A New Approach for Industrial Diagnosis by Neuro-Fuzzy systems: Application to Manufacturing System

[a] Rafik Mahdaoui, Hayet Mouss, [c] Djamal Mouss

[a,b,c] Laboratoire d'Automatique et Productique (LAP) Université de Batna

1, Rue Chahid Boukhlouf 05000 Batna,Algeria.

[a] mahdaoui.rafik@yahoo.fr, [b] hayet_mouss@yahoo.fr, [c] d_mouss@yahoo.fr

Abstract

In this study we propose a strategy for the follow-up of the process behavior and detection of failures. An approach of industrial diagnosis based on the statistical pattern recognition Neuro-Fuzzy being based on a digital representation and symbolic system of the forms is implemented. Within this framework, data-processing interactive software of simulation baptized NEFDIAG (NEuro Fuzzy DIAGnosis) version 1.0 is developed. This software devoted primarily to creation, training and test of a classification Neuro-Fuzzy system of industrial process failures. NEFDIAG can be represented like a special type of fuzzy perceptron, with three layers used to classify patterns and failures.The system selected is the workshop of SCIMAT clinker , cement factory in Algeria.

Keywords: Diagnosis; artificial neuronal networks; fuzzy logic; Neuro-fuzzy systems; pattern recognition; FMEAC.

1. Introduction

The function of diagnosis is a very complex task and can be only one part solved by the technique of pattern recognition (PR). The diagnosis by PR can be presented as an alternative solution at the model approach since the operating modes are modeled, in an analytical manner, but by using only one whole of measurements of these operating [8]. Therefore the human expert in his mission of diagnosing the cause of a failure of a whole system uses quantitative or qualitative information. On another side, in spite of the surprising results obtained by the ANN in monitoring, and precisely in diagnosis, the results remain far from equal human sensory capacities and reasoning. Fuzzy logic provides another very effective technique in industrial diagnosis.

Also, can we entirely replace the human expert for automating the task of diagnosis by using the neuro-fuzzy approach? In addition, how did the human expert gather all relevant information and permit him to make their decision? Our objective consists of the following: making an association (adaptation) between the techniques of fuzzy logic and the neural techniques (Neuro-fuzzy system), choosing the types of neural networks, determining the fuzzy rules, and finally determining the structure of the Neuro-Fuzzy system to maximize the automation of the diagnosis task

In order to achieve this goal we organize this article into three parts. The first part presents principal architectures and principles for Neuro-Fuzzy systems operation and their applications (sections 2 and 3). The second part is dedicated to the workshop of clinker on the level of cement factory (section 4). Lastly, in the third part we propose a Neuro-Fuzzy system for system of production diagnosis (section 5).

2. Neuro-Fuzzy systems

The hybrid systems which combine fuzzy logic, genetic algorithms, neural networks, and expert systems prove their effectiveness in a variety of real world problems and in industry. Each intelligent technique has particular properties (for example capacity of training, explanation of decisions). Each technique is appropriate to solve particular problems.

As an example, neural networks for example are used for the recognition of the models. However, they are unable to explain how they reach their decisions. Therefore for the fuzzy logic using information and can explain their decisions still cannot automatically acquire the rules they

use action to make these decisions. These limits were a reason behind the creation of intelligent hybrid systems where, two or more techniques are combined in order to overcome the limitations of only one technique.
In order to summarize the contribution of the Neuro-Fuzzy systems, Table 1 gathers the advantages and the disadvantages of fuzzy logic and ANN.

Table 1

Comparing neural networks and fuzzy systems

Neural network	Fuzzy system
Black box.	Rules must be available.
No mathematical process model required.	No mathematical process model required.
Rules cannot be extracted.	Rules must be available.
Prior knowledge cannot be used	Prior knowledge can be used.
(Learning from scratch).	Cannot learn.
No guarantee that leaning convergence.	Tuning may be not successful.
	Simple implementation and interpretation.
Different learning algorithms	

The applications show the advantages of fuzzy logic when the model of the systems is difficult to implement. Unfortunately, with the increase in the complexity of the process model, we encountered a difficulty to develop fuzzy rules and membership functions.
This difficulty led to the development of another approach which is similar to Neuro-fuzzy approaches. The integration of the neural networks and the fuzzy inference systems can be grouped in three principal categories: cooperative, concurrent and hybrid Neuro-Fuzzy [5]. As, one can say as the Neuro-Fuzzy systems are models of connection which allow the training like a Artificial Neural Network, but their structure can be interpreted like a set of fuzzy rules.

