Faults Diagnosis by Neurons Networks Application on DAMADICS Benchmark

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***Abstract-* The automatic control of the failures becomes increasingly essential for cause of the weakness of the human operator. This work is an organization system of diagnosis faults, based on the technique of artificial intelligence "the networks of neurons", applied for DAMADICS Benchmark's model (Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems). This technique with its generalization capacities and memorizing, gives an effective tool for diagnosis.**

In the first part of this work, we studied the modeling of an industrial actuator; simulation gives an idea on the behavior of this actuator in normal operation. Then, we realized the diagnosis of faults containing model during abnormal operations by using a neuronal classifier.

Keywords: *Fault **D**iagnosis, **M**odeling, **R**esidual **G**eneration, **R**esidual **E**valuation, Neuronal **C**lassifier, Neuronal **N**etworks.*

I. Introduction

The industrial diagnosis with an imperative value in the objective, to put the light on unspecified industrial failures of the systems. Where, the first vocation is to detect and locate a failure of the industrial systems plays a paramount part to contribute by a fast or early detection of the faults.

The important for a speed to detect and locate a failure because of the needs for industry and the complexity of the systems calls upon techniques of artificial intelligence. These last occupied the great interest of the researchers; then containing the artificial intelligence, the task carried out by the operator or more precisely the maintenance became easier, which must only observe the systems of production; and the principal task with knowing the observation of the symptoms and the analysis of the data or interpretation of information is carried out by the system of diagnosis based on the artificial intelligence.[1]

The principal axis of our research resides in the diagnosis by the networks of artificial neurons. The networks of neurons artificial are an idea takes care, attracted research (this is undoubtedly due to the aptitude of this method to represent, to approximate and to generate that it nonlinear functions). [3].

The diagnosis actually fits in a more complete procedure indicated under the name of monitoring moreover; it is carried out by carrying out three quite distinct tasks: detection, localization and identification of the faults [4].

Detection of faults: Detection makes it possible to determine if the physical system functions normally and aims to announce the presence of a fault by comparing the behavior running of the system with that given for reference.

Localization of faults: the localization has as an aim the localization of a detected fault occurring on the actuators, the sensors of instrumentation, the order or the system ordered while indicating which body or component is affected by this one.

Identification of faults: the purpose of the identification is to characterize the fault in duration and amplitude to classify it by types and degrees of severity. Thus, it can be used for ensuring the follow-up of its evolution, which is extremely useful in the case of a change of slow behavior due to ageing and wear. Moreover, the identification can understand a procedure aiming at determining the cause of the fault, i.e. its origin.

Indeed, the bibliographical analysis showed that the RNA is largely used in the field of the diagnosis, because of their advantages and their simplicity. The first stage of a monitoring system containing model consists in generating indicators of faults. They contain information on the anomalies or dysfunctions of the system to be supervised. The principle is to measure the difference between measurements of the signals of the process, sensors or actuators, and the theoretical value provided by the model under nominal operating conditions. The generation of residues is a crucial problem for the systems of diagnosis (fig.1). Indeed, on the structure of the system of residues generated the robustness will depend on the localization.

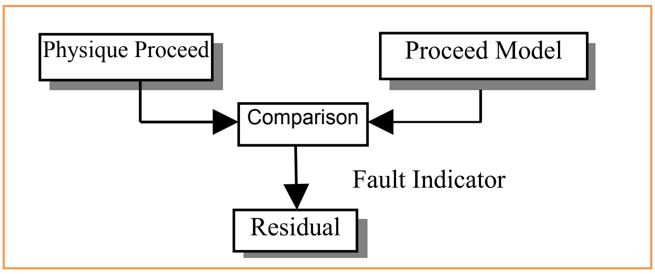

Fig.1. Residual Generation

II. GENERATION OF RESIDUES USING NEURONAL MODEL:

The techniques derived from this modeling are varied but not always effective. Indeed, the physical processes are very often complex dynamic systems, having strong non-linearties in their operation. Simplifications are essential to formulate an exploitable model. Thus, the techniques of linearization around a point of operation or the reduction of order are as many methods degrading the performances of the mathematical model. In the same way, other problems remain with certain parameters of the model measurable or variable in time [6]. Another approach lies in the neuronal modeling of the processes. The goal remains to design a neuronal model for the generation of residues. The concept general of the generation of residues remains the same one as for the analytical models. By analogy with the theory of the observers, the models neuronal generate observers neuronal. It consists in comparing the exits of the process with their estimated. But in this case, estimated are calculated by a neuronal model. The vector of residues r(t) east calculates by the difference between the vector exit of actuator y(t)and the vector exit of the neuronal model $\hat{y}$ (t) (fig.2) [6].

