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Proposition of a MANFIS-PID Hybrid System for the Prediction of Several Interdependent Parameters

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Abstract—**This paper is devoted to the definition of a MANFIS (Multi-output Adaptive Neuro-Fuzzy System) system combined with PID (Proportional Integral Derivative) regulators for the prognostic of failure. The input selection is implemented to improve the performance of the prediction system. The MANFIS subsystem performs the prediction of three interdependent parameters, and the PID controllers correct for each parameter the prediction error. For the control of the prediction error, we propose PID controllers with optimal parameters remaining constant in the medium term. Research oriented towards the development of neuro-fuzzy prediction systems suggests that multi-parameter models would be closer to the requirements of real industrial systems. Moreover, it emerges from this work that it is also necessary to improve the accuracy of these prediction systems without necessarily increasing the complexity of the algorithm. This is why the prognostic system proposed here allows the prediction of three interdependent parameters and the control of the prediction error. We will begin the work reported here by presenting the place of the prognostic in the maintenance activity. A presentation of the predictive system of type MANFIS-PID is carried out. The Lorenz dynamic system is used to illustrate our prediction architecture. The approach for determining the optimal parameters of PID controllers is presented. A comparative analysis of the prediction error distribution of the MANFIS-PID system and its MANFIS subsystem at different horizons of prediction is also presented**

Keywords— prognostic; MANFIS-PID; optimal parameters of PID; prediction Error

I. INTRODUCTION

Improving reliability has been one of the major challenges facing industrial companies of our time [1]. The anticipation of failures (preventive maintenance) now at the center of maintenance activity allows a real improvement in the availability and reliability of the systems. The implementation of such a maintenance policy requires the provision of adequate resources for monitoring, diagnostics and prediction of the state of the systems [2] [3].

These perpetual challenges have contributed to the development of surveillance systems and the birth of new maintenance concepts. These maintenance concepts increase the autonomy and intelligence of current monitoring systems [4] [5]. These new maintenance concepts thus give a privileged place to the industrial prognostic in the maintenance activity [6]. Today, failures prediction is considered as a research theme [7].

In the field of industrial prognostic, several approaches have been implemented. The data-driven approach is widely used. This approach is used when the modeling of the system is complex and the data collected are reliable. It offers a place of choice to the techniques of artificial intelligence [8].

Concerning prognostic of failure via the data-guided approach, several mutations have been observed. We started with the use of Neural Networks (NN), to the NN loops of [9]. To improve precision, [10] associate a PID controller with the NN loops. Today, the data-driven prognostic is based on hybrid systems such as Neuro-Fuzzy (NF) networks. It is for this purpose that the system chosen for the development of our work is an ANFIS (Adaptive Neuro-Fuzzy Inference System) proposed by [11]. Most of the ANFIS systems developed in the literature focus on the reduction of the prediction error and for others on the control of this error. However, this work reveals the need to develop multi-parameters prediction systems. Indeed, the real industrial systems can't be satisfied with the prediction of a single parameter. Furthermore, [12] reveal the need for the selection of optimal parameters for the prediction of neuro-fuzzy systems. Moreover, the work of [10] reveals that a PID controller could contribute to the improvement of prediction performance without increasing the complexity of the treatment.

We therefore propose a hybrid system consisting initially of a MANFIS subsystem which applies the selection of inputs for the efficient prediction of three interdependent parameters. In a second step, the proposed system also consists of three PID controllers that control the prediction error of each parameter. For the control of the prediction error, we have defined for each PID controller, optimal parameters (Kp, Ki and Kd) remaining constant in the medium term.

The MANFIS-PID system thus proposed is able to predict the evolution of three parameters while controlling the prediction error. It allows efficient prediction without increasing the complexity of the algorithm.

The rest of this paper is organized as follows: Section 2 is reserved for the definition of the problem. In this section we will start from the position of the prognosis in industrial maintenance and some work to reduce and control the error to introduce the need to propose an efficient multi-parameter prediction system.

Section 3 presents the ANFIS and MANFIS systems. In section 4 we present the proposed MANFIS-PID system and the process of obtaining the optimal parameters of the PID controller (Kp, Ki and Kd) remaining constant in the medium term. These results will be analyzed and discussed in Section 5. Section 6 is devoted to the conclusion and definition of future work.

II. PROBLEM DEFINITION

A. *Place of prognostic in industrial maintenance*

The maintenance applied to an equipment (systems, subsystem or component) contributes to the improvement of the availability and the reliability of the service rendered by this equipment. In addition to the purpose of enabling an asset to fulfill its required function, new requirements of quality, safety and cost must be taken into account. These new requirements make up the new challenges of maintenance and worth its evolution. Indeed, the increase in maintenance costs, the advent of automation and the new requirements of customers demand a high level of flexibility of industrial equipments [13]. Formerly the so-called traditional maintenance activity was based on the anomaly detection, the comprehension and identification of the causes of this anomaly (diagnosis) and finally the choice and implementation of an adequate action. However, nowadays, the a posteriori comprehension of a failure gave place to the anticipation of the failure. The prognostic of failure seems to meet these new maintenance requirements.

