TEMPORAL NEURO-FUZZY SYSTEMS IN FAULT DIAGNOSIS AND PROGNOSIS

Mahdaoui Rafik , Mouss Hayet Leyla, Mouss Djamel , Chouhal Ouahiba

Laboratoire d'Automatique et Productique (LAP) Université de Batna,
1, Rue Chahid Boukhlouf 05000 Batna, Algérie
Centre universitaire Khenchela Algérie,
Route de Batna BP:1252, El Houria, 40004 Khenchela Algérie

mehdaoui.rafik@yahoo.fr, chouhal_wahiba@yahoo.fr, hayet_mouss@yahoo.fr, moussdj@yahoo.fr

ABSTRACT
Fault diagnosis and failure prognosis are essential techniques in improving the safety of many manufacturing systems. Therefore, on-line fault detection and isolation is one of the most important tasks in safety-critical and intelligent control systems.

Computational intelligence techniques are being investigated as extension of the traditional fault diagnosis methods. This paper discusses the properties of the TSK/Mamdani approaches and neuro-fuzzy (NF) fault diagnosis within an application study of an manufacturing systems. The key issues of finding a suitable structure for detecting and isolating ten realistic actuator faults are described.

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 of Ain Touta " Batna, Algeria ".

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

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, not analytical manner, but by using only one whole of measurements of this modes [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 results largely surprising obtained by the ANN in monitoring and precisely in diagnosis they remain even enough far from equalizing the sensory capacities and of reasoning human being. Fuzzy logic makes another very effective axis in industrial diagnosis.

Also, can we replace the human expert for automating the task of diagnosis to 100%, by using the neuro-fuzzy approach? And How made the human expert to gather all information allowing him to learn its decision? Our objective consists to make an association (adaptation) techniques of fuzzy logic with the neuronal techniques (a system Neuro-fuzzy), to choose the types of networks of neuron, to determine the fuzzy rules and finally the structure of the system Neuro-Fuzzy to automate the maximum of the task diagnosis.

In order to achieve this goal we organize this article thus. The first part presents principal architectures and principles Neuro-Fuzzy systems operation and their applications. The second part is dedicated to the workshop of clinker on the level of cement factory. Lastly, in the third part we propose a Neuro-Fuzzy system for system of production diagnosis.

Neuro-Fuzzy systems

The Neuro-fuzzy model combines, in a single framework, both numerical and symbolic knowledge about the process. Automatic linguistic rule extraction is a useful aspect of NF especially when little or no prior knowledge about the process is available (Brown and Harris, 1994; Jang, 1995). For example, a NF model of a non-linear dynamical system can be identified from the empirical data.

This model can give us some insight about the onlinearity and dynamical properties of the system.

The most common NF systems are based on two types of fuzzy models TSK (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) and Mamdani (1995, 1996) combined with NN learning algorithms. TSK models use local linear models in the consequents, which are easier to interpret and can be used for control and fault diagnosis (Füssel, et al 1997; Ballé et al 1997). Mamdani models use fuzzy sets as consequents and therefore give a more qualitative description. Many Neuro-fuzzy structures have been successfully applied to a wide range of applications from industrial processes to financial systems, because of the ease of rule base design, linguistic modeling, application to complex and uncertain systems, inherent non-linear nature, learning abilities, parallel processing and fault-tolerance abilities. However, successful implementation depends heavily on prior knowledge of the system and the empirical data (Ayoubi, 1995).

Neuro-fuzzy networks by intrinsic nature can handle limited number of inputs. When the system to be identified is complex and has large number of inputs, the fuzzy rule base becomes large.

NF models usually identified from empirical data are not very transparent. Transparency accounts a more meaningful description of the process i.e less rules with appropriate membership functions. In ANFIS (Jang, 1993, 1995) a fixed structure with grid partition is used. Antecedent and consequent parameters are identified by a combination of least squares estimate and gradient based method, called hybrid learning rule. This method is fast and easy to implement for low dimension input spaces. It is more prone to lose the transparency and the local model accuracy because of the use of error back propagation that is a global and not locally nonlinear optimization procedure. One possible method to overcome this problem can be to find the antecedents & rules separately e.g. clustering and constrain the antecedents, and then apply optimization.

