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Hierarchical Fuzzy Signature and Neuro-Fuzzy Hybrid System for QMS Control

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***Abstract*— Recently, the Quality Management System (QMS) control supports organizations managers identifying the best practices to upgrade the efficiency and effectiveness. This control has become a successful tool to improve the organization decision-making process. However, QMS encloses several performance indicators inputs that necessitate to be managed. In fact, it may include as inputs, customers requirements, quality policies, standard procedures and many other criteria. Hence, to provide the control of QMS problem insurance, two approaches are investigated which are Hierarchical Fuzzy Signature (HFS) and Neuro-Fuzzy Hierarchical Hybrid system (NFHH), respectively. These approaches are applied in the case of an industrial company operating in the electromechanical sector. This company has to be creative, agile, responsive and especially ready for fierce competition. Then, the obtained results are compared to Adaptive Neural Fuzzy Inference and Neural Network Systems, regarding the learning phase. Consequently, all of them help the company to assess its overall performance. However, NFHH reaches the best accuracy, reduces the number of neurons and uses the parameters that keep the universal approximated property of neural networks and fuzzy systems.**

***Keywords*—Quality management system, Fuzzy logic, Neuro-Fuzzy, hierarchical structure, fuzzy signature.**

I. INTRODUCTION

The multi-criteria approach for decision making problems profoundly insists on the precision and exact description of specific systems. Furthermore, the use of these approaches has to be justified for a well-defined system. However, when the complexity of the system increases, these approaches become insufficient and less efficient because they offer a severe aid on a strict interval [1]. In fact, for relatively complicated systems which enclose too many details and several criteria, the fuzzy logic was successfully applied for resolving their problems and challenges.

It is considered as a competitive concept in various fields including power regulating system [2], signal processing [3], quality control of food products [4], image processing [5] and many others

For the decision making process, fuzzy logic is also able to solve problems which include structured data and defined number of inputs [6,7]. Nevertheless, recent researchers deal with high dimensional data. Hence, the concept of fuzzy signature is innovated, especially for medical decision support systems [8].

Otherwise, the neural networks (NN) have been applied in multiple decision making processes, namely the budget allocation [11], the modelling heterogeneous patients [12], the detection and classification of defects [9] and the fault diagnosis [10].

However, the NN are not able to link digital data to linguistic one in classification tasks. Consequently, hybrid structure between fuzzy logic and NN is investigated in a Neuro-Fuzzy architecture. This structure is major in handling qualitative and quantitative inputs data [13].

For example, the heterogeneous input data which are treated in QMS control have to be managed by effective and robust structures. This subject is still studied to ensure the continuous improvement of organisations processes. On this basis, hybrid approaches are applied in this paper, to provide the control of QMS problem insurance. They are Hierarchical Fuzzy Signature (HFS) and Neuro-Fuzzy Hierarchical Hybrid system (NFHH).

This paper includes five sections as follows. Section 2 defines the problem. Section 3 details the two proposed approaches. Section 4 deals with the investigation of the two hybrid approaches to the case of an industrial company. Finally, in order to evaluate the obtained results in the learning phase, a comparative study between NFHH, Adaptive Neural Fuzzy Inference Systems (ANFIS) and NN is done.

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II. PROBLEM FORMULATION

Based on International Standards Organization series ISO 9001, Figure 1 shows the continual improvement of the QMS which is composed of four processes i.e. Management responsibility, Resource management, Product realization and Improvement process. The inputs of this system are the customer's requirements for the product realization process, the expectations for the direction process and the measuring customer satisfaction for the improvement process.

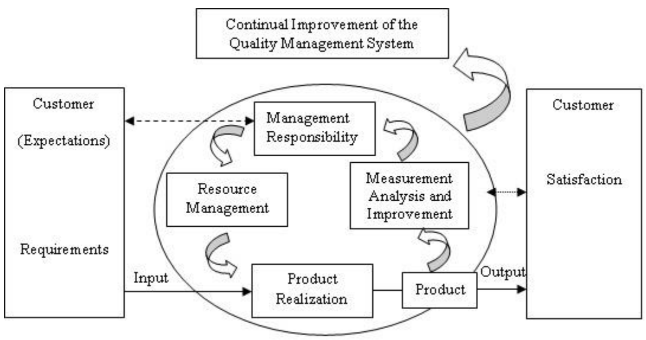

FIGURE 1.QMS MODEL (ISO 9001).

In recent years, the QMS control has become a strategic consideration for companies' businesses. Some companies aim to increase their productivity and to improve the effectiveness and efficiency of their systems. Hence, the complexity of QMS control is managed from a multitude of quantitative and qualitative objectives OBJ_i (i=1,…, n) which are composed of a set of imprecise performance indicators inputs $IP_{i,j}$ (i=1,…, n et j=1,…, m).All these indicators have to be handled. Therefore, in this paper, we present fuzzy hierarchical hybrid approaches that are able to ensure the control of QMS problems.

III. HIERARCHICAL APPROACHES FOR QMS CONTROL

Resolution of multi-criteria problems which ensure a large number of variables is considered as effectual by the use of hierarchical structures [11].Their advantage consists of the treatment of quantitative and qualitative variables. Therefore, hierarchical forms have been useful in classification issues which are similar to QMS control. In this subject, the purpose of this study is to apply Hierarchical Fuzzy Signature (HFS) and Neuro-Fuzzy (NFHH) approaches. They are mainly used in a QMS control problem which contains fuzzy, large, and diverse performance indicators inputs.

A. Hierarchical Fuzzy Signature

The signature concept has been used in various applications such as: clustering dynamic measurements [14], storage in electronic archives [15] and managing a library of reference software [16]. HFS with its hierarchical structure deals with the tasks ensuring diverse inputs. Therefore, decision-making experts' problems could be resolved by applying HFS, especially for classification or comparison of multiple cases and/or missing elements. The advantage of this concept is to manage complex problems with many diverse variables [17]. Indeed, HFS categories interdependent variables into sub-groups that determine the result in the upper level [18].

