CEAI, Vol.15, No.3 pp. 61-69, 2013 Printed in Romania

Fault detection and isolation in industrial control valve based on artificial neural networks diagnosis

Ahmed Hafaifa, Ahmed Zohair Djeddi,
Attia Daoudi

Applied Automation and Industrial Diagnostic Laboratory,
Faculty of Science and Technology, University of Djelfa 17000 DZ, Algeria.
(hafaifa@hotmail.com, laadi@univ-djelfa.dz)

Abstract: The industrial systems become more complex in our days; the increasing complexity explains the need for a monitoring system performance, safe and reliable. This need for security and reliability requires the implementation of preferment diagnostic systems to report any malfunction in this industrial processes. In this paper, we develop a supervision system based on artificial neural networks approach to generate defects indicators for our examined industrial control valve.

Keywords: Fault detection and isolation, neural networks diagnosis, monitoring system, supervision system, security, reliability, industrial processes, industrial valve.

1. INTRODUCTION

In recent years, industrial automation systems become more sophisticated with the increasing complexity of these systems. This is explained by the need for efficient systems, safe and reliable, thus increasing the risk of failure can affect the system itself (Chen Y.M. *et al.*, 2002; Karpenko M. *et al.*, 2003; Karpenko M. *et al.*, 2002). The need for safety and reliability is even more crucial when it comes to systems where a malfunction can be dangerous, especially about human life and its environment. This is why the above procedure automation in the classical sense (control system), it is necessary to implement a diagnostic system to report any malfunction given by (Hafaifa A. *et al.*, 2011b; Joseph McGhee *et al.*, 1997).

In fact, detect a fault is up to announce its presence, that is to say whether the current state of the system and its components are normal or not, indicating any deviation from expected behavior, developed by (Chii-Shang T. *et al.*, 1995 ; Hafaifa A. *et al.*, 2010b ; Yang S.H. *et al.*, 2000). While the task of isolation is to analyze events, so as to determine the defects in the system (sensor defaults, actuator faults or system faults). To answer these diagnosis stains, there are many diagnostic methods can be divided into two categories given by (Hafaifa A. *et al.*, 2012; Leger R.P., *et al.*, 1998 Zhang J. *et al.*, 1994): methods that rely on the existence of a formal model of the equipment to be monitored, and methodologies based solely on the analysis of monitoring variables as well as the a priori knowledge of human experts. These methods are then used to call procedures and learning pattern recognition and artificial intelligence.

The objective of this work is to synthesize a fault diagnosis system and develop a neural networks model to detect and locate faults applied to industrial control valve, based on artificial intelligence, the task performed by the operator has become easier, it only needs to observe the production systems, and the main task is to know symptoms observation and data analysis where the interpretation of information is carried out by our provide diagnostic system based on artificial intelligence.

2. DIAGNOSIS BASED ON NEURAL NETWORKS

The diagnosis decision can be done using a simple test of threshold on the instantaneous values of the residues, we appeal to the theory of statistical decision. From a practical view, the decision logic of thresholds plays an important role because most of the methods mentioned is reduced, a term, a thresholding given by (Hafaifa A. *et al.*, 2010a; Shengwei Wang *et al.*, 2004). If the threshold is chosen constant unknown inputs that excite the system disrupts the decision. Also, if the threshold is chosen too small, there are a lot of false alarms and if too large, low amplitude defects are not detected. It is therefore interesting to use adaptive thresholds which change depending on the operating point of the process being monitored. In this work, we develop a decision system for fault diagnosis based on neural networks.

In this paper, we are interested by the fault detection and isolation methods (FDI) based on neural networks, shown in figure 1, which involves three basic principles that are waste generation, detection, localization.

The advantage of using neural networks in the case of the diagnosis decision is that they can build borders linear or nonlinear decision between the different classes in a non-parametric and offer a convenient method to solve the complex problems in the diagnosis decision. The combination function returns the scalar product of the input vector and the vector of the synaptic weights.

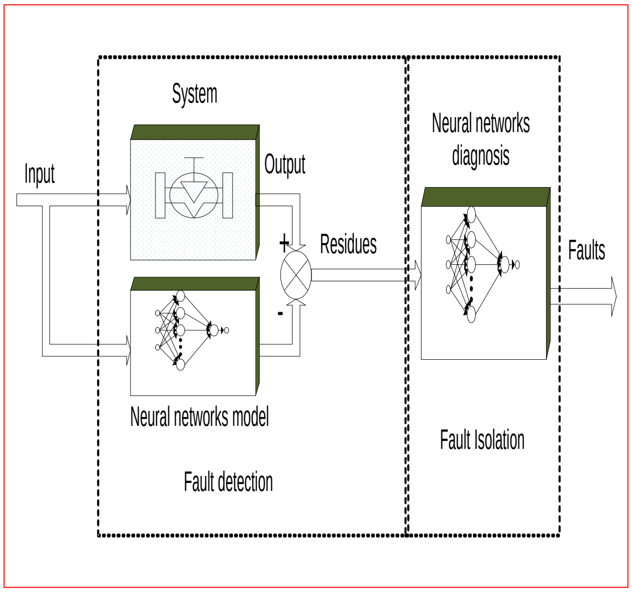

Fig. 1. Proposed fault detection and isolation methods (FDI) based on neural networks.