B. *Failure prognostic concept*

The prognostic is defined by [14] as "an estimate of the duration of operation before failure and the risk of the existence or subsequent appearance of one or more modes of failure". The prognostic is further defined by [7] as a process designed to determine the remaining life of a system. [15] Asserts that the prognosis may also be considered as an estimate of the probability of occurrence of a failure.

The prognostic of failure is based both on the notion of degradation and on the existence of a critical threshold. From a given instant t, the prognostic activity consists first of all in predicting the evolution of the degradation of the system at an instant t + dt. After prediction, the second step of the prognostic consist in evaluating the state of the system according to the predefined referential [8].

C. *Reduction and control of the prediction error*

The prognostic of the state of a system being inherently uncertain, it is important to determine measures defining the confidence level of the prognostic system. RMSE (Root Mean Squared Error) is currently used in the literature.

Several works in the literature aim at reducing this error. To improve the performance of data-based prognostic systems, we have moved from not curly networks [16], [17], and [18] etc. to the curly networks of [19] and [20].

Improved performance and the desire to reduce the complexity of prognostic systems led researchers to migrate to hybrid systems such as NF networks [21], [22], [23], [24] and [25] etc.

Beside the reduction of the prediction error, [26] and [1] focus their work on controlling prediction error. [26] Propose a new cost function and a new prediction model composed of two ANFIS systems with four inputs connected in series. [1] Implements the input selection governed by the method of [27]. It seems clear at the end of the analysis of these works that, the prediction of several parameters would be closer to the requirements of real industrial systems.

From what is the prediction of several parameters, [27] developed the MANFIS (Multiple Adaptive Neuro-Fuzzy Inference System) model. In addition, [28] proposed a MANFIS model for the approximation of three sinusoidal functions. However, actual industrial systems exhibit a much more complex evolution than those represented by sinusoidal functions.

[29] Propose a MANFIS system for the prediction of three parameters and the genetic algorithm is associated to improve the performance.

[10] Associate the PID with the RRFBR for the control of the prediction error. However, [10] propose for the PID controller combinations of parameters (Kp, Ki and Kd) for

each horizon of prediction. This change in the values of the parameters (Kp, Ki and Kd) at each horizon of prediction seems tedious.

It is to improve the accuracy of a multi-parameters prediction system without increasing the complexity of the prediction algorithm that, the work proposed in this paper applies the selection of inputs and the PID controller (with constant parameter values in the medium term) to a MANFIS system with three interdependent parameters.

III. NEURO-FUZZY PREDICTION SYSTEM

A. ANFIS Architecture

[30] Effectuates the analysis of some NF architectures and realizes that ANFIS architecture offers a better RMSE.

TABLE I. PERFORMANCE OF SOME NF MODELS [30]

Model	Epochs	RMSE
ANFIS	75	0.0017
NEFPROX	216	0.332
EfuNN	1	0.0140
dmEFuNN	1	0.0042
SONFIN	1	0.0180

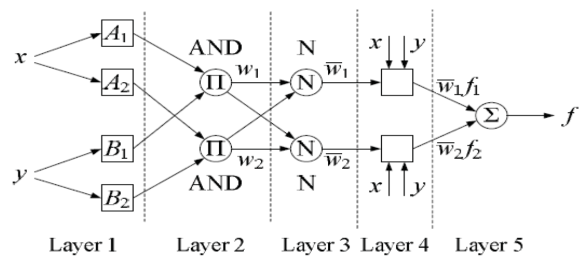

Fig. 1. Network structure of ANFIS model [27]

Layer 1. Generates the membership grades:

$$O_i^1 = \mu_{A_i}(x), \quad \text{i=1, 2} \tag{3}$$

$$O_i^1 = \mu_{B_i}(y), \quad \text{i=1, 2} \tag{4}$$

Where μ_{A_i} and μ_{B_i} can be any membership functions.

Layer 2. Generates the firing strengths.

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad \text{i=1, 2} \tag{5}$$

Layer 3. Normalizes the firing strengths.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad \text{i=1, 2} \tag{6}$$

Layer 4. Calculates rule outputs based on the consequent parameters.

$$O_i^4 = \bar{w}_i f_i = \bar{w}(p_i x + q_i y + r_i) \quad \text{i=1, 2} \tag{7}$$

Where p_i, q_i and r_i are the so-called consequential parameters.

Layer 5. Output calculation

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \quad \text{i=1, 2} \tag{8}$$

After this phase, the optimal values of these membership function parameters and consequential parameters are set by a hybrid learning algorithm that combines the method of least squares with the backpropagation learning algorithm. Finally, the ANFIS output is calculated by means of consequential parameters.