2.1 Definition

A hybrid Neuro-Fuzzy System is a neural network with a fuzzy signal, fuzzy weights, a fuzzy transfer function and a module of adaptation of the structure of NFS by a training of set of data [7].

2.2 Principle of function

The hybrid Neuro-Fuzzy Networks learn from scratch and formulate the models by using an algorithm of supervised training that examines the data in a data set which is comprised of examples of inputs and their associated outputs.
During the phase of training, a hybrid Neuro-Fuzzy system modifies its internal structure to reflect the relationship between the inputs and the outputs in the set of the measurements (knowledge bases). The accuracy of a Neuro-Fuzzy Network is checked after the cycle of training is complete by using a separate input set and outputs called the validation.

2.3 The Fuzzy Perceptron

The architecture of the fuzzy perceptron is identical to that of the usual multi-layer perceptron, but the weights are modeled by fuzzy sets. Activations, inputs, and the functions of propagation will be changed. The functioning of this model is interpretable by linguistic rules and uses knowledge bases of the rules a priori, therefore the training can not start at zero (the rule base is not empty), «Fig. 1» illustrates a fuzzy perceptron with *N* inputs, *M* fuzzy rules and *P* outputs. The neurons of the first layer carry out the first phase of the fuzzy inference. With each observation, the neurons of the first layer of input are tasked to calculate the degrees of membership of the fuzzy variables to the various subsets of linguistic terms. The function of membership uses the symmetrical triangular function. The neurons of the second layer calculate the degree of truth of the antecedents of the fuzzy rules via T-norm.
The number of neurons of this layer is equal to the basic size of rules. A total connection between the first layer and the second layer can exist because the connections are not constrained by the structure of the linguistic rule. The output values of the third layer are the maximum of the activation values of all the rules units that are associated within a class.
In order to implement this type of fuzzy perceptron architecture for diagnosing a dedicated production system we developed the data-processing software NEFDIAG.

3. Description of NEFDIAG.

3.1 Introduction

NEFDIAG is a data processing program for interactive simulation. The NEFDIAG development was carried out within LAP (University of Batna), written under DELPHI, and was primarily dedicated to the creation, the training, and the test of a Neuro-Fuzzy system for the classification of the breakdowns of a dedicated industrial process. NEFDIAG models a fuzzy classifier *Fr* with a whole of classes $C = \{c_1, c_2 ...... c_m\}$.
The structure and training of NEFDIAG can be represented using a special type of fuzzy perceptron, with three layers used to classify failures.
NEFDIAG makes it's training by a set of forms and each form will be affected (classified) using one of the preset classes. Next NEFDIAG generates the fuzzy rules by:

evaluating of the data, optimizing the rules via training and using the fuzzy subset parameters, and partitioned the data into forms «characteristic» and classified with parameters of the data. NEFDIAG can be used to classify a new observation. The system can be represented in the form of fuzzy rules

If symptom1 is A_1
Symptom2 is A_2
Symptom3 is A_3
Symptom $_N$ is A_n
Then the form (x_1, x_2, x_3..., x_n) belongs to class «Failure mode 1».

For example A1 A_2 A_3 A_n are linguistic terms represented by fuzzy sets. This characteristic makes it possible to complete the analyses on our data, and to use this knowledge to classify them. The training phase of the networks of artificial Neuro-Fuzzy systems makes it possible to determine or modify the parameters of the network in order to adopt a desired behavior. The stage of training is based on the decrease in the gradient of the average quadratic error made by network RNF.
The NEFDIAG system typically starts with a knowledge base comprised of a collection partial of the forms, and can refine it during the training. Alternatively NEFDIAG can start with an empty base of knowledge. The user must define the initial number of the functions of membership for partitioning the data input fields. And it is also necessary to specify the number K, which represents the maximum number of the neurons for the rules which will be created in the hidden layer. The principal steps of the training algorithm.