In this work, the proposed HFS is applied to classify the objectives OBJ_i (i = 1… n) of the QMS control problem. Every objective consists of m performance indicators $IP_{i,j}$ (i = 1… n and j = 1… m). Furthermore, every performance indicator is associated with k measurements $M_{i,j,\alpha}$ (i = 1,…, n, j = 1,…, m and α = 1,…, k) $\{IP_{i,j}= f(M_{i,j,\alpha})\}$. Every measurement is included in the fuzzy set of the correspondent performance indicator. It is then interpreted that i refers to the target number, j to the indicator number and k to the measurement number. For example, $M_{5,1,3}$ is the third measure of the first performance indicator of the fifth objective.

The equations (1), (2) and (3) define the relationship between the indicator upper level and the measurement lower one, the objective upper level and the indicator lower one and the last level, denoted $a_{i,j,\alpha}$, $a_{i,j}$ and a_i, a_i.

$$a_{i,j;\alpha} = \frac{\sum_{\alpha=1}^{k} W_{i,j,\alpha} M_{i,j,\alpha}}{\sum_{\alpha=1}^{k} W_{i,j,\alpha}} \tag{1}$$

$$a_{i,j} = \frac{\sum_{j=1}^{m} W_{i,j} IP_{i,j}}{\sum_{j=1}^{m} W_{i,j}} \tag{2}$$

$$a_{i} = \frac{\sum_{i=1}^{n} W_{i} OBJ_{i}}{\sum_{i=1}^{n} W_{i}} \tag{3}$$

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Where: $W_{i,j,\alpha}$ is the weight associated with the measurement leaf $M_{i,j,\alpha}$,$W_{i,j}$ is the weight associated with the indicator branch $IP_{i,j}$ and W_i is the weight associated with the objective branch OBJ_i. In fact, the integration of the weight concept for the QMS control is essential for the measurement standardization that varies proportionally [19]. Figure 2 shows the HFS structure used for QMS control.

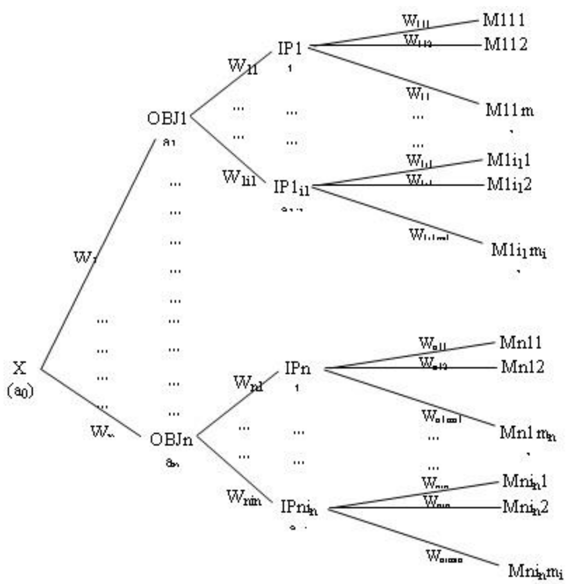

FIGURE 2.HFS FORQMS CONTROL.

B. Hierarchical Neuro-Fuzzy Hybrid System

Neural Network (NN) and Fuzzy Inference System (FIS) paradigms are frequently applied together. In fact, these two concepts have been combined due to the difficulties and inherent limitations of each isolated paradigm. Therefore, when combined, they are called Neuro-Fuzzy Systems. This system has the advantages of learning through patterns and the easy interpretation of its functionality. The proposed approach NFHH requires structural and parametric identifications [20].

- *Structural identification:* The QMS control problem includes various performance indicators which are the principal elements of the decision-making process.

These indicators are quantitative and qualitative. This heterogeneous aspect is mostly managed by the application of cooperative structure between the NN and the FIS, namely.

Thus, the NFHH structure is investigated. By the way, the FIS located on the lower level, transforms quantitative indicators (IP_{11}, IP_{12}… $IP_{p,m,p}$) into qualitative objectives. Therefore, NFHH manages two types of inputs which are the outputs of qualitative FIS (OBJ_1,…, OBJ_p) and the qualitative indicators (IP_1, IP_2,…, IP_z).

The NFHH structure is illustrated in Figure 3.

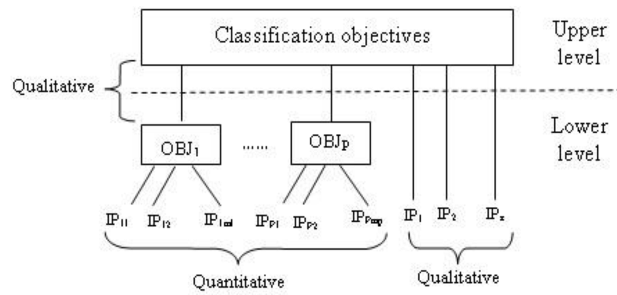

FIGURE 3. STRUCTURE OF NFHH.

- *Parametric identification:* In this study, parametric identification deals with the fuzzy membership functions and the neural connective weights. However, it requires an adaptation law. Figure 4 illustrates the block diagram of NFHH structure in the learning phase.

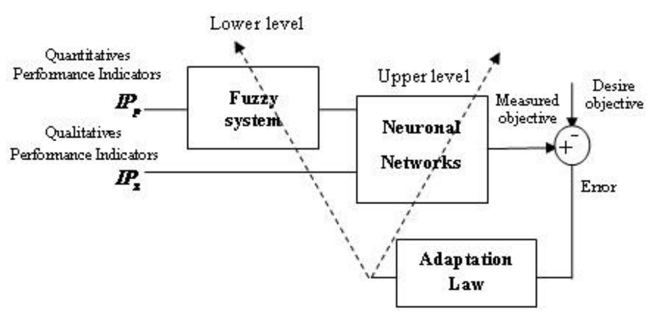

FIGURE 4. LEARNING SYSTEM OF NFHH.