Hierarchical NF networks can be used to overcome the dimensionality problem by decomposing the system into a series of MISO and/or SISO systems called hierarchical systems (Tachibana and Furuhashi, 1994). The local rules use subsets of input spaces and are activated by higher level rules[12].

The criteria on which to build a NF model are based on the requirements for faults diagnosis and the system characteristics. The function of the NF model in the FDI scheme is also important i.e. Preprocessing data, Identification (Residual generation) or classification (Decision Making/Fault Isolation).

For example a NF model with high approximation capability and disturbance rejection is needed for identification so that the residuals are more accurate.

Whereas in the classification stage, a NF network with more transparency is required.

The following characteristics of NF models are important:

- Approximation/Generalisation capabilities
- transparency: Reasoning/use of prior knowledge /rules
- Training Speed/ Processing speed
- Complexity
- Transformability: To be able to convert in other forms of NF models in order to provide different levels of transparency and approximation power.
- Adaptive learning

Two most important characteristics are the generalising and reasoning capabilities. Depending on the application requirement, usually a compromise is made between the above two.

In order to implement this type of fuzzy perception and exploited to diagnose of dedicated production system we have to propose data-processing software NEFDIAG.

2. NEFDIAG PRESENTATION

NEFDIAG is a data processing program of interactive simulation, carried out within LAP (university of Batna) written under DELPHI, dedicated primarily to creation, the training and the test of a Neuro-Fuzzy system of classification of the breakdowns of a dedicated industrial process. NEFDIAG models a fuzzy classifier Fr with a whole of classes C = {c1, c2...... cm}.

Structure and training NEFDIAG can be represented like a special type of fuzzy perception, with three layers to use to classify failures.

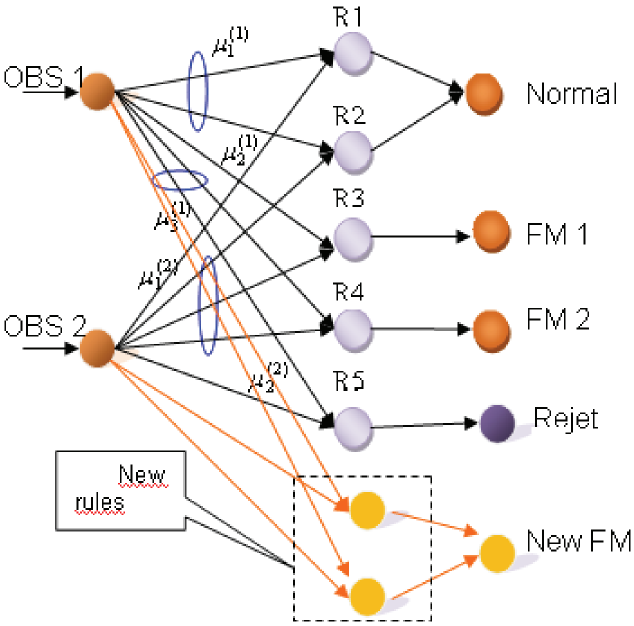

Fig. 1. Neuro-Fuzzy Architecture

NEFDIAG makes it's training by a set of forms, such as each form will be affected (classified) towards one of the preset classes. then NEFDIAG generates the fuzzy rules by a course of the data optimizes the rules by training the parameters of the subsets fuzzy which are used for partitioned the data " characteristic " of the forms with classified and the 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 A1 Symptom2 is A2
Symptom3 is A3 Symptom N is An
Then the form (x1, x2, x3..., xn) is belonged to class « Failure mode 1».

Such as A1 A2 A3 An are linguistic terms represented by fuzzy sets. This characteristic will make it possible to know the analyses on our data, and to use this knowledge to classify them. The training of the networks of artificial Neuro-Fuzzy is a phase which 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 descent of gradient of average quadratic error made by network RNF.