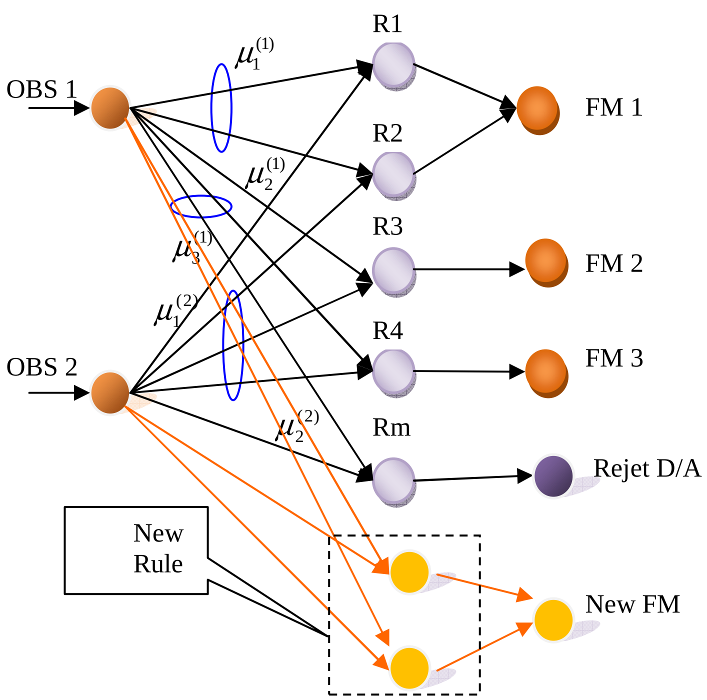

Fig. 1. *Neuro-Fuzzy Architecture*

Initialization: For each data originating from the sensors there is an input unit, and for each mode of failure there is an output unit. For each input unit there is an initial fuzzy partition specified with number of the of triangular membership functions.

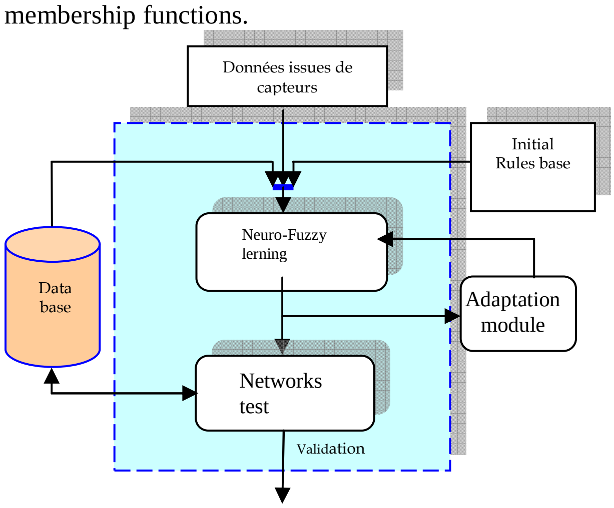

Fig. 2. *Neuro-Fuzzy learning phases.*

Training of the rules:
As mentioned, the NEFDIAG system starts with a base of knowledge comprised of a partial of forms, and can refine the knowledge base during the training «Fig. 3». The rule will be created by analyzing (for a given form F) the combination of the functions of membership, such as each combination producing the greatest function of membership «Fig.3 ». If this combination is not identical for the rules that exist in the rules knowledge base, and number of rules is not maximum, then new rules will be created and added to the rules knowledge base « Fig. 1»,

$$\varepsilon_r = \tau_r(1-\tau_r)\frac{1}{m}\sum_{j=1}^{m}(2v_r^{(j)}(t_j)-1)\left|E_j\right| \qquad (1)$$

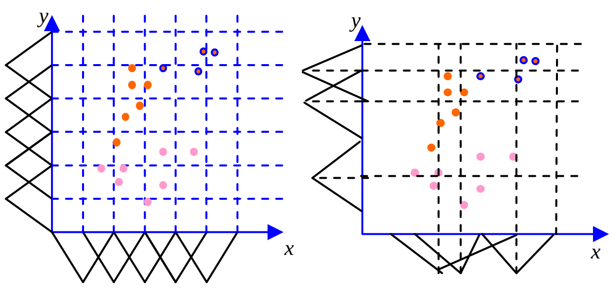

Fig. 3. *Neuro-Fuzzy learning rules.*

The algorithm of training detects determines all the antecedents of the rules, and then creates the list of the antecedents. Initially this list is empty, or contains antecedents of rules of knowledge a priori. The algorithm selects then antecedent A and seeks to create the basic list of rule candidates. The best rules will be selected from the knowledge base of the rules candidates, based upon their measurement of performance [7].

$$P_R = \frac{1}{s} \sum_{(p,t)\in\Gamma} (-1)^c R(p) \qquad (1)$$

In this case some classes (mode of failure) would not be represented in the knowledge base of rules, especially if the rules for this mode of failure represent a value of very small performance.