Design of the Fuzzy system: The adopted fuzzy structure is identical to that of ANFIS with Mamdani type rules. Indeed, the premises (if) and the consequence (then) of a rule R^i are fuzzy propositions of the form (4).

$$R^i : \text{IF}\left(x_1 \text{ is } \mu_1^i\right)\text{AND ....AND } \left(x_n \text{ is } \mu_n^i\right)\text{THEN } \left(Y \text{ is } B^i\right) \quad (4)$$

Where: $X=[x_1 .. x_j…x_n]^T$ and Y are respectively the input and output vectors, μ^i_p and B_i are respectively the linguistic terms of X and Y.

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In the QMS study, we choose for the p^{th} objective, X_p as input vector representing the corresponding performance indicators $IP_p = (IP_{P1}, IP_{P2},\ldots, IP_{Pmp})$ with m_p input variables X_p.

The defuzzification method is chosen to transform the information provided by the fuzzy inference mechanism into numerical value. In this study, the aggregation method is selected. It is represented by the equation (5).

$$\widehat{IP}_p(X_p) = OBJ_p = \frac{\sum_{k_1,k_2,\ldots,k_{mp}}^{k} IP_p^{k_1,k_2,\ldots,k_{mp}} \bigwedge_{i=1}^{mp} \mu_{pi}^{k_i}(x_{pi})}{\sum_{k_1,k_2,\ldots,k_{mp}}^{k} \bigwedge_{i=1}^{mp} \mu_{pi}^{k_i}(x_{pi})} \quad (5)$$

Where: $\widehat{IP}_p$ is the output of p^{th} objective, $IP_p^{k_1,k_2,\ldots,k_{mp}}$ is the consequence of fuzzy rule$(k_1, k_2,\ldots, k_{mp})^{th}$ and $\mu_{pi}^{k_i}(x_{pi})$ is the membership degree corresponding to (x_{pi}) for the fuzzy term k_i^{th}.

The equation (5) can be transformed in the form (6).

$$\widehat{IP}_p(X_p) = OBJ_p = \sum_{k_1,k_2,\ldots,k_{mp}}^{k} \left[\frac{\bigwedge_{i=1}^{mp} \mu_{pi}^{k_i}(x_{pi})}{\sum_{k_1,k_2,\ldots,k_{mp}}^{k} \bigwedge_{i=1}^{mp} \mu_{pi}^{k_i}(x_{pi})} \right] IP_p^{k_1,k_2,\ldots,k_{mp}} \quad (6)$$

Let, $$A_p^{k_1,k_2,\ldots,k_{mp}} = \frac{\bigwedge_{i=1}^{mp} \mu_{pi}^{k_i}(x_{pi})}{\sum_{k_1,k_2,\ldots,k_{mp}}^{k} \bigwedge_{i=1}^{mp} \mu_{pi}^{k_i}(x_{pi})}$$

The equation (6) can be written in the form (7).

$$\widehat{IP}_p(X_p) = \sum_{k_1,k_2,\ldots,k_{mp}} A_p^{k_1,k_2,\ldots,k_{mp}}(X_p) IP_p^{k_1,k_2,\ldots,k_{mp}} \quad (7)$$

Design of Neural Network block: We have chosen the unidirectional type of the NN structure for the QMS control. This structure is represented by an input layer treating the ANFIS outputs (OBJ1,…, OBJp) and qualitative indicators (IP1,…, IPz) and an output layer delivering the final decision y. One of the advantages of this structure is the capability of automatic learning and simplicity of rules. Figure 5 shows the selected neural structure.

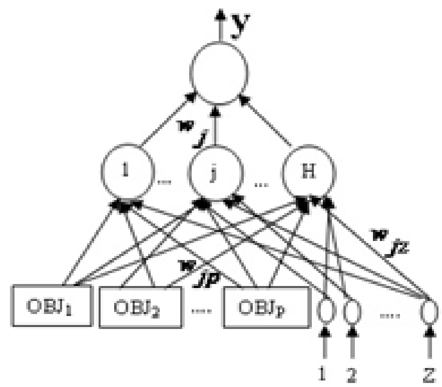

FIGURE 5. NEURAL STRUCTURE.

This network is a multilayer perceptron type with an output y given by equation (8).

$$y = f(X) = \sum_{j=1}^{H} w_j h_j \quad (8)$$

Where X is the input vector, j is the index of hidden neurons and H is the total number of neurons.

The h_j parameter, which represents the j^{th} output neuron, is given by equation (9).

$$h_i = \sigma\left(\sum_{p=1}^{P} w_{jp} \widehat{IP}_p + \sum_{z=1}^{Z} w_{jz} IP_z \right) \quad (9)$$

Where p = (1,2,…, P) is the index of measurement number to the lower level, $\widehat{IP}_p$ is the input of p^{th} objective to the upper level, IP_z is the z^{th} qualitative input for the upper level, w_j is the connection weights and σ is the activation function chosen sigmoid.

If we replace h_j and $\widehat{IP}_p$ by their expressions (9) and (7) into (8), the output y is represented by equation (10).

$$y=\sum_{j=1}^{H}\left[w_i\sigma\left(\sum_{p=1}^{P}w_{jp}\widehat{IP}_p+\sum_{z=1}^{Z}w_{jz}IP_z\right)\right]$$

Learning based on the gradient algorithm: The goal of the learning phase is to modify, by adapting the network parameters (weight), the behaviour of the network until a desired one. For this adaptation, the learning algorithm used is the back propagation method using the gradient descent.