In other, it calculates the weighted sum of inputs according to the following expression:

$$a_j = \sum_{j=1,n} w_{ij} x_j \tag{1}$$

From this value, a transfer function (or the activation function) calculates the value of the neuron state. This will be sent to downstream neurons.

$$y_i = \varphi(a_i - \theta_i) \tag{2}$$

Neurons that are most frequently used are those for which the function is nonlinear (usually a hyperbolic tangent) linear combinations of inputs. For our application we chose a multilayer structure, but the activation function is a Gaussian type. The architecture of this network, its most commonly used learning rule error correction and rule by competitive learning. It can make be a learning that combines simultaneously supervised learning and unsupervised learning. This network has better performance than other networks, learning is faster and simpler are the tools of choice for many applications types (Feyzullah Temurtas, 2009; Orhan Er. *et al.*, 2010). However, this network, shown in figure 2, use the Gaussian function defined by the equation (3):

$$y_{i(x)} = \exp\left(\frac{-\|x - c_i\|^2}{\sigma_i^2}\right) \tag{3}$$

With c_i and σ_i respectively the center and the radius of the Gaussian function. The output of the network is as follows:

$$y = \sum_{i}^{k} \beta_i y_i \tag{4}$$

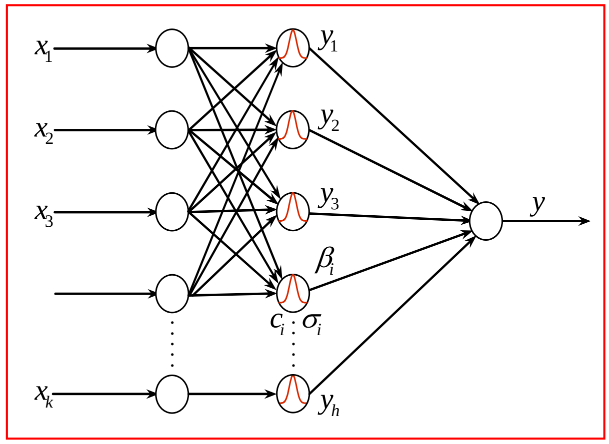

Fig. 2. Neural networks multilayer structure.

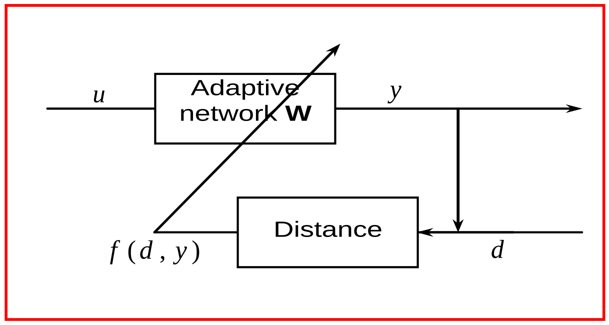

Fig. 3. Used supervised learning.

We dispose a learning database for our application, which contains a set of observation pairs associated inputs / outputs of the examined control valve. The weights are modified according to our desired output in the monitoring system. We use a learning rule to minimize the square error, given by the following equation:

$$E = \frac{1}{2}\sum_i (d_i - y_i)^2 = \frac{1}{2}\sum_i \left(d_i - \sum w_{ij} x_j\right)^2 \tag{5}$$

The gradient descent algorithm consists in changing each weight w_{ij} by an amount Δw_{ij} proportional to the gradient of the error:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = \eta \sum_i (d_i - y_i) x_i \tag{6}$$

In our investigation we used the diagnostic based models, shown in the following figure 4, which are based on the approach of residuals generation and evaluation. A generic way to construct a residue is to estimate the output $y(t)$ vector of the system.

The estimate $\hat{y}(t)$ is then subtracted from the output signal $y(t)$ to form the residuals vector $r(t)$ following:

$$r(t) = y(t) - \hat{y}(t) \tag{7}$$

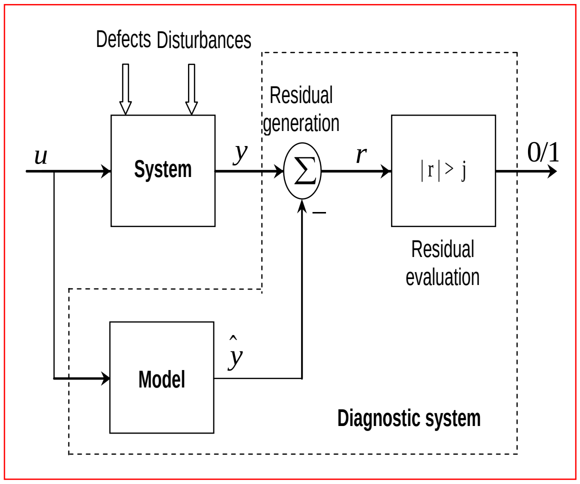

Fig. 4. Model-based diagnostic system structure.

3. INDUSTRIAL CASE STUDY

The examined system is a control valve mounted in the process boosting of the pumping station SP2 Biskra in Algeria. She mov222 reference in the installation diagram of the station, shown in figure 5. This control valves is used in the pumping station SP2 to ensure the leveling of the flow, have a vital interest in the protection systems in case of defects enormously dangerous.