B. MANFIS Architecture

The ANFIS architecture is similar to the new MANFIS system proposed in this paper. Indeed, the MANFIS architecture can be considered as an aggregation of several ANFIS [31].

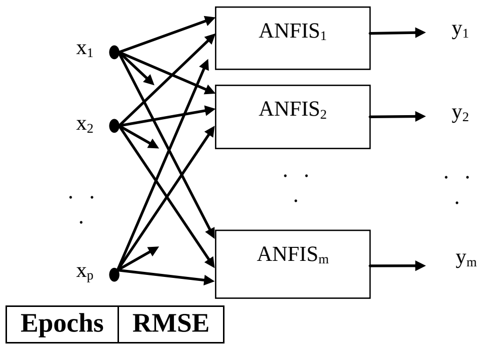

Fig. 2. Architecture of the MANFIS network [31]

In this model, the input variables x_i (i=1, 2,…,p) are independent and the output variables y_i (i=1, 2,…,p) are functions of the input variables.

$$x = x_1, x_2, \ldots, x_p \tag{9}$$

$$y_i = f_i(x) + \varepsilon_i, \quad i = 1, 2, \ldots, m \tag{10}$$

IV. MANFIS-PID SYSTEM FOR THE PREDICTION OF THREE INTERDEPENDENT PARAMETERS

In this section, we propose a MANFIS-PID system capable of performing the prediction of three interdependent parameters. This system consists of two subsystems. The MANFIS subsystem performs the prediction of three interdependent parameters, and the PID controllers (with constant parameters) perform the control of prediction error for each parameter (X, Y and Z).

A. *Structure of the MANFIS subsystem*

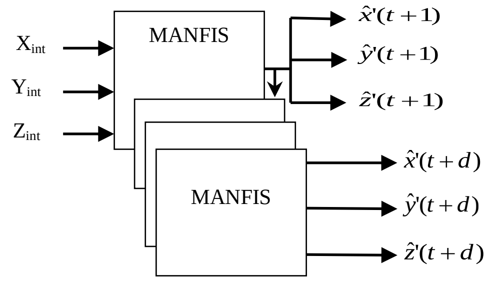

Fig. 3. MANFIS prediction subsystem of three interdependent parameters

For this sub-system, the variable "d" represents the horizon of prediction. For each of the input variables (X, Y, Z), the components chosen as inputs are those corresponding to the four previous instants to the instant of prediction. Input Variables X_{int}, Y_{int} and Z_{int} are vectors defined as follows:

$$X_{\text{int}} = [x(t-3) \quad x(t-2) \quad x(t-1) \quad x(t)]^{\mathrm{T}} \qquad (11)$$

$$Y_{\text{int}} = [y(t-3) \quad y(t-2) \quad y(t-1) \quad y(t)]^{\mathrm{T}}$$

$$Z_{\text{int}} = [z(t-3) \quad z(t-2) \quad z(t-1) \quad z(t)]^{\mathrm{T}} \qquad (13)$$

For this sub-system, the prediction of the state of the parameters at a given instant takes into account the state of these parameters at the four previous instants. The incrementation of the horizon of prediction is done by cascading the base system.

B. *Structure of the MANFIS-PID system and determination of the optimal parameters Kp, Ki and Kd of the PID controllers*

For the MANFIS-PID system, the prediction errors $\varepsilon_{x1}(t)$, $\varepsilon_{y1}(t)$ and $\varepsilon_{z1}(t)$ are respectively calculated between the values $\hat{x}'(t)$, $\hat{y}'(t)$ and $\hat{z}'(t)$ predicted by the MANFIS subsystem and the real values $x(t)$, $y(t)$ and $z(t)$. The controllers PID_1, PID_2 and PID_3 respectively deliver the commands *com₁₁*, *com₂₁* and *com₃₁* capable of adjusting the predictions of the MANFIS subsystem. The control of the prediction error thus performed allows us to obtain $\hat{x}(t+1)$, $\hat{y}(t+1)$ and $\hat{z}(t+1)$.

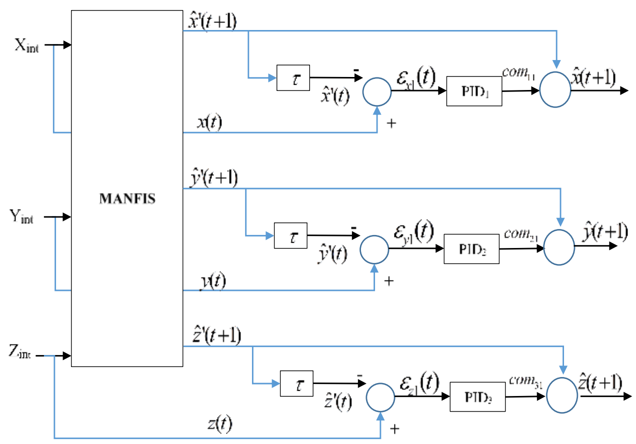

Fig. 4. MANFIS-PID system

Unlike the PID controller proposed by [10], the particularity of the PID controllers proposed here is that they keep constant, parameter values Kp, Ki and Kd in the medium term.