Training of the Functions of Membership:

For the training of the membership functions, a simple reverse propagation technique is used. It depends on the error of output for each **unit** of rules. Each rule changes its membership functions by the amount of change in their supports « fig. 7 ».

It is necessary that the error of each rule is calculated [5].

τ_r is fulfillment of a rule *r*.

After the appearance of a new mode of failure in the training phase of our system, the Neuro-fuzzy network will make an adaptation or a reorganization of the system to adapt to the new situation «Fig. 2».

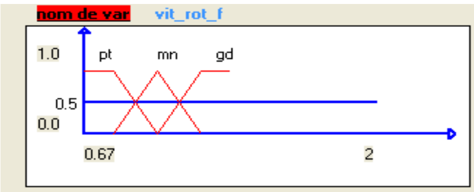

Fig. 4. *V_R_F before training*

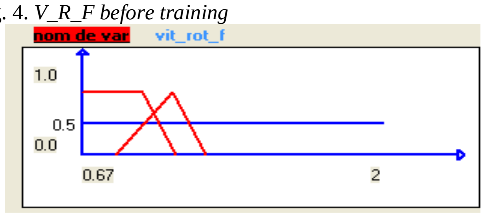

Fig. 5. *V_R_F after training*

Initially the layers of rules (or rules bases) will be added all rules for failure mode detected. Then in the layer of the modes of failure, another node will be connected to the Neuro-Fuzzy network «fig.7 »

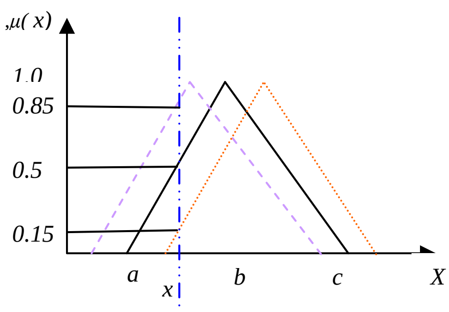

Fig. 7. *The training of membership function*

4. The workshop of clinker

Our application is illustrated on an industrial process for the manufacture of cement. This installation is at the cement factory. This cement factory has a capacity of 2.500.000 t/year Two furnaces comprised of several units determine the various phases of the manufacturing process of cement. The cooking workshop gathers two furnaces whose flow clinker is 1560 t/h. The cement crushing includes two crushers that are each rated 100t/hour. Forwarding of cement is carried out from two stations, one for the trucks and another for the coaches «Fig.6, ".

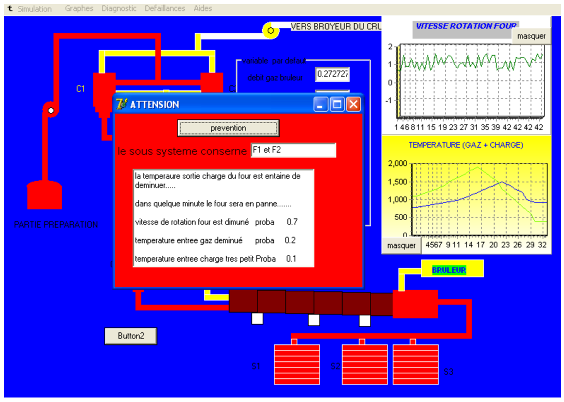

Fig.. 6. *Alarm message.*

5. Neuro-Fuzzy diagnosis

5.1 Dysfunctions analyses

This step has an objective of the identification of the dysfunctions which can influence the mission of the system. This analysis and recognition are largely facilitated using the structural and functional models of the installation. For the analysis of the dysfunctions we adopted the method of Failure Modes and Effects Analysis and their Criticality (FMEAC). While basing itself on the study carried out by [6], on the cooking workshop, we worked out an FMEAC by considering only the most critical modes of the failures (criticality >10), and for reasons of simplicity [6]. Therefore we have a Neuro-fuzzy system of 27 inputs and 4 outputs which were used to make a diagnosis of our system. The rules which are created with the system are knowledge a priori, a priori the base of rule. Each variable having an initial partition will be modified with the length of the phase of training (a number of sets fuzzy for each variable). The reasoning for the diagnosis is described in the form of fuzzy rules inside our Neuro-fuzzy system.

The principal advantage of the use of the base of fuzzy rules lies in its modularity and its facility of expansion (suppression or addition of other rules). The initial rules base to establish the diagnosis of the failures is built by evaluating the model worked out during dysfunction phases of our system (FMEAC). Indeed, this analysis makes it possible to establish the bonds between the components failing and the symptoms observed. These bonds are represented as of fuzzy rules, in turn building the knowledge base that will be trained and later tested, and finally used to carry out the fuzzy reasoning necessary to lead to the results expressing the function of diagnosis.