For the QMS control, the adaptation takes into account the membership functions noted A_p for the fuzzy system, and the connection weights noted (w_j, w_{jp} and w_{jz}) for the neural system.The principle of this algorithm is to minimize the sum E of squared errors given by expression (11) during a predefined time horizon. The quadratic form is required to deliver positive quantities.

$$\min_{w_j,w_{jp},w_{jz},A_p} E=\sum_k E_k \tag{11}$$

Where E_k is the square error which is a function of the error e_k between the desired output y_k^d and the neuron output y_k is given by equation (12).

$$E_k=\frac{1}{2}\left(y_k-y_k^d\right)^2=\frac{1}{2}e_k^2 \tag{12}$$

However, minimizing E is equivalent to minimizing E_k because it represents a positive quantity which should converge to 0. To this end, calculating the derivative $\frac{\partial E_k}{\partial x}$ of E_k relative to x with x ϵ {w_j, w_{jp}, w_{jz}, A_p} is sufficient. For a step gradient η_1, the adaptation of x is given by equation (13).

$$x(k+1)=x(k)-\eta_1\frac{\partial E_k}{\partial x} \tag{13}$$

- *Learning for the neural network block*

For the network output, calculating $\min_{w_j} E_k$ is given $\frac{\partial E_k}{\partial w_j}$ in form (14).

$$\frac{\partial E_k}{\partial w_j}=\frac{\partial E_k}{\partial y_k}*\frac{\partial y_k}{\partial w_j}=\frac{\partial E_k}{\partial e_k}*\frac{\partial e_k}{\partial y_k}*\frac{\partial y_k}{\partial w_j} \tag{14}$$

However, $\frac{\partial E_k}{\partial e_k}=e_k$ and $\frac{\partial y_k}{\partial w_j}=h_j$ (seen in equation (9)), given by:

$$\frac{\partial E_k}{\partial w_j}=e_k*h_j \tag{15}$$

Therefore, the adaptation of parameter w_j is presented by equation (16).

$$\begin{aligned}w_j(k+1)&=w_j(k)-\eta_1*\frac{\partial E_k}{\partial w_j}\\ w_j(k+1)&=w_j(k)-\eta_1*e_k*h_j\end{aligned} \tag{16}$$

For the output of the hidden layer, we obtain equations 17 and 18.

$$\begin{aligned}&\frac{\partial E_k}{\partial w_{jp}}=\frac{\partial E_k}{\partial y_k}*\frac{\partial y_k}{\partial w_{jp}}=e_k*\frac{\partial y_k}{\partial w_{jp}}\\ &\text{with}:\frac{\partial y_k}{\partial w_{jp}}=\frac{\partial y_k}{\partial h_j}*\frac{\partial h_j}{\partial w_{jp}}=w_j*h_j*\left(1-h_j\right)*IP_p\end{aligned} \tag{17}$$

$$\begin{aligned}&\frac{\partial E_k}{\partial w_{jz}}=\frac{\partial E_k}{\partial y_k}*\frac{\partial y_k}{\partial w_{jz}}=e_k*\frac{\partial y_k}{\partial w_{jz}}\\ &\text{with}:\frac{\partial y_k}{\partial w_{jz}}=\frac{\partial y_k}{\partial h_j}*\frac{\partial h_j}{\partial w_{jz}}=w_j*h_j*\left(1-h_j\right)*IP_z\end{aligned} \tag{18}$$

What gives the equations 19 and 20.

$$\frac{\partial E_k}{\partial w_{jp}}=w_j*h_j*\left(1-h_j\right)*IP_p \tag{19}$$

$$\frac{\partial E_k}{\partial w_{jz}}=w_j*h_j*\left(1-h_j\right)*IP_z \tag{20}$$

The adaptation of the two parameters w_{jp} and w_{jz} are given by equations (21) and (22).

$$\begin{aligned}w_{jp}(k+1)&=w_{jp}(k)-\eta_1*\frac{\partial E_k}{\partial w_{jp}}\\ w_{jp}(k+1)&=w_{jp}(k)-\eta_1*e_k*w_{j*}h_j*\left(1-h_j\right)-IP_p\end{aligned} \tag{21}$$

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$$w_{jz}(k+1) = w_{jz}(k) - \eta_1 * \frac{\partial E_k}{\partial w_{jz}}$$
$$w_{jz}(k+1) = w_{jz}(k) - \eta_1 * e_k * w_{j*} h_j * (1-h_j) - IP_z \tag{22}$$

- *Learning for the fuzzy system*

For learning fuzzy system, the adaptation takes into account the membership functions $A_p^{k_1,k_2,....,k_{mp}}$. To do so, we must calculate the derivative of E_k relative to $A_p^{k_1,k_2,....,k_{mp}}$.

$$\frac{\partial E_k}{\partial A_p^{k_1,k_2,...,k_{mp}}} = \frac{\partial E_k}{\partial \widehat{IP}_p} * \frac{\partial \widehat{IP}_p}{\partial A_p^{k_1,k_2,...,k_{mp}}} = \frac{\partial E_k}{\partial y_k} * \frac{\partial y_k}{\partial \widehat{IP}_p}$$
$$\frac{\partial E_k}{\partial A_p^{k_1,k_2,...,k_{mp}}} = e_k * \frac{\partial y_k}{\partial \widehat{IP}_p} * \frac{\partial \widehat{IP}_p}{\partial A_p^{k_1,k_2,...,k_{mp}}} \tag{23}$$

Where:

$$\frac{\partial y_k}{\partial \widehat{IP}_p} = \sum_{j=1}^{H} \frac{\partial y_k}{\partial h_j} * \frac{\partial h_j}{\partial \widehat{IP}_p} = \sum_{j=1}^{H} w_j * h_j * (1-h_j) * w_{jp}$$

$$\text{And } \frac{\partial \widehat{IP}_p}{\partial A_p^{k_1,k_2,...,k_{mp}}} = IP_p^{k_1,k_2,...,k_{mp}} \tag{24}$$

Replacing the two expressions of equation (24) in equation (23), we obtain the equation (25).

$$\frac{\partial E_k}{\partial A_p^{k_1,k_2,...,k_{mp}}} = e_k \sum_{j=1}^{H} w_j * h_j * (1-h_j) * w_{jp} * IP_p^k \tag{25}$$

The adaptation of parameter $A_p^{k_1,k_2,....,k_{mp}}$ is given by equation (26).

$$A_p^{k_1,k_2,...,k_{mp}}(k+1) = A_p^{k_1,k_2,...,k_{mp}}(k) - \eta_1 * \frac{\partial E_k}{\partial A_p^{k_1,k_2,...,k_{mp}}}$$
$$A_p^{k_1,k_2,...,k_{mp}}(k+1) = A_p^{k_1,k_2,...,k_{mp}}(k) - \tag{26}$$
$$\eta_1 * e_k * \sum_{1}^{H} w_j * h_j * (1-h_j) * w_{jp} * IP_p^{k_1,k_2,...,k_{mp}}$$

- *Learning algorithm*

The learning gradient algorithm developed for the overall structure NFHH consists of several steps which are defined in Figure 6.