Consider the variable X, the control of the prediction error can be written: (12)

$$\hat{x}(t+1) = \hat{x}'(t+1) + K_P \varepsilon_{x1}(t) + K_i \int_0^t \varepsilon_{x1}(\tau) d\tau + K_d \frac{\partial \varepsilon_{x1}(t)}{\partial t} \qquad (14)$$

With $\varepsilon_{x1}(t)$ the prediction error for the horizon t+1

By induction, at the horizon t + d we can also write:

$$\hat{x}(t+d) = \hat{x}'(t+d) + K_P \varepsilon_{xd}(t) + K_i \int_0^t \varepsilon_{xd}(\tau) d\tau + K_d \frac{\partial \varepsilon_{xd}(t)}{\partial (t)} \qquad (15)$$

With $\varepsilon_{xd}(t)$ the prediction error for the horizon t+d

The command com_{11} delivered by the PID_1 controller to predict the state of the variable X at instant t+1 can be written as:

$$com_{11} = K_P \varepsilon_{x1}(t) + K_i \int_0^t \varepsilon_{x1}(\tau) d\tau + K_d \frac{\partial \varepsilon_{x1}(t)}{\partial t} \qquad (16)$$

$$com_{11} = \hat{x}(t+1) - \hat{x}'(t+1) \qquad (17)$$

Similarly, the command com_{1d} delivered by the PID_1 controller at time t+d can be written:

$$com_{1d} = \hat{x}(t+d) - \hat{x}'(t+d) \qquad (18)$$

Ideally,

$$\hat{x}(t+d) = x(t+d)$$

This implies that:

$$com_{1d} = x(t+d) - \hat{x}'(t+d) \qquad (20)$$

Considering the previous expressions, there are constant and optimal values Kp, Ki and Kd satisfying the following equation system:

$$\begin{cases} com_{11} = K_P \varepsilon_{x1}(t) + K_i \int_0^t \varepsilon_{x1}(\tau) d\tau + K_d \dfrac{\partial \varepsilon_{x1}(t)}{\partial t} \\ \vdots \\ com_{1d} = K_P \varepsilon_{xd}(t) + K_i \int_0^t \varepsilon_{xd}(\tau) d\tau + K_d \dfrac{\partial \varepsilon_{xd}(t)}{\partial (t)} \end{cases} \tag{21}$$

The resolution of this system of equation allows us to find the optimal parameters Kp, Ki and Kd to obtain optimal PID controls. These parameters remain unchanged up to the horizon t+d. The same approach is applied to the variable Y and Z.

C. *Training base*

For the validation of our system we used the time series of Lorenz. This series of data is chaotic, therefore non-periodic and non-convergent. The time series of Lorentz presents the evolution over time of three interdependent parameters [32]. Although widely used in the field of climatic predictions, we have found it interesting to validate our system whose application is in the field of industrial maintenance.

D. *Prediction Methodology Implemented*

The prediction methodology begins with the formation of 150 training data and 100 test data. The data of each of the parameters X, Y and Z are arranged in the form of five-column matrices (the four inputs and the desired output) and "n" rows (n being the size of the training / test set). These data are used for the generation of fuzzy inference systems and the training of three ANFIS systems, each for the prediction of one of the three parameters. The symbiosis of the three systems allowed us to form a MANFIS subsystem. The MANFIS subsystem performs the prediction by delivering the values $\hat{x}'(t+d)$, $\hat{y}'(t+d)$ and $\hat{z}'(t+d)$. To this system is associated the controllers PID_1, PID_2 and PID_3 who issue the commands respectively com_{1d}, com_{2d} and com_{3d}. Commands com_{1d}, com_{2d} and com_{3d} are applied to the values previously predicted by the MANFIS subsystem to give respectively $\hat{x}(t+d)$, $\hat{y}(t+d)$ and $\hat{z}(t+d)$. These values thus constitute the prediction effectuated by the MANFIS-PID system.

The cascade of the previously formed system makes it possible to increment the horizon of prediction. The variable "d" corresponds to this horizon of prediction. This cascading is inspired by the work of [33] and taken over by [26].

Consider A, the matrix (K×3) containing the expected values of the three parameters for the K tests and $\hat{A}$, the matrix (K×3) containing the predicted values of the three parameters for the K tests.