3.1. Examined industrial control valve

The mass velocity u , which shows the amount of retraction of a mass passed through the unit cross section of the flow m^2 in time unit, we have :

$$\left.\begin{aligned} \Delta H &= \xi \frac{v^2}{2g} \\ V &= \frac{Q_V}{S} \end{aligned}\right\} \Rightarrow \Delta H = \xi \frac{Q_V^2}{S^2 2g} = \xi \frac{16 Q_V^2}{\pi^2 d^4 2g} \Rightarrow \Delta H = \xi \frac{8 Q_V^2}{\pi^2 d^4 g} \tag{8}$$

$$\left.\begin{aligned} \Delta H &= \frac{\Delta P}{\rho g} \\ \Delta H &= \xi \frac{8 Q_V^2}{\pi^2 d^4 g} \end{aligned}\right\} \Rightarrow \frac{\Delta P}{\rho g} = \xi \frac{8 Q_V^2}{\pi^2 d^4 g} \Rightarrow Q_V = \frac{\pi d^2}{\sqrt{8\xi}} \sqrt{\frac{\Delta P}{\rho}} \tag{9}$$

The empirical formula is $Q_V = 0{,}95.10^3 E d_0^2 \sqrt{\frac{\Delta P}{\rho}}$ (m3/days), if E = 0,8 ; d0 (mm); ΔP (N/m²), so we have $Q_V = 760 d_0^2 \sqrt{\frac{\Delta P}{\rho}}$. At the pressure P_e which deforms the elastic membrane spring system with a value x_0 , the state equilibrium is expressed by:

$$\sum \vec{F} = \vec{0} \Rightarrow P_e.s + mg - kx_0 = 0 \tag{10}$$

Any disturbance in the process varies the pressure acting on the actuator to a value ΔP_e . This change distorts the system diaphragm spring displacement A_x. According to the basic principle of dynamics is to:

$$\sum \vec{F} = M\vec{a} \Rightarrow$$

$$(P_e - \Delta P_e)\cdot s + m \cdot g - k(x_0 + \Delta x) - r\frac{d}{dt}(x_0 + \Delta x) = m\frac{d^2}{dt^2}(x_0 - \Delta x) \tag{11}$$

Therefore:

$$P_e \cdot s - \Delta P_e \cdot s + mg - k \cdot x_0 + k \cdot \Delta x - r\frac{d}{dt} \cdot x_0 - r\frac{d}{dt}\Delta x = m\frac{d^2}{dt^2} \cdot x_0 + m\frac{d^2}{dt^2}\Delta x \tag{12}$$

Taking into account the equation (10), and $X_0 = 0$, we have:

$$m\frac{d^2}{dt^2} \cdot \Delta x + r \cdot \frac{d}{dt}\Delta x + k \cdot \Delta x = \Delta P_e.s \tag{13}$$

$$\frac{m}{k} \cdot \frac{d^2}{dt^2} \cdot \Delta x + \frac{r}{k} \cdot \frac{d}{dt} \cdot \Delta x + \Delta x = \frac{s}{k} \cdot \Delta P_e \tag{14}$$

After the Laplace transform we have:

$$\frac{m}{k} \cdot S^2 \cdot \Delta x(S) + \frac{r}{k} \cdot S \cdot \Delta x(S) + \Delta x(S) = \frac{s}{k} \cdot \Delta P_e(S) \tag{15}$$