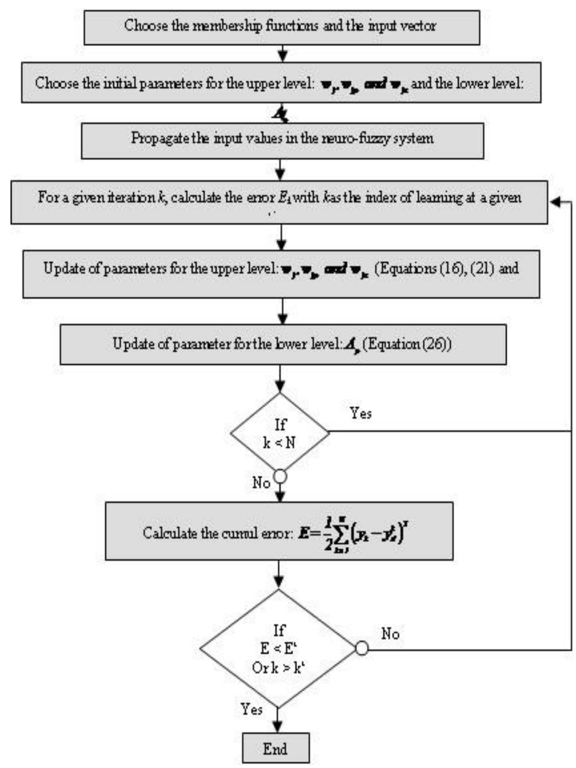

FIGURE 6. NEURAL STRUCTURE LEARNING ALGORITHM.

Firstly, the learning parameters (A_p, w_j, w_{jp} and w_{jz}) are initialized. Then, they are propagated in the Neuro-Fuzzy network in order to calculate the error E_k for a given iteration k. Then, it is necessary to update the parameters and calculate the accumulated error $E = \frac{1}{2}\sum_{k=1}^{n}\left(y_k - y_k^d\right)^2$, in case k is less than the size of the training set. If the conditions (E less than the tolerated error E^t or k superior than the number of iterations tolerated k^t) are true then end of the algorithm. Else, we go back to the previous step (calculating for a given iteration k the error E_k).

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IV. CASE STUDY: INDUSTRIAL COMPANY

The case of an industrial company, operating in the electromechanical sector, is invested in this paper. This company incorporates a fleet of plastic injection, molding machines and component assembly workshops. A quality production level is requested in order to reach its customers requirements. Thus, the challenge for this company is how to manage its objectives and consequently improve its production. Therefore, the company has to update regularly its objectives by taking into consideration different indicators. Figure 7 cites the company main objectives.

Table I shows the different indicators and objectives per process.

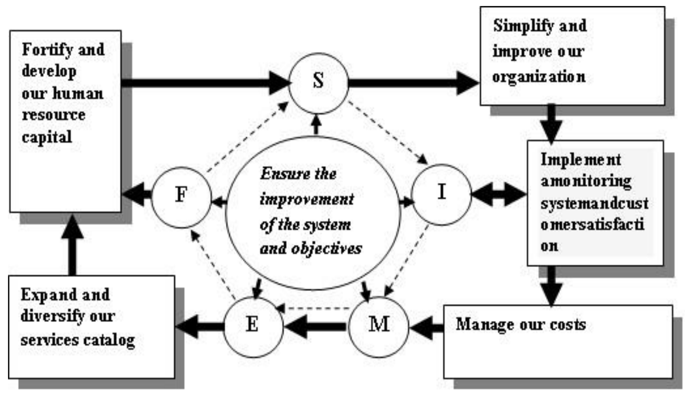

FIGURE 7. COMPANY OBJECTIVES.

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TABLE I
OBJECTIVES AND PERFORMANCE INDICATORS PER PROCESS.

Objective	Process	Performance indicators
Simplify and improve our organization (S)	Procurement and inventory management processes	Compliance rate of clearance time
	Color and cabling process	Internal rate of non-compliance workshop coloring
		Rate of return (workshop wiring)
	Cutting process	Internal noncompliance rate of cutting
		Synthetic rate of return (workshop cut)
	Injection and assembly process	Internal rate of non-compliance workshop injection
		Rate of noncompliance internal molding workshop
		Synthetic rate of return (workshop injection)
		Synthetic rate of return (molding workshop)
		Internal rate of non-compliance workshop accessory
		Rate of return (workshop accessory)
	Maintenance process	Availability rate of molding presses
		Synthetic rate of return
		Discontinuation rate workshop accessories
		Discontinuation rates wiring workshop
		Rate cut-off workshop
		Discontinuation rate electronic workshop
		Discontinuation rate of injection molding machines
		Discontinuation rates molding presses
		Discontinuation rate of injection devices
Implement a monitoring system and customer satisfaction (I)	Customer process	Rate of customer complaints
		Rate of customer satisfaction
	Color and cabling process	Non-compliance rate detected by the customer coloration
		Non-compliance rate detected by the customer wiring workshop
	Cutting process	Non-compliance rate detected by the customer cutting workshop
	Injection and assembly process	Non-compliance rate detected by the customer workshop injection
		Non-compliance rate detected by the customer molding workshop
		Non-compliance rate detected by the customer accessories
Manage our costs (M)	Customer process	Rate of customer complaints
	Process management and continuous improvement objectives	Rate of overall non-compliance
	Human resource management process	Rate of absenteeism
	Injection process	Rate of non-compliance injection
Expand and diversify our services catalog (E)	Industrialization process	Average rate of industrialization of a product
		Rate of industrialization of new products
Fortify and develop our human resource capital (F)	Human resource management process	Competence rate of injection
		Competence rate of maintenance
		Competence rate of quality
		Competence rate of wiring
		Competence rate of cuttings
		Overall competence rate
		Competence rate of mounting accessories
		Success rate of training
		Polyvalence rate of wiring
		Polyvalence rate of cutting
		Overall polyvalence rate
		Polyvalence rate of injection
		Polyvalence rate of maintenance
		Polyvalence rate of mounting accessories
		Polyvalence rate of quality