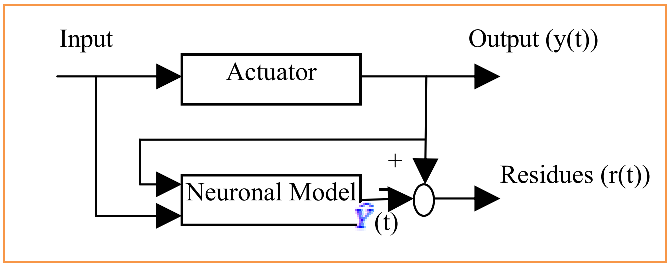

Fig. 2: Neuronal Observatory output for residual generation

III. NEURONS NETWORKS IN THE DIAGNOSIS OF FAULT:

The detection of fault based on the use of models can be divided into two principal stages:

The generation of residues and the decision-making. At the time of first stage, and the exit input signals of the system are use to generate a residue, i.e. a signal highlighting the presence of a fault. In general, in normal operation, this signal is statistically null and deviates notably from zero in the presence of faults. The generation of residues is specific to the method used. During second stage, residues are analyses to decide if there is or not presence of fault, on which component of the system it intervened (operation often called localization) and in certain cases, to determine the nature of the fault and its cause (identification). The decision can be carried out using a simple test of going beyond of threshold on the instantaneous values or moving average of the residues or call upon the statistical decision theory. This decision can also call upon the networks of neurons, [38]. From a point of view practices, the logic of decision has thresholds plays an important part because the majority of the quoted methods are brought back, in the long term, has a thresholding. If the selected threshold is constant, the unknown entries which excite the system disturb the decision. If the threshold is selected too small, many false alarms are observed and if it is too large, the faults of low amplitude are not detect. It is thus interesting to use adaptive thresholds which move according to the point's operation of the supervised process [38]. The advantage use of the network's neurons in the case of classification is that they can build or not linear borders of decision between the various classes in a nonparametric way and offer a practical method to solve the complex problems of classification. We are interested to the known methods under the name of FDI (Fault detection, insulation), which, as we saw, utilize the three guiding principles that are the generation of residues, detection, the localization. This method can be interpreted as indicates by (fig.3).

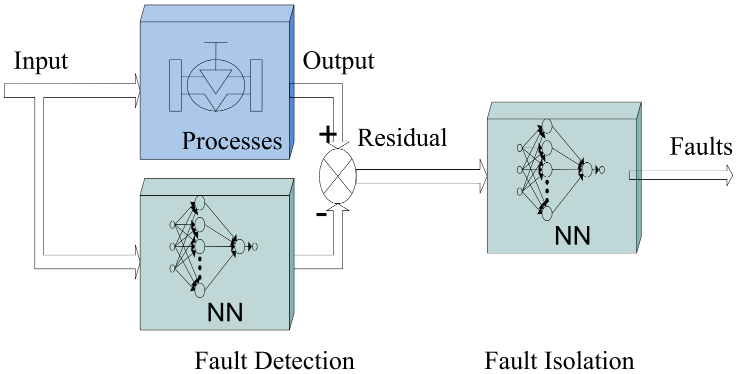

Fig.3: Structure methods FDI using NN

We have to take an electro pneumatic actuator for simulation, this actuator is a final element of order, called "Actuator simply" Fig.4. According to the operation of the actuator quoted in the work of Mr. 'Mrugalski and all' [3], we chose a model composed of two networks neuron, from including two following equations represented different the interaction between the entries and the exits:

$$X = Rx\ (CV, P1, P2, T1)$$
$$F = Rf\ (X, P1, P2, T1)$$

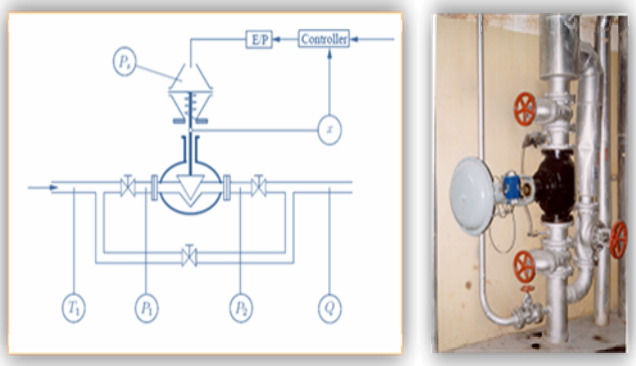

Fig.4. Descriptive Schema of actuator

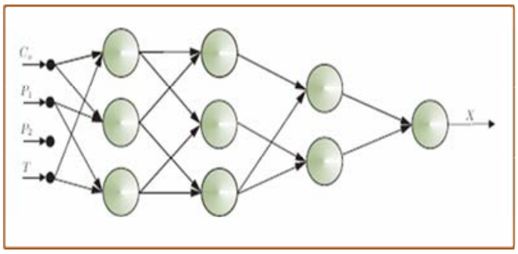

Fig.5: NN model (Rx)

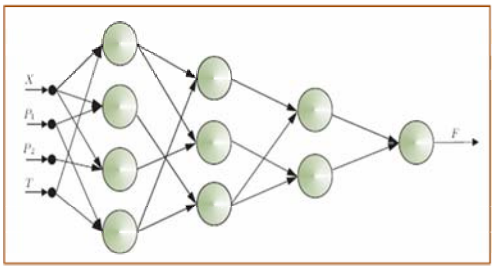

Fig.6: NN Model (Rf)

The real data are downloaded with the site [3], the latter contain the entries and the exits of real process such as they contain also exits with natural faults. One carried out several tests to obtain the architecture which simulates the operation of the actuator; these experiments take much time, such as the choice of the number of hidden layers and number it neurons by layers.

IV. Result of modeling:

The two tables according to gives some architecture tested for the modeling of this industrial system:

Table 2: networks (X-ray) optimal obtained.

NN (Rx)	Layer 1	Layer 2	Output layer	MSE
Operation 1	6	3	1	0.00033
Operation 2	10	8	1	0.00149
Operation 3	21	12	1	0.00491

Table 2: networks (X-ray) optimal obtained.

NN (Rf)	Layer 1	Layer 2	Output layer	MSE
Operation 1	6	3	1	0.000199
Operation 2	4	2	1	0.000849
Operation 3	8	4	1	0.00949

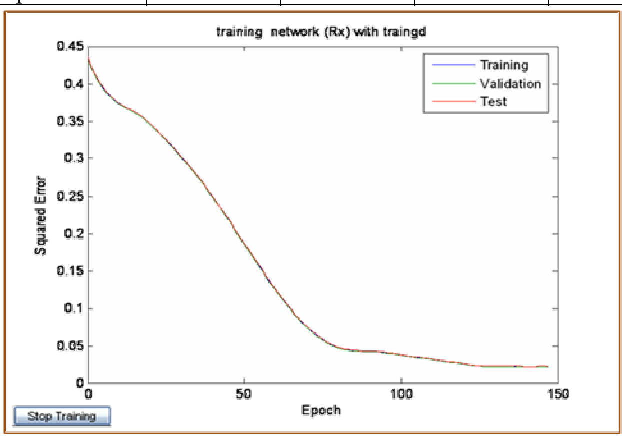

Fig.7. *square error* of learning for (Rx)

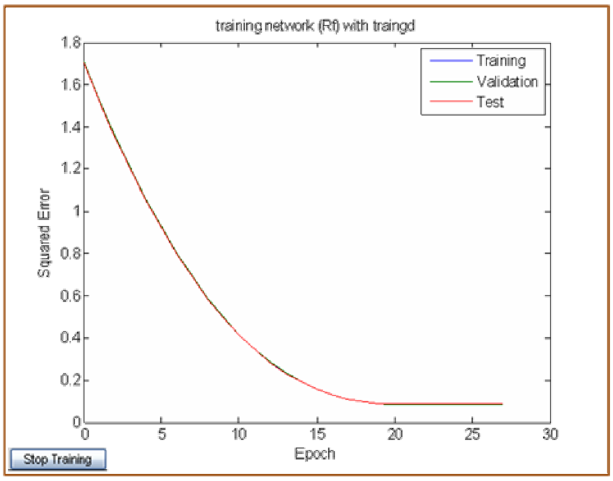

Fig.8. *square error* of learning for (Rf)