System NEFDIAG can starts with a base of knowledge partial of the forms, and can then refine it during the training, or it can start with an empty base of knowledge. The definite user the initial number of the functions of membership for partitioning fields of the data input. And it is also necessary to specify the number K, a number maximum of the neurons of the rules which will be created in the hidden layer. The principal steps of algorithm of training are thus presented.

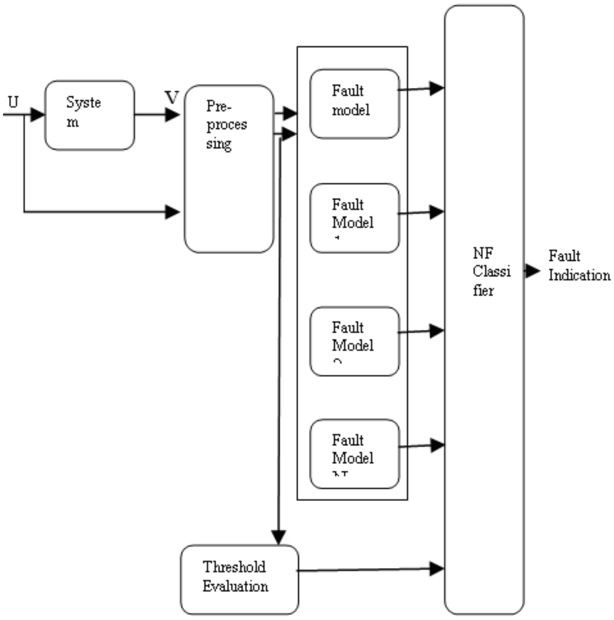

Fig. 2. Neuro-Fuzzy Fault detection.

Initialization: for each data resulting by sensors there is an input unit, for each mode of failure there is an output unit. For each input unit an initial fuzzy partition is specified « exp: A number of the of triangular membership functions.

2.1. Training of the rules

System NEFDIAG can starts with a base of knowledge partial of forms, and can then refine it during the training «Fig. 3», the rule will be created by research (for a given form F) the combination of the functions of membership such as each produced entry the greatest function of membership «fig.3 ». If this combination is not identical for the rules exist in the rules base, and numbers of rules is not maximum, then rules will be created and added to the rules base « Fig. 1»,

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

The algorithm of training detects (calculates) all the antecedents of the rules and then creates the list of the antecedents. In the first time this list is empty, or contains antecedents of rules of knowledge a priori. The algorithm selects then consequent to seek antecedent A and to create the basic list of rule candidates. The best rules will be selected base of the rules candidates, in base of measurement of performance [7].

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

Training of the Functions of Membership

For the training of the membership functions, a simple retro propagation is used. It depends on the error of output for each unit of rules. Each rule changes its membership functions by the change as of the 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 another new mode of failure in the phase of training our system is the degree Neuro-fuzzy will make an adaptation or a reorganization of the system to be adapted has the new situation «fig. 2».