IJETAE EXPLORING RESEARCH AND INNOVATIONS

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A. Use HFS

The configuration of the HFS demands the identification of the objectives (level1), performance indicators (level 2) and indicators measures (level 3.

In this case study, five objectives OBJ1-OBJ5 are identified. For every objective a set of indicators IP11-IP515 is associated. For instance, the upper level of variable OBJ3 ("Manage our costs") handles four performance indicators. These indicators form a sub-group (IP31 "rate of customer complaints", IP32 "Rate of overall non-compliance", IP33 "rate of absenteeism" and IP34 "rate of non-compliance injection"). For each performance indicator corresponds five measures. For example, $M_{3,1,1}$, $M_{3,1,2}$, $M_{3,1,3}$, $M_{3,1,4}$ and $M_{3,1,5}$ belong to IP31 fuzzy set.

The measure vectors associated to performance indicators IP31, IP32, IP33 and IP34 with weights equal to one are presented as follows:

$$\begin{aligned} IP31 &= [0.14, 0.23, 0.45, 0.73, 0.90] \\ IP32 &= [0.08, 0.25, 0.46, 0.74, 0.91] \\ IP33 &= [0.09, 0.25, 0.46, 0.74, 0.90] \\ IP34 &= [0.08, 0.26, 0.46, 0.75, 0.90] \end{aligned}$$

The upper level (IP31) and the lower one (M311, M312, M313, M314 and M315) are grouped together with an aggregation function a31. This function is identical for the other indicators (a11 = … = a120 = a21… = a28 = a31… = a34 = a41… = a415).

Weighting the performance indicator is a new concept adopted by the company. Therefore, by applying this concept, the company standardizes its production practices across the year. Indeed, the company, under its production strategy, selects the associated weights with each correspondent branch (objective-indicator). For example, the corresponding branch weights (OBJ3-IP3i) are fixed: w31 = 0.4, w32 = 0.3, w33 = 0.1 and w34 = 0.2. In this case, OBJ3 is calculated using the expression for ai, and is equal to:

$$OBJ3 = [0.196, 0.146, 0.048, 0.098]$$

However, minimizing the rate of customer complaints such as: absenteeism, non-compliance and overall injection (see Table I), is necessary to ensure a good cost control.

The following expression defines the use of the aggregation functions a_3=Min, between the upper (OBJ3) and lower (IP31, 32, 33 and 34) levels.

$$OBJ3 = \begin{cases} \text{Min IP31} \\ \text{Min IP32} \\ \text{Min IP33} \\ \text{Min IP34} \end{cases}$$

Consequently, the obtained results by applying the minimum aggregation operator are as follows: Min (0.196, 0.146, 0.048, 0.098) =0.048.

The final HFS structure links the upper level (X) and the lower level (OBJ1, OBJ2, OBJ3, OBJ4 and OBJ5) by involving aggregation functions a0 = (a1,a2, a3, a4 and a5).

As a result, by referring to the expression below, it is deduced that OBJ4 has to be done firstly, followed by OBJ5, OBJ2, OBJ3 and OBJ1, respectively.

$$X = [0.022, 0.051, 0.048, 0.075, 0.057]$$

B. Use NFHH

The design and development of NFHH approach require structured steps to guarantee a judicious choice of the different parameters involved in the system.

Configuration NFHH: In our case study, we have selected the triangular membership functions because it is the most suitable for this type of problem. This choice is not arbitrary but it is the fruit of several tests of various types and number of membership functions. Therefore, a fuzzy set {Very Sensitive (VS), Sensitive (S), Medium (M), High (H) and Very High (VH)}, characterized by a membership function, is associated with every measure (variable). The fuzzy sets for classification objectives are also expressed linguistically ("too little", "slightly little", "little", "high" and "too high") are distinguished by a membership function and. These linguistic terms belong to the set T = {VS, S, M, H and VH} and they are defined on the universe of discourse [0, 1]

Figure 8 shows the performance indicators membership functions.

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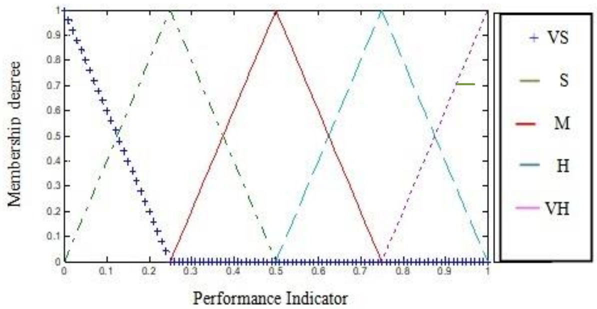

FIGURE 8. MEMBERSHIP FUNCTION OF PERFORMANCE INDICATORS.

In addition, a rule base that consists of collection rules of the form (4) has been established based on expert judgment and history.