The RMSE between the expected values and the estimated values is calculated by the equation (24).

$$A = \begin{pmatrix} x_1 & y_1 & z_1 \\ \vdots & \vdots & \vdots \\ x_k & y_k & z_k \end{pmatrix} \tag{22}$$

$$\hat{A} = \begin{pmatrix} \hat{x}_1 & \hat{y}_1 & \hat{z}_1 \\ \vdots & \vdots & \vdots \\ \hat{x}_k & \hat{y}_k & \hat{z}_k \end{pmatrix} \tag{23}$$

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left[A(k) - \hat{A}(k)\right]^2} \tag{24}$$

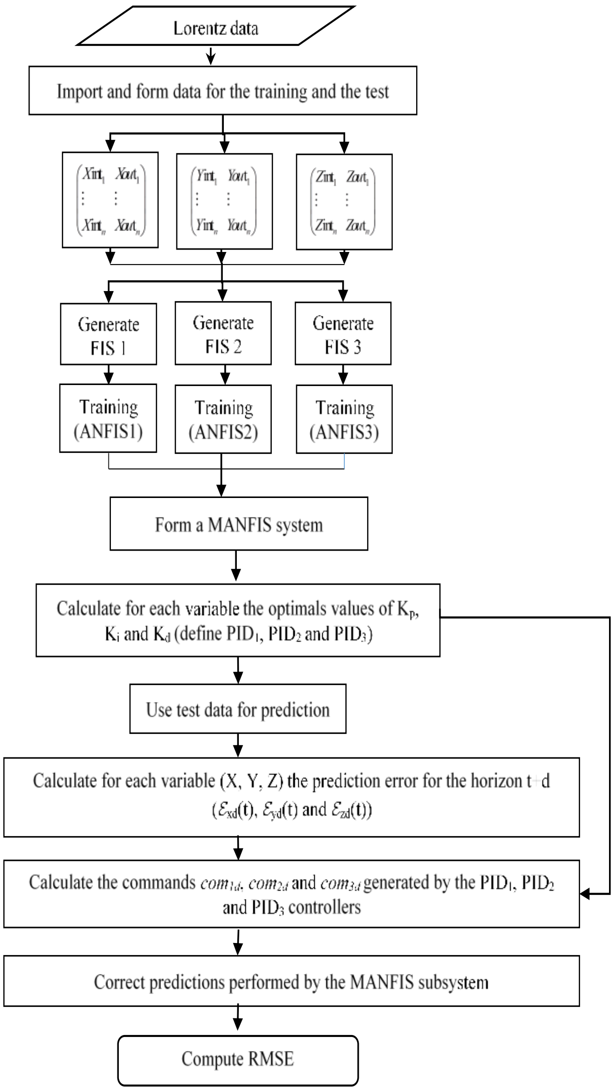

Fig. 5. Process deployed in the MANFIS-PID prediction system

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V. RESULT AND ANALYSIS

Table 2 presents the different values of the Kp, Ki and Kd parameters obtained for each of the three variables. The integration parameter Ki being zero, we have PD type controllers (Proportional Derivative).

TABLE II. VALUES OF OPTIMAL PARAMETERS KP, KI AND KD FROM HORIZON t+1 TO t+20

	K_p	K_i	K_d
Variable X	1.1019	0	0.1183
Variable Y	1.1901	0	0.1784
Variable Z	0.8907	0	1.1165

A comparative analysis of the performance of the MANFIS-PID prediction system and its MANFIS subsystem is presented in Table 3 and Figure 6. This analysis shows a real decrease in the RMSE of the MANFIS-PID system compared to the RMSE of the MANFIS subsystem. We can see that the PD controller increases the prediction performances without requiring the variation of the values of the parameters Kp, Ki and Kd with the horizon of prediction.

TABLE III. COMPARATIVE ANALYSIS OF PID MANFIS SYSTEM PERFORMANCE COMPARED TO ITS SUBSYSTEM MANFIS

Horizon of prediction	Prediction System	RMSE test set
t+1	MANFIS	0.0003
	MANFIS-PID	0.0001
t+2	MANFIS	0.0018
	MANFIS-PID	0.0010
t+4	MANFIS	0.0109
	MANFIS-PID	0.0047
t+6	MANFIS	0.0330
	MANFIS-PID	0.0170
t+8	MANFIS	0.0761
	MANFIS-PID	0.0475
t+10	MANFIS	0.1463
	MANFIS-PID	0.0960
t+12	MANFIS	0.2468
	MANFIS-PID	0.1765
t+14	MANFIS	0.3766
	MANFIS-PID	0.1561
t+16	MANFIS	0.5310
	MANFIS-PID	0.3147
t+18	MANFIS	0.7019
	MANFIS-PID	0.5545
t+20	MANFIS	0.8802
	MANFIS-PID	0.6274