We put: $T_1 = \frac{m}{k}$; $T_2 = \frac{r}{k}$; $K_{van} = \frac{s}{k}$

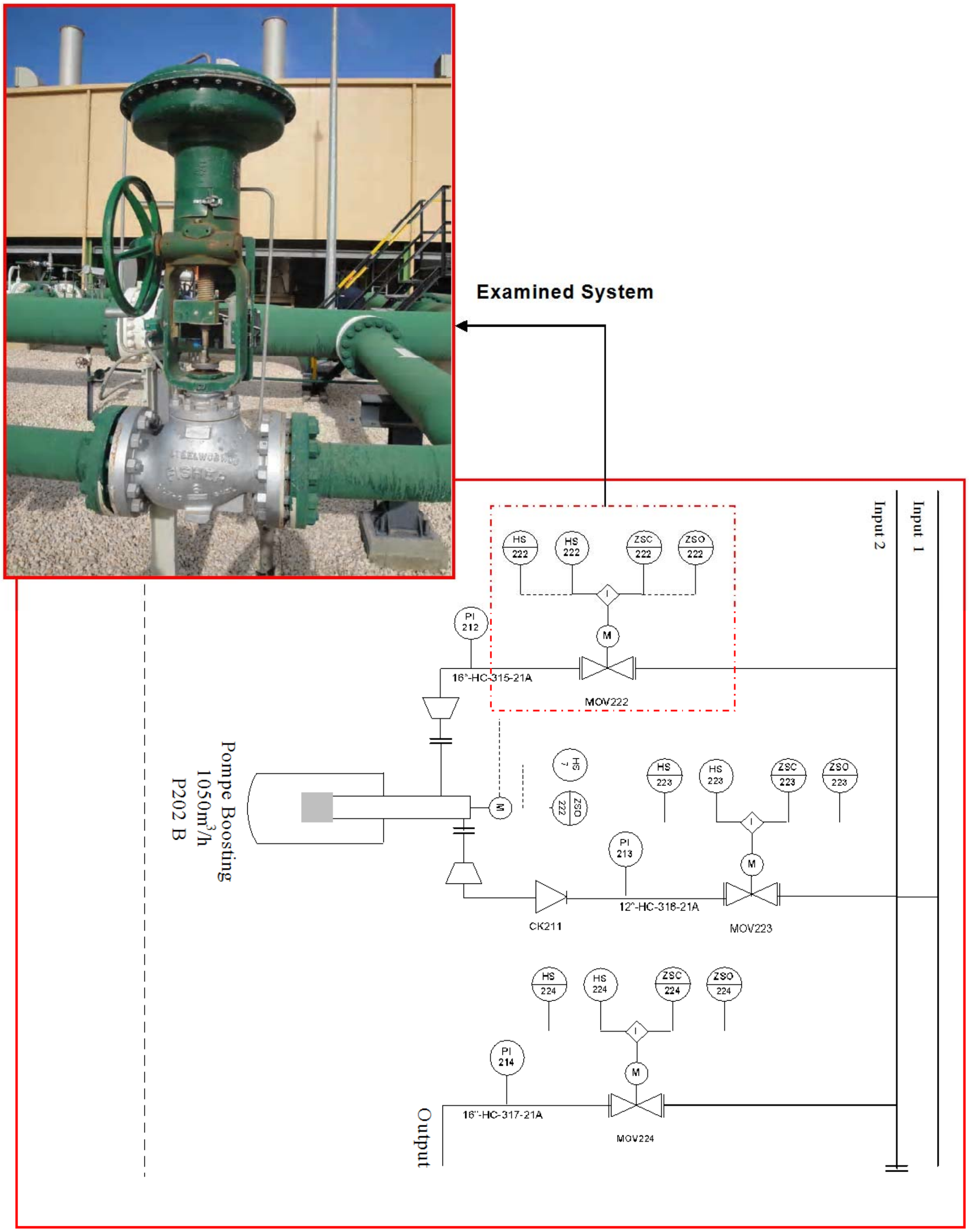

Fig. 5. Installation and pipe part of the pumping station SP2 Biskra, Algeria.

The used control valve function becomes:

$$F_{van}(S) = \frac{\Delta x(S)}{\Delta P_e(s)} = \frac{K_{van}}{T_1 \cdot S^2 + T_2 \cdot S + 1} \tag{16}$$

Partaical $T_1 \ll T_2$ so $\frac{m}{k} \ll \frac{r}{k}$ where $m \ll r$,

So we have:

$$F_{van}(S)=\frac{K_{van}}{T_{van}\cdot S+1}\cdot e^{-\tau s} \tag{17}$$

$$\text{With : } T_{van}=\frac{128\cdot\upsilon\cdot L\cdot\gamma}{\pi\cdot d^{2}\cdot R\cdot T} \quad , \quad K_{van}=\frac{Q_{\max}-Q_{\min}}{P_{\max}-P_{\min}}$$

$$\text{and } \tau=L\cdot\frac{\sqrt{\frac{x\cdot d\cdot g\cdot t\cdot\mu}{S\cdot e}+1}}{\sqrt{\frac{x\cdot p}{\mu}}}$$

To generate the residues were selected Feed-Forward network, for examine our control valve system. Our examined system contains four variables inputs and two outputs as these variables and these variations are more interesting to choose the architecture of neural networks which provides a good model and more effectively. We made several tests to get the good architecture to reflect the valve operation; these experiments are time consuming, as the choice of the number of hidden layers and number of neurons in layers. For learning we used is the back propagation learning. The function is called learning "train" function applied to the same type given in the first.

3.2. Experimental Results

To obtain these results must iterate '1000 'epochs (iterations) and purpose '0 .0001' learning in the two networks. The increased number of learning give better results but takes longer.

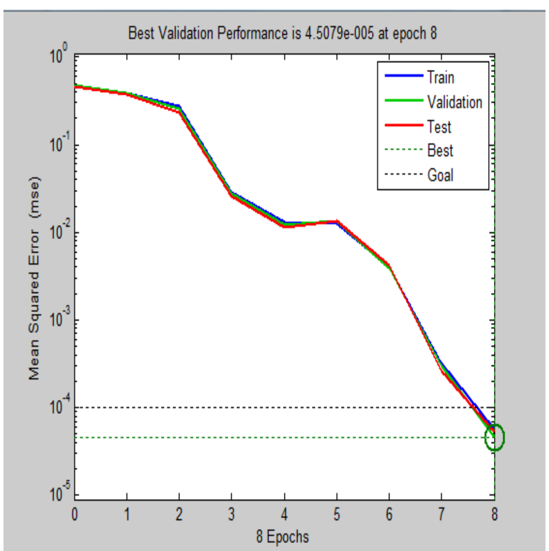

Fig. 6. The mean square error learning (Rx).