To identify the main objective rate, it is recommended to take into consideration the performance indicators measurements and the desired output, by referring to history or experts knowledge. The collected measurements are treated by the inference system. In this case study, the number of rules is eighty one (81). After that, the second layer neurons use T-norm MIN to calculate the accuracy of the antecedent's fuzzy rules. Nevertheless, output objectives are defuzzied by T-conorm MAX and the weighted sum system, as it is represented by the equation (27).

$$\hat{OBJ}_p\left(X_p\right) = \frac{\sum_{k_1,k_2,\ldots,k_{mp}} OBJ_p^{k_1,k_2,\ldots,k_{mp}} \mu_{p,i}^{k_i}\left(x_{p,i}\right)}{\sum_{k_1,k_2,\ldots,k_{mp}} \mu_{p,i}^{k_i}\left(x_{p,i}\right)} \quad (27)$$

It is then required to reduce the obtained error in order to ensure the convergence of the approach. Indeed, when the error is under a defined threshold, a learning algorithm will identify the FIS membership functions. The obtained system will be used as an input for the neural system whose its weights have to be calculated by referring to the corresponding objective indicators.

Simulation Results: Simulation data are used to prove the NFHH advantages over the other approaches regarding the approximation accuracy. Due to the large number of inputs (objective and performance indicator), we present in Table II, the learning models developed for the objective 3 "Manage our costs," which depend on 4 performance indicators (see Table II) denoted by IP31, IP32, IP33 and IP34.

The obtained membership functions of performance indicators (IP31, IP32, IP33 and IP34), after applying the learning algorithm, are presented in Figure 9.

Based on these results, the changes have affected mostly the parameters of the membership functions and particularly the overall non-compliance rate IP32. This indicates the overall level of quality linked to the fixed objective and it is explained by the high non-compliance previous rate and the large number of proposed actions to implement.

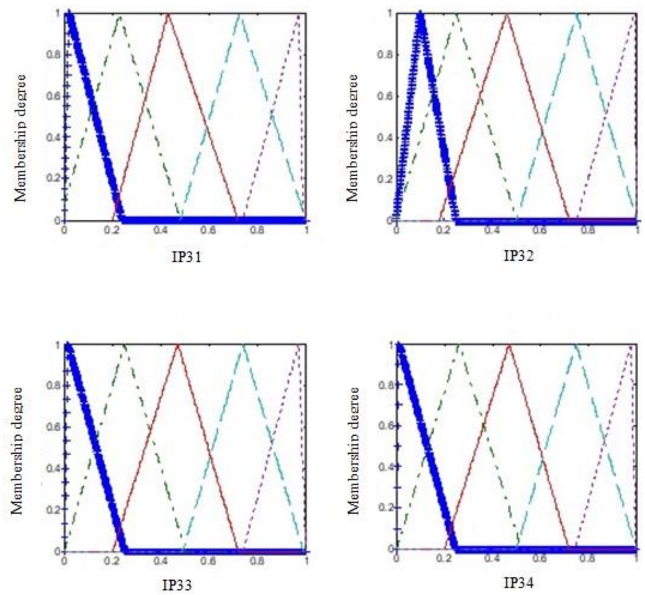

FIGURE9. MEMBERSHIP FUNCTIONS AFTER LEARNING OF PERFORMANCE INDICATORS

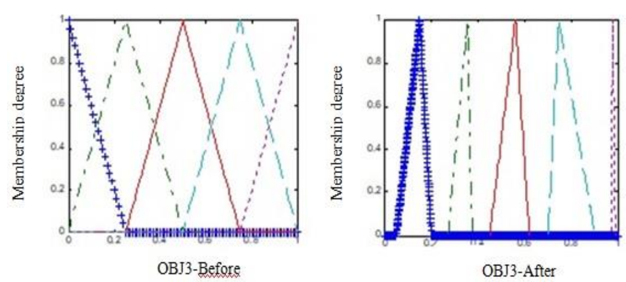

FIGURE 10. MEMBERSHIP FUNCTIONS BEFORE AND AFTER LEARNING OF OBJ3

Figure 10 indicates that all membership function parameters of OBJ3 were affected after the learning phase.

This result depends on the selected initial parameters of membership functions. In fact, they can disrupt the stabilization of the system. Furthermore, it is also notable that the obtained error after 20 iterations, before and after learning, is less than or equal to 0,5 10^{-4}.

Furthermore, the error after learning converges faster than that before learning. This error is used as an indicator to highlight the importance of NFHH to link the real system behaviour to the proposed Neuro-Fuzzy structure.

TABLE II
PAPERS LEARNING MODELS FOR OBJ3

Iteration N°	Indicators		Objective	N° Iteration	Indicators		Objective
1	IP31	0.01	0.247	11	IP31	0.02	0.141
	IP32	0.87			IP32	0.5	
	IP33	0.066			IP33	0.035	
	IP34	0.043			IP34	0.011	
2	IP31	0.01	0.218	12	IP31	0.02	0.114
	IP32	0.81			IP32	0.39	
	IP33	0.026			IP33	0.025	
	IP34	0.026			IP34	0.022	
3	IP31	0.01	0.221	13	IP31	0.02	0.107
	IP32	0.82			IP32	0.35	
	IP33	0.043			IP33	0.03	
	IP34	0.013			IP34	0.028	
4	IP31	0.04	0.213	14	IP31	0.009	0.096
	IP32	0.72			IP32	0.35	
	IP33	0.063			IP33	0.014	
	IP34	0.031			IP34	0.011	
5	IP31	0.02	0.192	15	IP31	0.01	0.086
	IP32	0.72			IP32	0.25	
	IP33	0.022			IP33	0.044	
	IP34	0.008			IP34	0.04	
6	IP31	0.02	0.180	16	IP31	0.02	0.074
	IP32	0.66			IP32	0.2	
	IP33	0.031			IP33	0.05	
	IP34	0.012			IP34	0.026	
7	IP31	0.04	0.184	17	IP31	0.01	0.066
	IP32	0.65			IP32	0.2	
	IP33	0.029			IP33	0.043	
	IP34	0.019			IP34	0.011	
8	IP31	0.04	0.175	18	IP31	0.01	0.053
	IP32	0.57			IP32	0.15	
	IP33	0.049			IP33	0.031	
	IP34	0.041			IP34	0.021	
9	IP31	0.03	0.173	19	IP31	0.01	0.053
	IP32	0.49			IP32	0.15	
	IP33	0.031			IP33	0.031	
	IP34	0.014			IP34	0.021	
10	IP31	0.03	0.144	20	IP31	0.01	0.053
	IP32	0.49			IP32	0.15	
	IP33	0.037			IP33	0.031	
	IP34	0.021			IP34	0.021	

In addition, we have represented in Figure 10 the corresponding membership functions before and after learning of OBJ3.