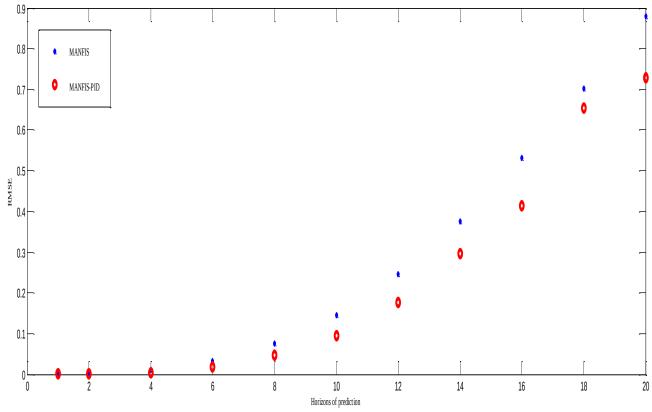
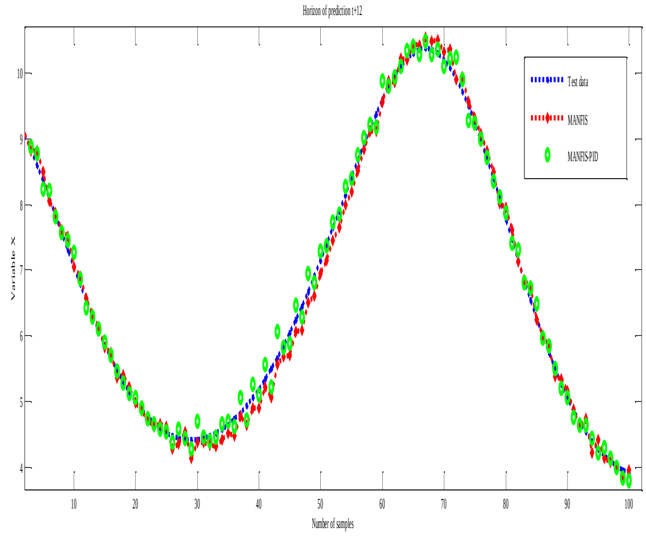


Fig. 6. Evolution of RMSE at different horizons of prediction

Figs. 7 to 9 show the results of the prediction obtained for the three variables at different horizons of prediction for the MANFIS-PID system and its MANFIS subsystem. A relative but perceptible increase in prediction is observed for variables X and Y by the MANFIS-PID system. On the other hand, the MANFIS-PID system provides an excellent improvement in the prediction performance for the variable Z.



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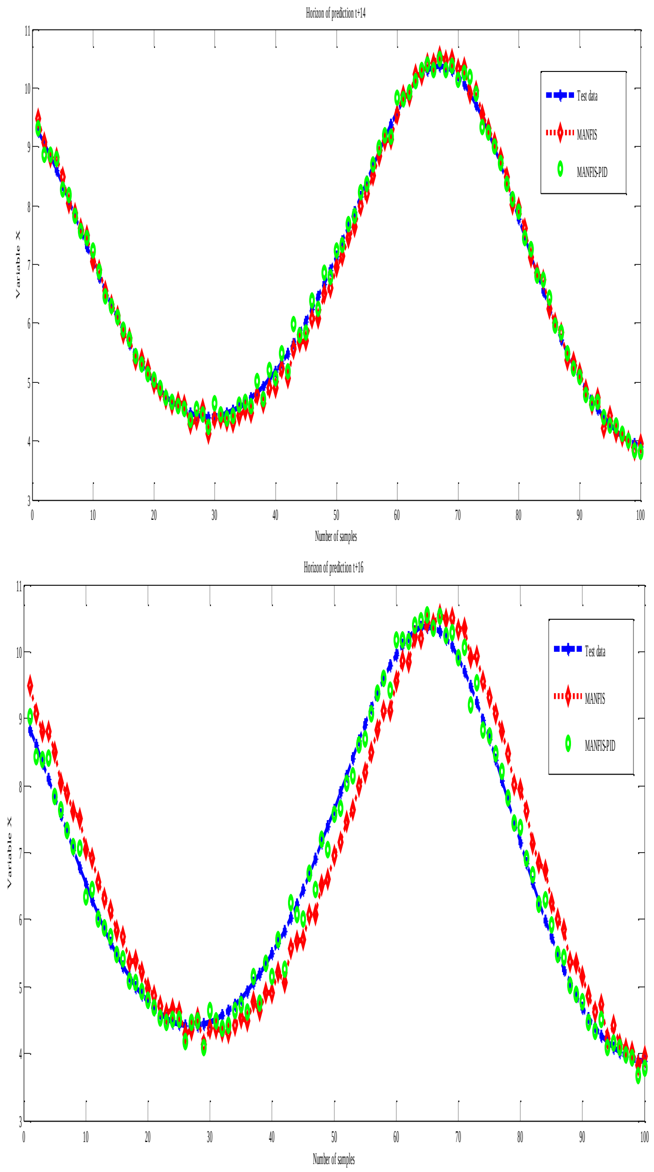


