface

Figure 12. Fault evaluation of F1 and F3.



Source: own

7. Conclusions

This paper presented the use of a Nonlinear Auto Regressive eXogenous Neural Networks model or NN-NARX for identification, fault detection and evaluation, in the actuator of an industrial thermal process. the approaches for the fault detection and diagnosis were presented, emphasizing in neural networks. The thermal process control system where the model was applied was described.

The network was trained with the data in normal operating conditions of the equipment, error correlation was used to validate network performance. Subsequently it was used to obtain the residual in the event of fault events, the residual generation allowed to detect and diagnose (due to the shape and magnitude of its profile) the type of fault affecting the thermal system.

From the results it is concluded that the model developed is suitable as a model of the process for the efficient fault detection and evaluation. The method proposed in this work combines the computing power and robustness of neural networks. The procedure leads to the fault detection, the estimation of the time of each one and finally its evaluation.

As could be seen, this technique can be used to detect multiple faults in line and be used to isolate the section of the plant when the fault is detected. The designed system is useful for implementation through a hardware device that can be incorporated into the process equipment. Among the limitations of the method is the need to have models of each of the faults, because it requires time, computational resources and a history of data.

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