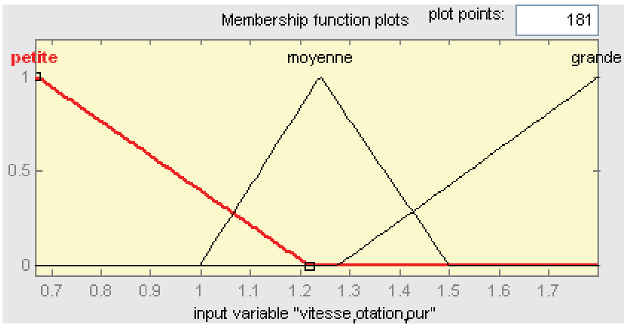

Fig. 3. V_R_F before training

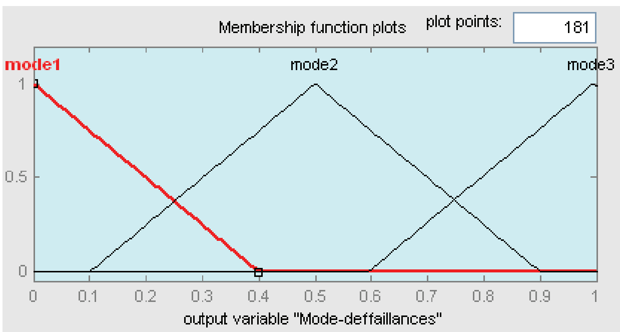

Fig. 4. V_R_F after training

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

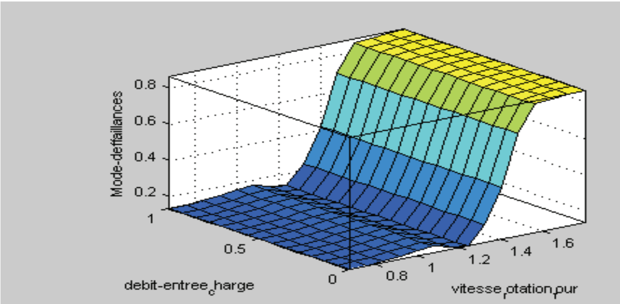

Fig. 5. The training of membership function

3. THE WORKSHOP OF CLINKER

Our application is illustrated on an industrial process of manufacture of cement. This installation belongs to cement factory of Ain-Touta (SCIMAT) ALGERIA. This cement factory have a capacity of 2.500.000 t/an " Two furnaces " is made up of several units which determine the various phases of the manufacturing process of cement. The workshop of cooking gathers two furnaces whose flow clinker is of 1560 t/h. The cement crushing includes two crushers of 100t/h each one. Forwarding of cement is carried out starting from two stations, for the trucks and another for the coaches «Fig.6, ".

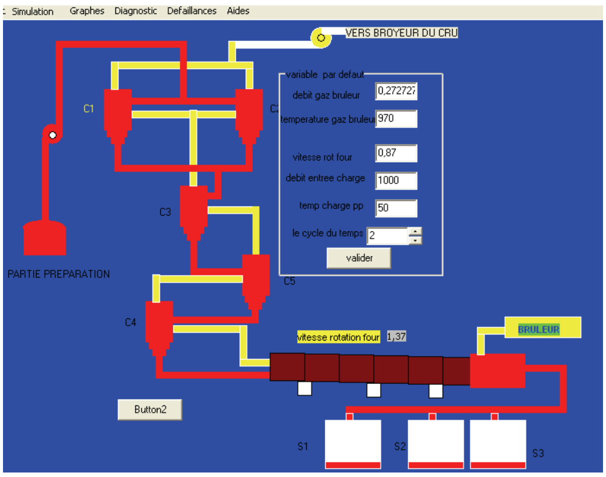

Fig. 6. Alarme message

4. NEURO FUZZY DIAGNOSIS

4.1 Dysfunctions analyse

This step has an objective of identification the dysfunctions which can influence the mission of the system. This analysis is largely facilitated by the recognition of the models structural and functional of the installation. For the analysis of the dysfunctions we adopted the method of analysis of the modes of failure, their effects and their criticality (AMDEC). While basing itself on the study carried out by [6], on the workshop of cooking, we worked out an AMDEC by considering only the most critical modes of the failures (criticality >10) and this for reasons of simplicity [6]. Therefore we have a system Neuro-fuzzy of 27 inputs and four outputs which were created 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 extension (suppression or addition of other rules). The initial rules base to establish the diagnosis of the failures is built by exploiting the model worked out in phase's dysfunction of our system (AMDEC). Indeed, this analysis makes it possible to establish the bonds of causes for purposes between the components failing and the symptoms observed. These bonds will be represented in the forms of fuzzy rules building the knowledge base which will be training later and then tested, to carry out the fuzzy reasoning necessary and to lead to the results expressing the function of diagnosis.