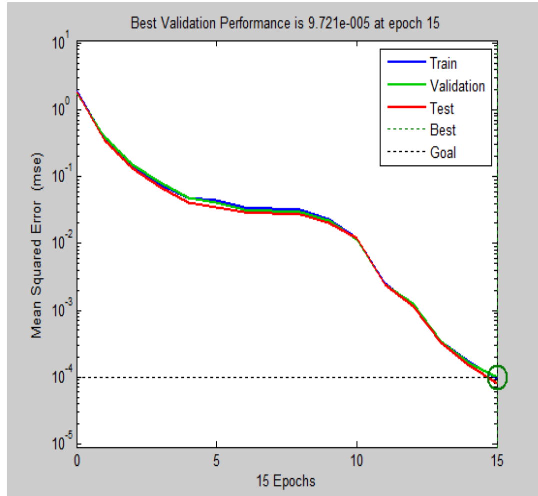

Fig. 7. The mean square error learning (Rd).

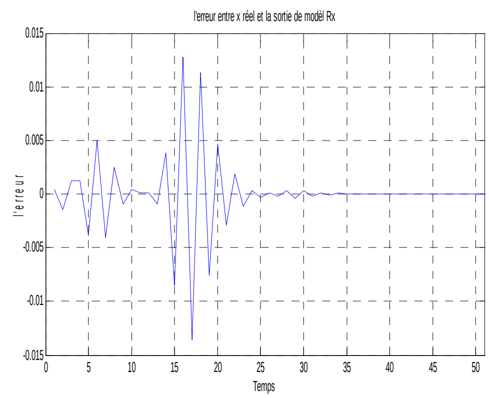

Fig. 8. The error between the actual model and Rx model.

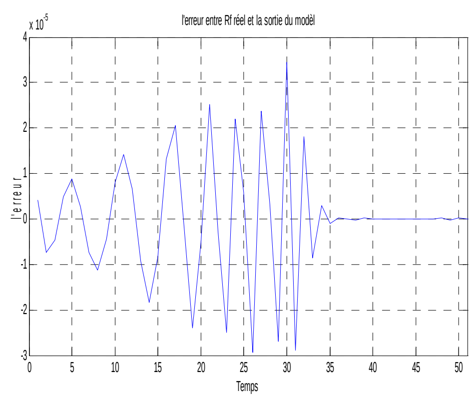

Fig. 9. The error between the actual model and Rd model.

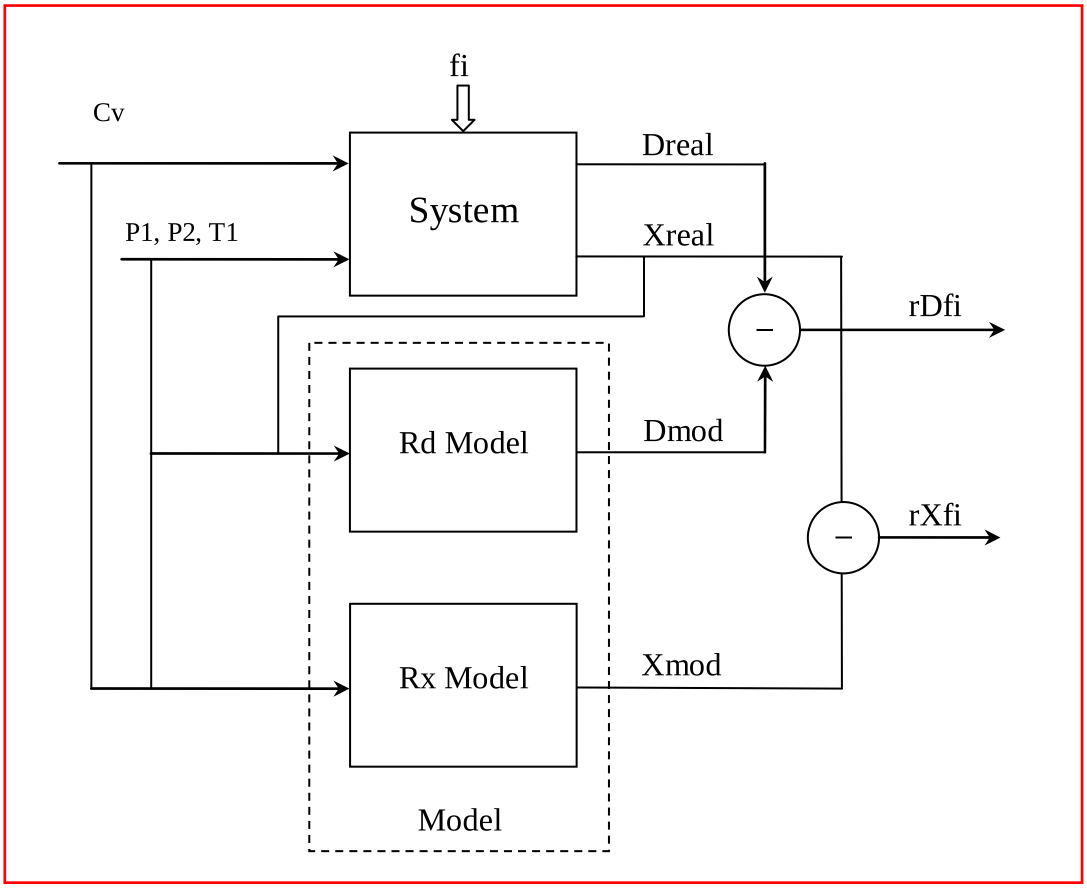

Fig. 10. Residuals generation using Rx and Rd models.