Fig. 7. Results of prediction of variable X at different horizons of prediction

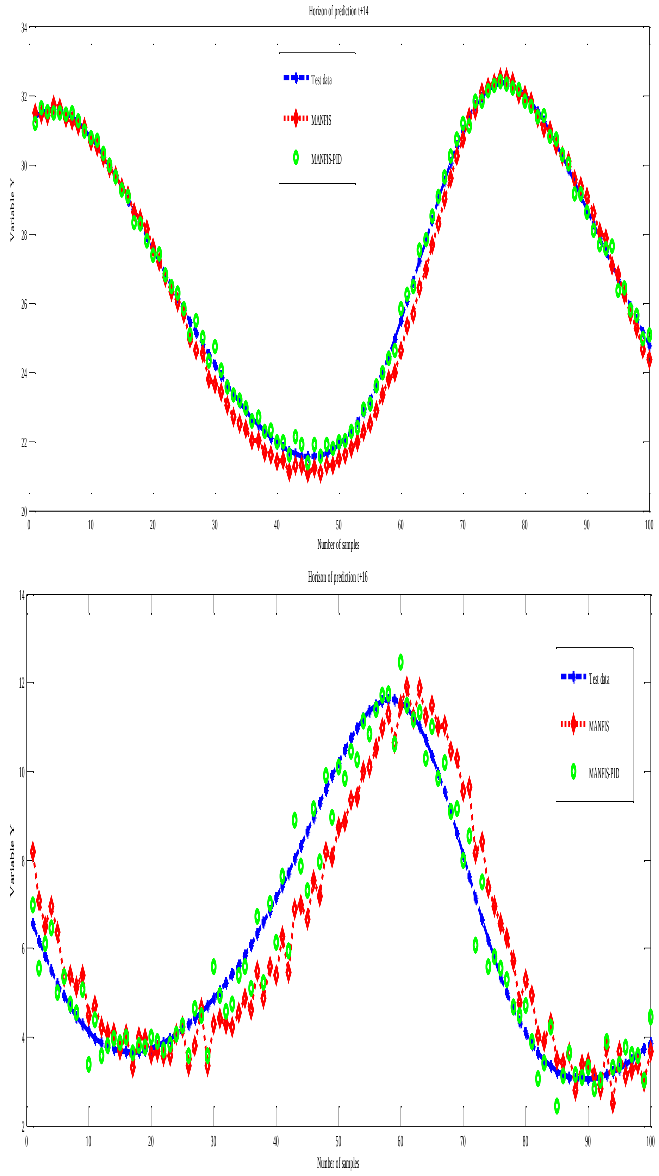
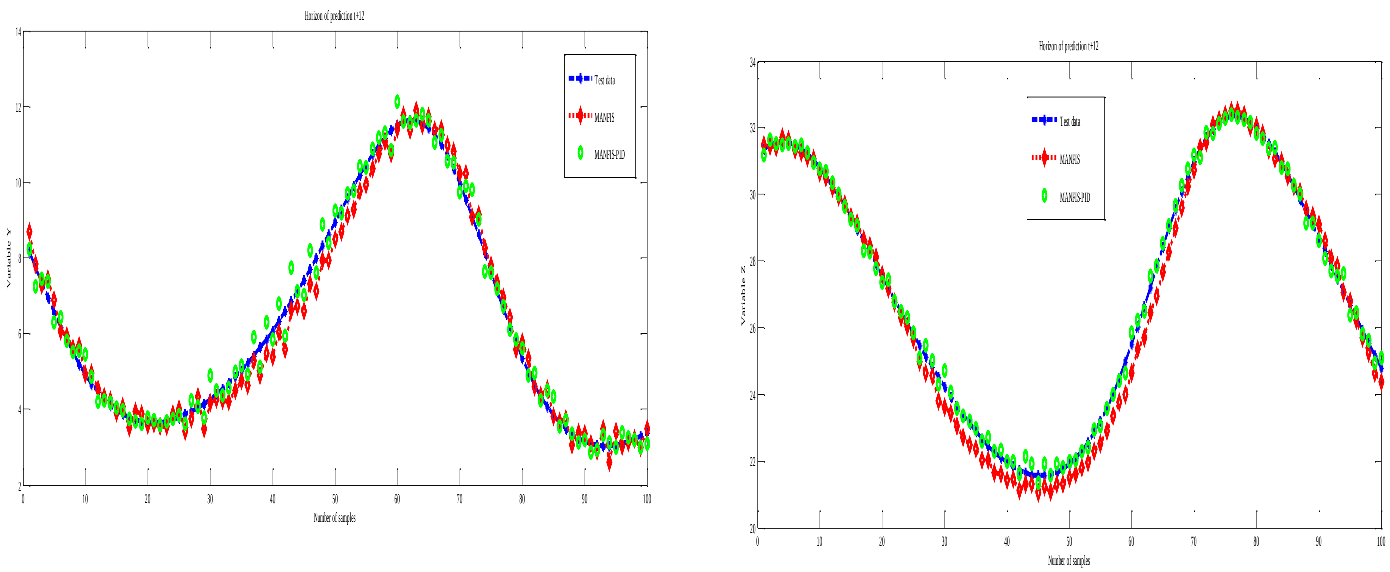