V. Comparative Study

The comparative study between NFHH, NN and ANFIS has been made to highlight the best NFHH performance including accuracy and number of parameters. All of them are applied to ensure the effectiveness and efficiency of the QMS [21-22-23].By keeping the same number of neurons, the identification of the parameters number and the computing of the mean square error are assessed.

The choice of determining the number of parameters for neural systems or fuzzy systems is very interesting. Indeed, if the parameter number increases then the connections number, the computing time and the rules number increase and therefore the risk of rules explosion and transforming the decisional system in a lengthy process.

Table III shows the different equations for calculating the parameters number of each model.

TABLE III
NFHH, ANFIS and NN Parameters NUMBER.

Models	Number of parameters	
NFHH	$\sum_{p=1}^{p} 2^{m_z} + (P+Z+1)*H+(H+1)$	(28)
ANFIS	$\sum_{p=1}^{p} 3^{m_z} + (P+Z+1)*H+(H+1)$	(29)
NN	$\left(\sum_{p=1}^{p} (m_p + Z + 1)\right)*H+(H+1)$	(30)

Where H is the entire neurons number, P is the lower level measures objectives index, Z is the upper level number of input variables and m_p is the input number for p^{th} objective. For a fixed number of neurons at 10 and 20, Table IV summarizes the results of a comparative study between NFHH, ANFIS and NN for the same number of neurons.

TABLE IV
Comparative study between NFHH, ANFIS and NN.

Approach	Neurons number	Parameters Number	Learning rate	Average error
NFHH	10	139	0.005	0.02168
			0.01	0.02471
			0.02	0.02799
	20	209	0.005	0.02250
			0.01	0.02542
			0.02	0.02901
ANFIS	10	482	0.005	0.02933
			0.01	0.03211
			0.02	0.03755
	20	552	0.005	0.03087
			0.01	0.03569
			0.02	0.04026
NN	10	171	0.005	0.07883
			0.01	0.08124
			0.02	0.08734
	20	341	0.005	0.07905
			0.01	0.08767
			0.02	0.09173

It is deduced that for the same number of neurons, NFHH can effectively reduce the number of hidden parameters. In fact, its hidden parameters (calculated by equation (28) are less than those of ANFIS and NN (calculated by equations (29) and (30). For example, NFHH requests 139 parameters for 10 neurons. However, ANFIS (482) and NN (171) demand more for the same number of neurons. Moreover, by keeping the same neurons number and modifying the learning rate values, NFHH achieves the best accuracy. For instance, by maintaining 10 neurons and 0.005 as the learning rate value, NFHH, ANFIS and NN acquire the following errors (0.02168 and 0.02933 and 0.07883), respectively. For 20 neurons, NFHH and ANFIS get an error of 0.02250 and 0.03087, while NN has an error of 0.07905. Therefore, it is notable that NFHH achieves the better accuracy by comparing its obtained rate with the desired one. Figure 11 illustrates the achievement evolution of the main objective rate ("Ensure the improvement of the system and objectives"), on one year, by applying the three different approaches (NFHH, ANFIS and NN).

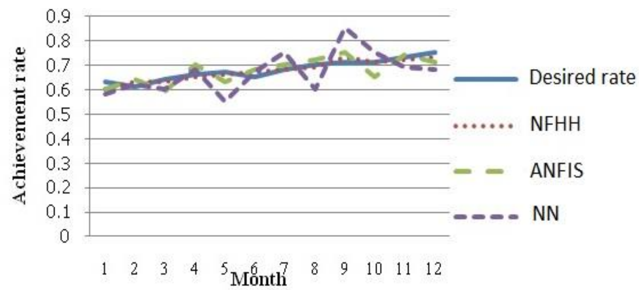

FIGURE 11. THE ACHIEVEMENT RATE EVOLUTION BY USING NFHH, ANFIS AND NN

This comparative study reveals that NFHH outperforms NN and ANFIS regarding accuracy and parameters number. Furthermore, NFHH reaches an achievement rate in the interval [0.6, 0.74] which surrounds the required realization rate [0.61, 0.73]. However, the realization rate obtained by applying ANFIS [0.59, 0.75] and NN [0.58, 0.85] are less important.

VI. CONCLUSIONS

In this paper, two approaches are investigated for a QMS control issue. They are Hierarchical Fuzzy Signature (HFS) and Neuro-Fuzzy Hierarchical Hybrid system (NFHH), respectively. Both of them are applied to ensure the effectiveness and the efficiency of companies' QMS. HFS was used to treat the case of an industrial company. Its hierarchical structure is able to treat fuzzy variables. Therefore, it reduces the complexity of the number and meta-levels of inputs and outputs. However, the NFHH approach consists of lower and upper levels. It is capable of dealing with heterogeneous variables such as quantitative and qualitative inputs. These inputs are optimized by a learning gradient algorithm and treated by the two levels.

In this study, it is deduced that NFHH has better performance over ANFIS and NN. NFHH reaches an effective accuracy, uses fewer parameters and also reduces the number of neurons. It also keeps the universal approximated property of neural and fuzzy systems.

This research leads to many perspectives such as the selection and the optimization of the number of input indicators, fuzzy rule number and membership functions. It is recommended to apply the metaheuristics algorithms, especially the genetic algorithms (GA). The hybrid network between the GA and the NFHH is mainly suggested to get the relevant number of performance indicators inputs, to reach a minimum set of membership functions and rules without knowing the topology of the overall fuzzy system.

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