The obtained outputs (rXfi, rDfi) are presented in the figures 11, 12, 13 and 14.

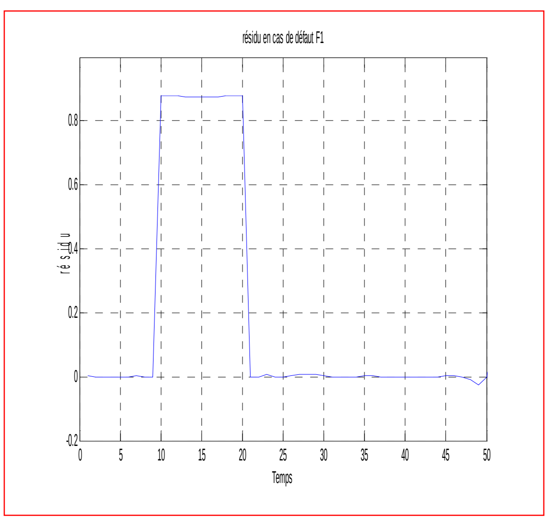

Fig. 11. Residues in default f1 four the output rXfi.

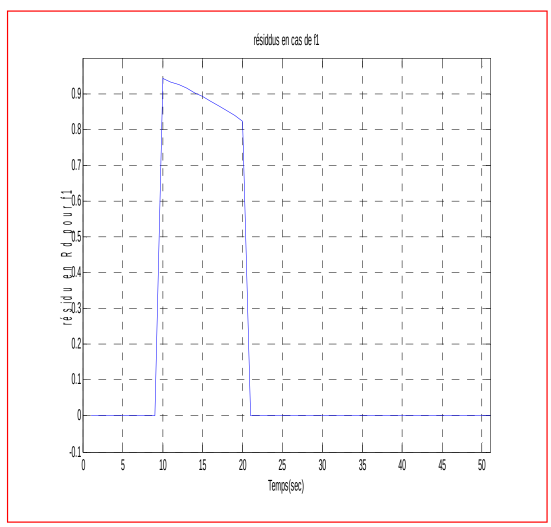

Fig. 12. Residues in default f1 four the output rDfi.

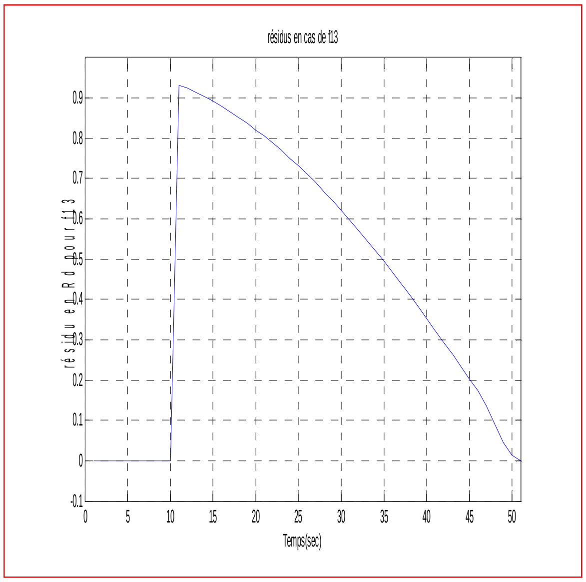

Fig. 13. Residues in default f13 four the output rXfi.

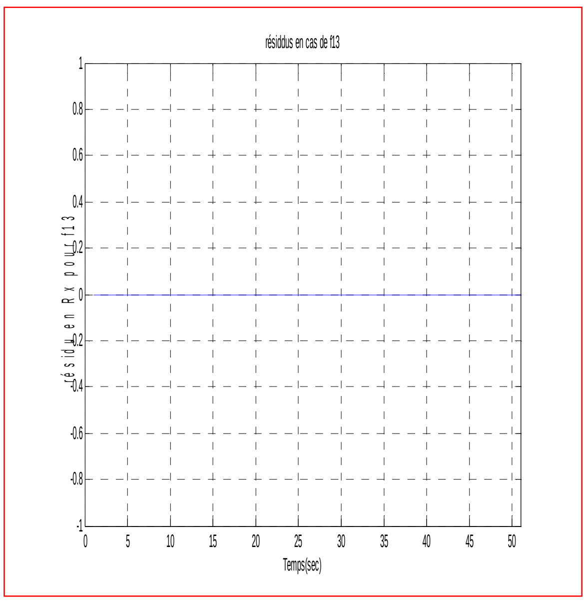

Fig. 14. Residues in default f13 four the output rDfi.

After the generation of residues and is survived evaluating these to diagnose faults which exist in the system. Residues provide information relevant to the diagnosis made in the second part of the work; we tested a classifier based on neural networks to classify these defects from such information.

The neural classifier consists of two MLP networks, each network with two inputs and two outputs, while learning these networks entries are residues (rXf1, rXf13, rDf1 and rDf13) and the outputs are defects (f1 and f13), and the classification outputs of the two networks, we added a gate to develop the fault.