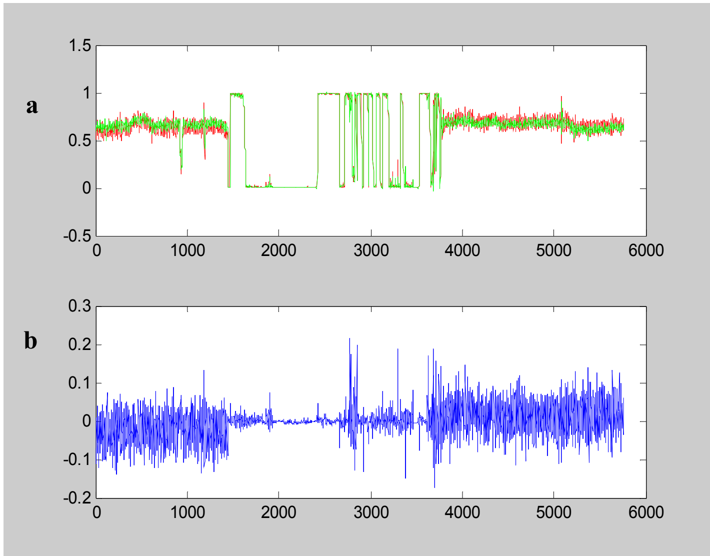

Fig.9: a. *The output of the Realized model (Rx) and X real*
b. *Error between the output of the Realized model (Rx) and X real*