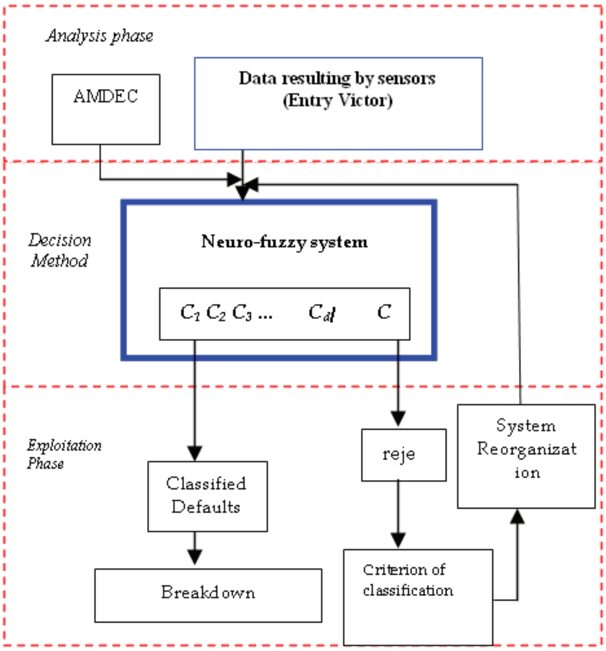

Fig. 7. The diagnosis by NEFDIAG.

Then the detection of the anomalies is represented in the form of alarm message intended to announce to the operator (user) the appearance of an anomaly (or anomalies) and makes it possible to identify the component responsible using a base for data which stock all the information provided by the AMDEC (mode of failure, possible causes, equipment, effects on the system).

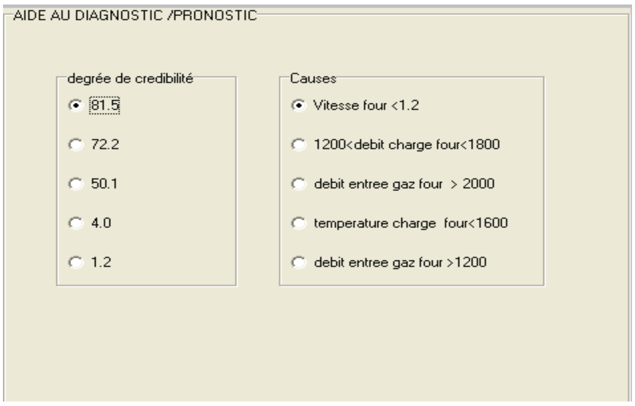

Fig. 8. diagnosis mode1

After appearance of an anomaly, a message of alarm makes it possible to the operator to detect the dysfunction and also to locate the responsible component. The " fig. 2, " illustrates the system of cooking with the presence of a dysfunction. Let us note that in this study, the anomalies or dysfunctions indicate functional anomalies.

After the posting of the message, the operator can consult this last for more information or to remove it " fig. 6, ". Then NEFDIAG makes interventions to control the variables which are the origin of the current failure "Fig. 8, ".

5. Conclusions

In this article we presented a new tool for diagnosis by Neuro-Fuzzy systems following approaches AMDEC, we detailed the implementation of an example of industrial application by the development tool NEFDIAG. We illustrated use of our tool of assistance to the prediction diagnosis in the form of a prototype NEFDIAG to install on a PC.We approached the various stages to be followed for the development of assistance system to the 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, by using the neuro-fuzzy system of the type 3. NEFDIAG makes training with two phases. A training of rules, and generates the fuzzy rules by the course of data and optimizes the rules by training of the parameters of the fuzzy sets which are used for partitioning the data of the forms to classify and the parameters of the data.

In spite of great importance of fuzzy neural networks for solving wide range of real-world problems, unfortunately, little progress has been made in their development.

we have discussed recurrent neural networks with fuzzy weights and biases as adjustable parameters and internal feedback loops, which allows capturing dynamic response of a system without using external feedback through delays. In this case all the nodes are able to process linguistic information.

As the main problem regarding fuzzy and recurrent fuzzy neural networks that limits their application range is the difficulty of proper adjustment of fuzzy weights and biases, we put an emphasize on the RFNN training algorithm.

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