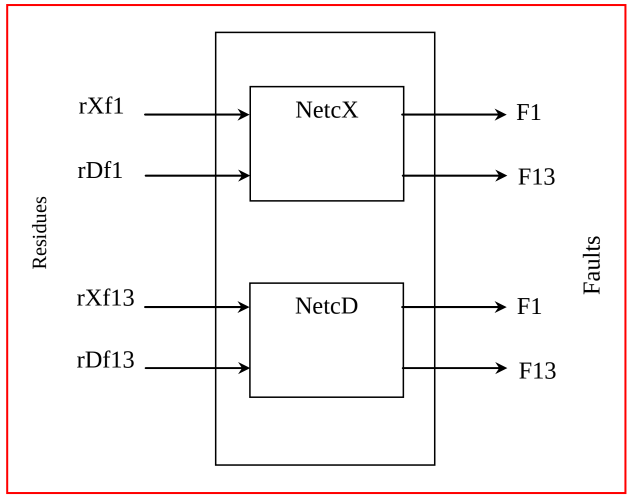

Fig. 15. Learning classifier data.

After the learning phase, we tested these two networks, the data with default. The outputs of the examined system are netcX if f1 defects, shown in figures 16 and 17.

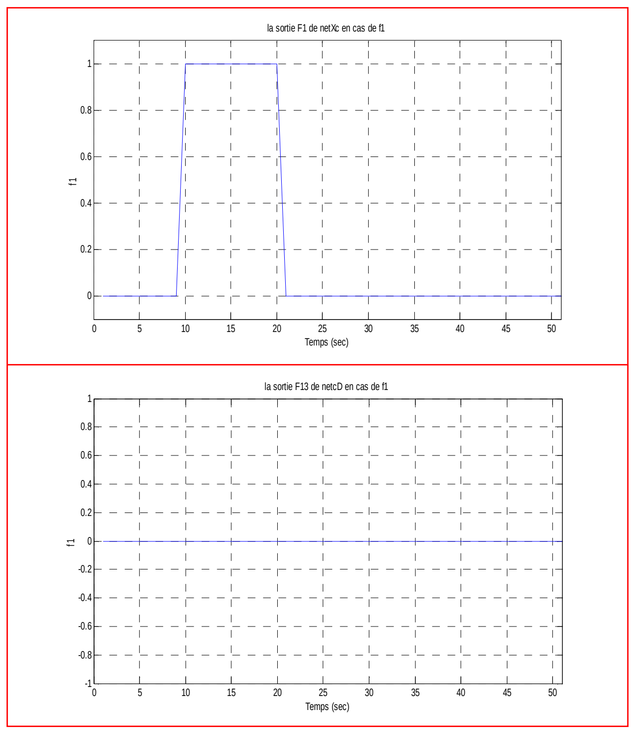

Fig. 16. Network outputs (netcX) for failure f1.

Neural networks are well suited to solving the problems of diagnosis, using the automatic classification of signals and shapes. In this context in our application, neural networks are used for fault diagnosis and isolation in industrial control valve.

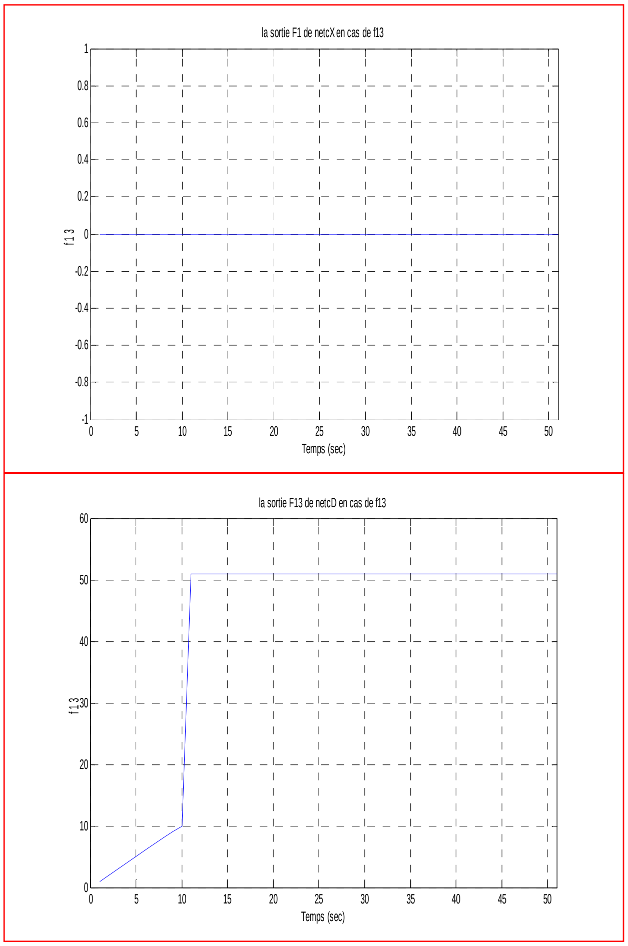

Fig. 17. Network outputs of r failure f13.