Fig. 8. Results of the prediction of variable Y at different horizons of prediction



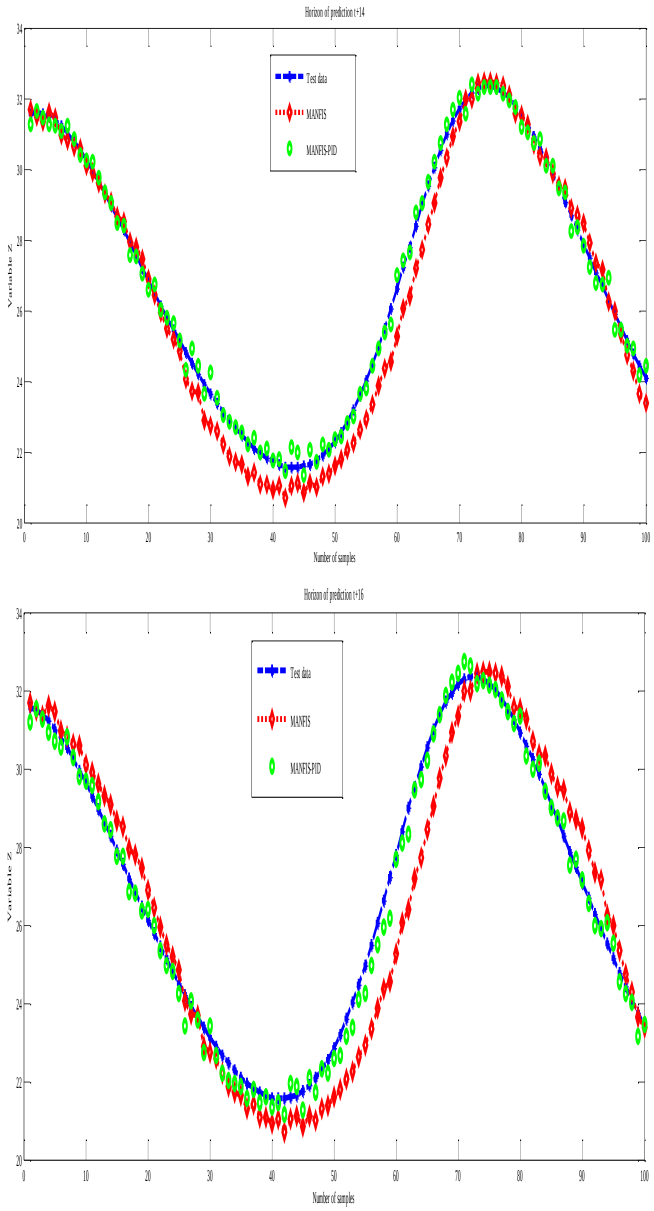


Fig. 9. Results of prediction of the variable Z at different horizons of prediction

VI. CONCLUSION

The industrial prognostic occupies today a place of choice in industrial maintenance. However, planning for the maintenance of real industrial systems very often depends on the evolution of several interdependent parameters. Moreover, the improvement of the performances of the prediction systems without increasing the complexity of the algorithm proves to be a major challenge in the field of industrial prognostic. It is strong from these remarks that, the work reported in this paper deals globally with the definition of a prognostic system capable of effectively predicting the evolution of three interdependent parameters. This system combines the neural-fuzzy network of the MANFIS type with PID controllers. These controllers have the particularity of keeping constant parameter values with several horizons of prediction.

The definition of the MANFIS-PID system proposed in this paper requires the definition of its MANFIS subsystem which implements the selection of inputs for the improvement of the prediction of three interdependent parameters. Three regulators of the PID type with constant gain values are associated with this prediction subsystem. The purpose of these controllers is to control the prediction error. The cascading of the prediction systems allowed the time variable to be incremented, an important element in the planning of maintenance activities.

The approach of obtaining the values of gains remaining constant at several horizons of prediction is presented. A comparative analysis of the RMSE of the MANFIS-PID system and its MANFIS subsystem is carried out. The representation of the predictions of the three variables is also performed at different horizons of prediction. The analysis of these different results reveals that the MANFIS-PID system offers better performance than its MANFIS subsystem. This improvement in the performance of the MANFIS-PID system is due to the control of the prediction error.

This work can be extended along several axes. In order to better meet the requirements of industrial systems, it will be possible to integrate the operating conditions and the future maintenance actions with this multi-parameter prediction model.

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