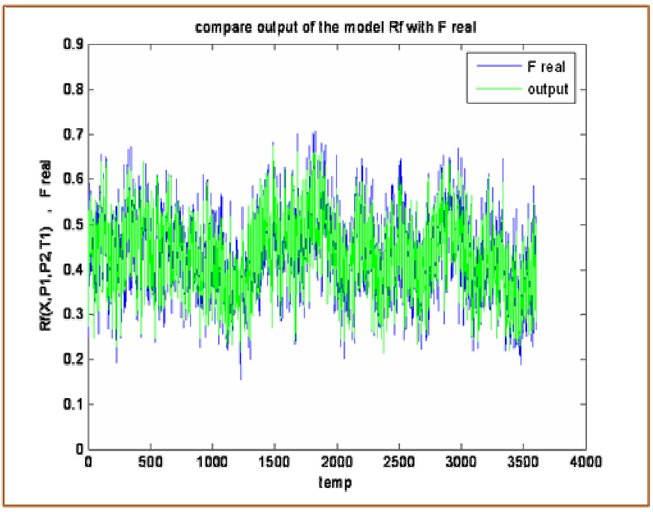

Fig.10. *The output of the model (Rf) and F real*

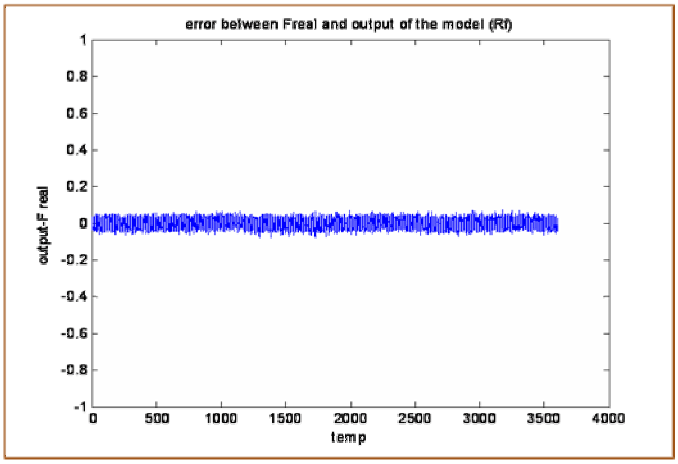

Fig.11. *Error between the output of the model (Rf) and F*

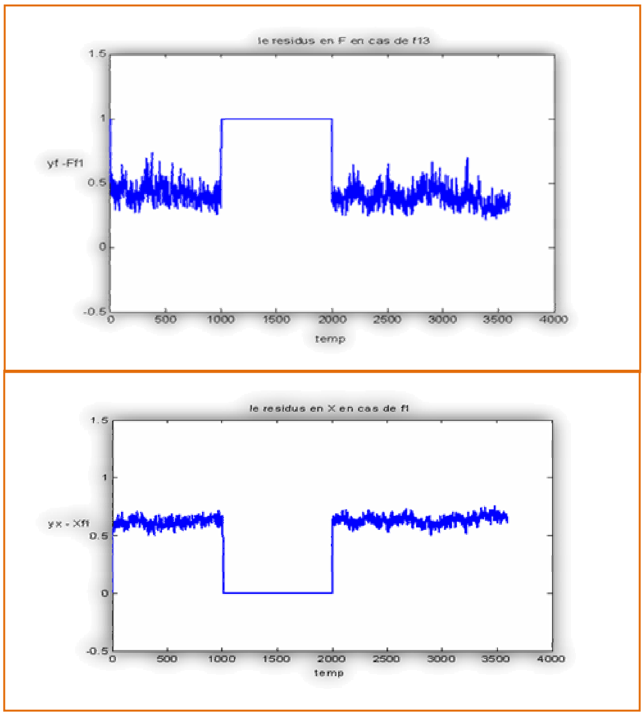

Fig.12. *The residues in case of defect f1*

V. THE EVALUATION OF THE RESIDUES:

After the generation of the residues there is remained the evaluation of the latter to diagnose the faults which exist in the system. The residues to give important information for fact the diagnosis, our second work are the classification of these faults from this information.

5.1 The Classification of the faults (Neuronal Classifier)

The neuronal classifier is composed of two networks of the type MLP, each network have two entries and two exits; with the training of these networks; these entries are the residues (rXf1, rXf13, rFf1 and rFf13) and these exits are the faults (f1 and f13), and for the classification the exits of the two networks, we added a logical door which work out the fault.

We realized several tests (training) to carry out this classifier, of these experiments; we give three optimal architectures in the following table:

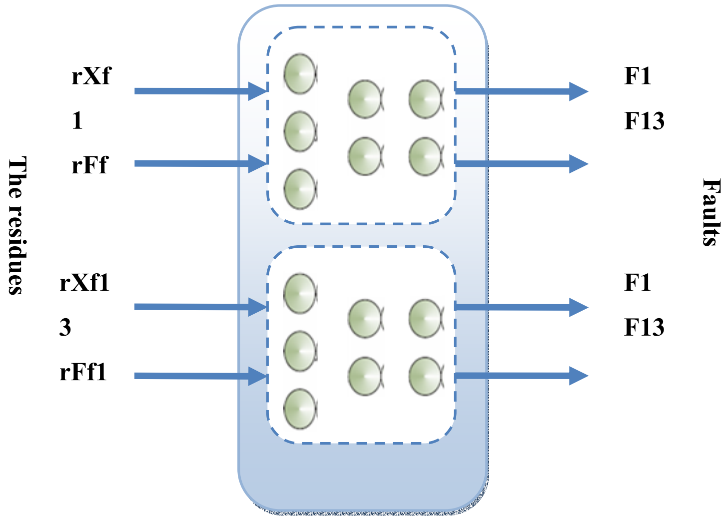

Fig.13. *the data of learning of the realized classifier Neuronal*

Table 5: Optimal networks obtained for the classifier

NN	Layer 1	Layer 2	Output	MSE
Netcx	2	2	2	0.00013
Netcf	2	3	2	0.000096

From the exits of the classifier, we can know the fault which to generate in the system; who's each exit, is a binary sequence takes the values “0” and “1” according to characteristics' of fault which to generate.

5.2 Establishment of the results: obtained with the training of networks “netcx” which evaluated the residues in the event of fault f1:

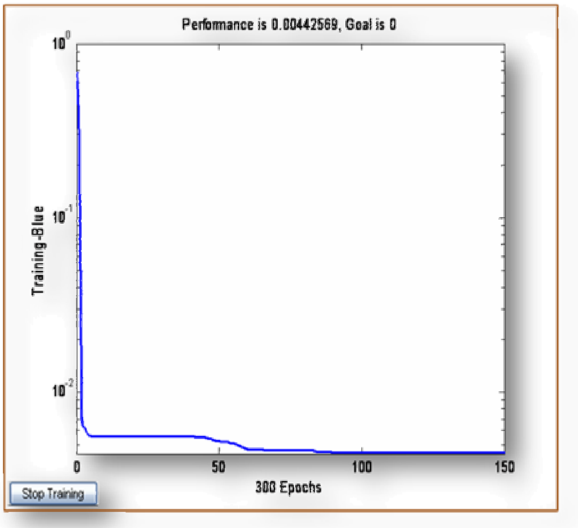

Fig.14. *Square Error of learning for (netcx)*

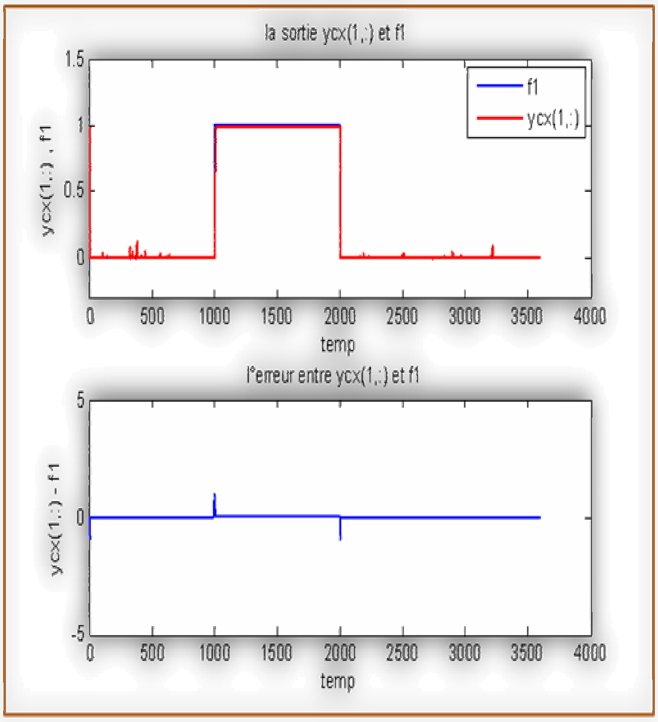

Fig.15. *The Output of (netcx)*

After the learning we tested these two networks, in the first place with the generation of f1

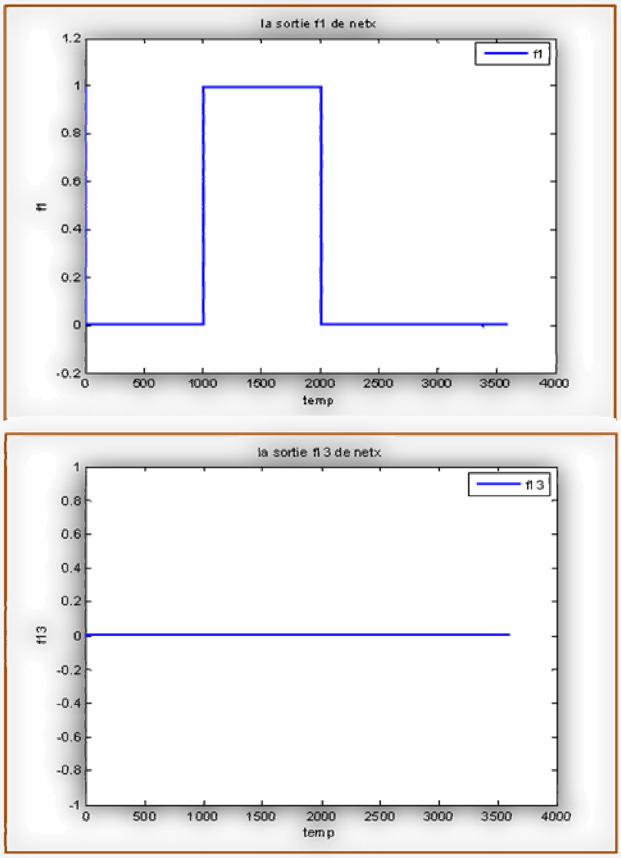

Fig.16. *The output of the NN (netcx) in case of defect f1*

VI. Conclusion

This article enabled us to present a model Neuronal of correct operation, extremely simple. This model is finally very close to the model of DAMADECS, already used for the ordering of this actuator. We especially showed that this model allowed:

1. To locate the phase at fault: it is enough for that to identify the type of fault.
2. To detect a fault: it is enough to supervise the value of leaving neuronal classifier. Lastly, the good correspondence enters the results obtained starting from the signals synthetic and experimental allowed to validate the use of the model's simulation in the objective of the diagnosis.

Finally certain technical points remain to be analyzed in future work. The networks of neurons constitute excellent tools for modeling and diagnosis of the nonlinear processes, but the problem which we have meeting in the memory is the choice of an optimal architecture according to the entries, which they owe relevant, thus the number of layer, and numbers neurons in each layer, the choice of an effective algorithm to ensure convergence towards the minimum, the choice of the weights and skews initial, that they have a great influence on the convergence of the algorithm, and the step of training which exploits an important part, the speed of convergence.

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