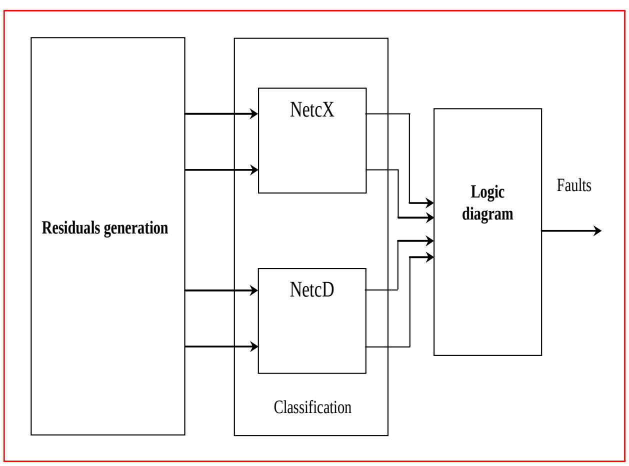

Fig. 18. Logic diagram of the network outputs (netcX and netD).

From the outputs of the classifier insert and use a logic gate, one can clearly infer the type of fault that occurs in our examined system.

4. CONCLUSION

The work presented in this paper focuses on the diagnosis of industrial systems. After the generation of residues and is survived assessment to diagnose these defects which exist in the system. Residues provide information relevant to the diagnosis made in the second part of the study; we simulated a detection based on neural networks to localize these defects from such information. In this work, we gave a neuronal model that reflects the operation of our industrial control valve system. We especially showed that the model was able to detect a fault and to locate the faulty phase.

REFERENCES

Chen Y.M., Lee M.L. (2002). Neural networks-based scheme for system failure detection and diagnosis. *Mathematics and Computers in Simulation*, vol. 58, no. 2, pp. 101-109.

Chii-Shang Tsai, Chuei-Tin Chang. (1995). Dynamic process diagnosis via integrated neural networks. *Computers & Chemical Engineering*, vol. 19, no. 1, pp. 747-752.

Djamel Halimi, Ahmed Hafaifa, Elahmoune Bouali and Mouloud Guemana. (2012). Vibrations detection and isolation in centrifugal pump used in petroleum industry using spectral analysis approach. *Archive of Sciences Journal*, vol. 65, no. 11, pp.234-245.

Feyzullah Temurtas. (2009). A comparative study on thyroid disease diagnosis using neural networks. *Expert Systems with Applications*, vol. 36, no. 1, pp. 944-949.

Hafaifa Ahmed, Mouloud Guemana and Attia Daoudi. (2012). Spectral analysis approach applied to the vibrations detection and isolation in centrifugal pump used in petroleum industry. Proceeding of the 5th International Congress on Technical Diagnostics, 3rd to 5th of September 2012, Didactics Center, 2012, Kraków, Poland.

Hafaifa Ahmed, Attia Daoudi and Kouider Laroussi. (2011a). Application of fuzzy diagnosis in fault detection and isolation to the compression system protection. *Control and Intelligent Systems*, vol. 39, no. 3, pp. 151-158.

Hafaifa Ahmed, Ferhat Laaouad, and Kouider Laroussi. (2011b). A Numerical structural approach to surge detection and isolation in compression systems using fuzzy logic controller. *International Journal of Control, Automation, and Systems*, vol. 9, no. 1, pp. 69-79.

Hafaifa Ahmed, Ferhat Laaouad and Kouider Laroussi. (2010a). Fuzzy approach applied in fault detection and isolation to the compression system control. *Studies in Informatics and Control (SIC)*, vol. 19, no. 01, pp. 17-26.

Hafaifa Ahmed, Ferhat Laaouad and Kouider Laroussi. (2010b). Fuzzy logic approach applied to the surge detection and isolation in centrifugal compressor. *Automatic Control and Computer Sciences*, vol. 44, no. 01, pp. 53–59.

Joseph McGhee, Ian A. Henderson, Alistair Baird. (1997). Neural networks applied for the identification and fault diagnosis of process valves and actuators. *Measurement*, vol. 20, no. 4, pp. 267-275.

Karpenko M., Sepehri N., Scuse D. (2003). Diagnosis of process valve actuator faults using a multilayer neural network. *Control Engineering Practice*, vol. 11, no. 11, pp. 1289-1299.

Karpenko M, Sepehri N. (2002). Neural network classifiers applied to condition monitoring of a pneumatic process valve actuator. *Engineering Applications of Artificial Intelligence*, vol. 15, no. 3–4, pp. 273-283

Leger R.P., Garland Wm.J., Poehlman W.F.S. (1998). Fault detection and diagnosis using statistical control charts and artificial neural networks. *Artificial Intelligence in Engineering*, vol. 12, no. 1–2, pp. 35-47.

Orhan Er, Nejat Yumusak, Feyzullah Temurtas. (2010). Chest diseases diagnosis using artificial neural networks. *Expert Systems with Applications*, vol. 37, no. 12, pp.7648-7655.

Shengwei Wang, Zhiming Jiang. (2004). Valve fault detection and diagnosis based on CMAC neural networks. Energy and Buildings, vol. 36, no. 6, pp. 599-610.

Yang S.H., Chen B.H., Wang X.Z. (2000). Neural network based fault diagnosis using unmeasurable inputs. *Engineering Applications of Artificial Intelligence*, vol. 13, no. 3, pp. 345-356.

Zhang J., Morris A.J, Montague G.A. (1994). Fault diagnosis of a cstr using fuzzy neural networks. *Annual Review in Automatic Programming*, vol. 19, pp. 153-158.