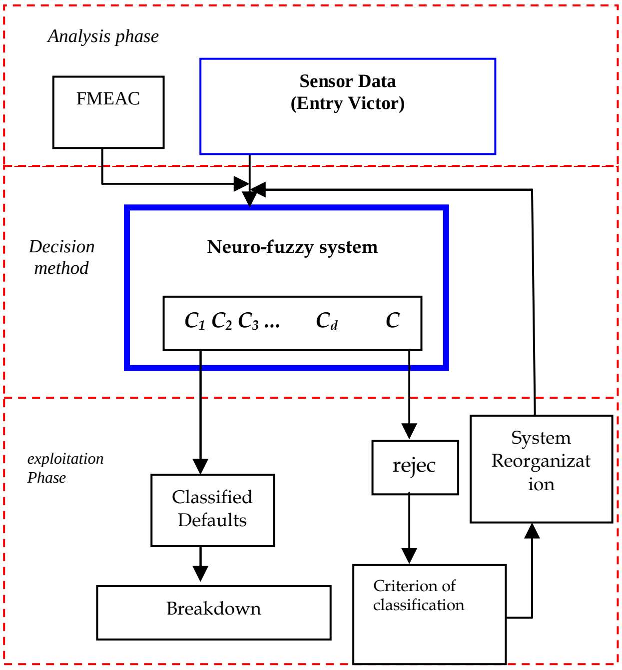

Fig. 7. *The diagnosis by NEFDIAG.*

The detection of anomalies is represented in the form of an alarm message announces to the operator (user) the appearance of an anomaly (or anomalies) and makes it possible to identify the component responsible using a data base containing the information provided by the FMEAC (mode of failure, possible causes, equipment, effects on the system).

Fig. 2 illustrates the system with the presence of a dysfunction in the cooking workshop. Let us note that in this study, the anomalies or dysfunctions indicate functional anomalies.

After the posting of the message, the operator can save the message or to remove it « Fig. 6». Additionally, NEFDIAG makes interventions to control the variables which are the origin of the current failure « Fig. 8»

6. conclusion

In this article, we presented a new tool for diagnosis by Neuro-Fuzzy systems using FMEAC; we detailed the implementation of an example of industrial application using the NEFDIAG tool. We illustrated our assistance tool to the diagnosis using a prototype NEFDIAG installed on a PC. We approached the various stages to be followed for the development of the assistance system for diagnosis, starting from the methods of classification and fuzzy recognitions of the forms. NEFDIAG is represented like a special type of fuzzy perceptron, with three layers used to classify failures (Type 3). NEFDIAG accomplishes training in two phases. The training phase generates the fuzzy rules using the collection of data, optimizes the rules using the parameters of the fuzzy sets, and finally uses the fuzzy sets for partitioning and classifying the form data and their parameters.

References

[1] H.K. Kwan and Y.Cai, " A fuzzy neural network and its application to pattern recognition" IEEE Transactions on Fuzzy Systems, 3 pp. 185-193. 1994

[2] J.-S. Roger Jang" ANFIS: Adaptive-network-based fuzzy inference system " *IEEE* Trans. Syst., Man, and Cybernetics, 23(1993) 665-685.

[3] J.M. Keller and H.Tahani "Implementation of conjunctive and disjunctive fuzzy logic rules with neural networks" International Journal of Approximate Reasoning,6(1992) 221-240.

[4] G. Zweingelstein " Diagnostic des défaillances, théories et pratique pour les systèmes industriels " Col. Traité des nouvelles technologies, séries diagnostic et maintenance, Hermès ,1995.

[5] L.-X wang and J.M Mendel "Generation fuzzy rules by learning from examples" IEEE trans. Syst., Man, and Cybernetics, (1992) 22(6):1414-1427.

[6] D. Mouss "Diagnostic et conduite des systèmes de production par approche a base de connaissances " Thèse de doctorat Université de Batna, 2006.

[7] D. Nauck "Neuro-fuzzy systems: review and prospects"European congress on intelligent technique and sift computing (EUFIT'97), Aachen, sep.8.11, (1997), pp.1044-1053.

[8] D. Racoceanu "contribution à la surveillance des systèmes de production en utilisant les techniques de l'intelligence artificielle" habilitation à diriger des recherches, université de Franche Comté de Besançon, 2006.