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# Proposition of multi-ANFIS Architecture Mounted in Series for the Multi-Parameters Prediction

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***Abstract*—This article is devoted to the proposed MANFIS (Multi-output Adaptive Neuro-Fuzzy System) system for the prognostic of failure. It is a system that predicts at short and medium term the evolution of three interdependent parameters with an acceptable accuracy without increasing the complexity of the treatments. The choice of inputs is implemented to improve the performance of the architecture. For this architecture, the cascading of the MANFIS systems is implemented for the incrementation of the horizon of prediction. Research oriented towards the development of prediction systems of the ANFIS type suggests that models with several parameters would be closer to real industrial systems. This is why the prognostic system proposed here allows the prediction of three interdependent parameters. We shall begin the work reported here by presenting the place of prognostic in the maintenance activity. A presentation of features of the predictive system of type MANFIS is proposed. The Lorenz dynamic system is used to illustrate our prediction architecture. A discussion of the distribution of the global architecture error at different horizons of prediction is presented.**

***Keywords— Maintenance; prognostic; choice of inputs; MANFIS in series; multi-parameters; 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. 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 [9]. 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, [10] reveal the need for the selection of optimal parameters for the prediction of neuro-fuzzy systems. The observations above permitted the proposal of a new architecture which uses input parameters considered optimal for the prediction of the evolutions of several interdependent parameters at short and medium interval of time with a satisfactory prediction error.

The rest of this article 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 prognostic in industrial

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maintenance and some work aimed at reducing and controlling the error to introduce the need to propose a multi-parameters prediction system.

Section 3 presents the NF systems, of the MANFIS and ANFIS types. In section 4 we shall present our proposed MANFIS network and the methodology by which we obtained the results of our work. These results will be analyzed and discussed in Section 5. Section 6 is devoted to the conclusion and definition of future works.

## 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 [11]. 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 [12] 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. [13] 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 [14], [15], and [16] etc. to the curly networks of [17] and [18].

Improved performance and the desire to reduce the complexity of prognostic systems led researchers to migrate to hybrid systems such as NF networks [19], [20], [21], [22] and [23] etc.

Beside the reduction of the prediction error, [24] and [1] focus their work on controlling prediction error. [24] 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 [25]. 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, [25] developed the MANFIS (Multiple Adaptive Neuro-Fuzzy Inference System) model. In addition, [26] 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.

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

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 to a MANFIS system with three interdependent parameters. The incrementation of the horizon of prediction is done by cascading the proposed MANFIS system.

The work presented here is aimed at proposing a MANFIS system capable of effectively predicting the parameters of a chaotic dynamic system in the short and medium term.

## III. NEURO-FUZZY PREDICTION SYSTEM

### A. *ANFIS Architecture*

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

TABLE I. PERFORMANCE OF SOME NF MODELS [28]

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

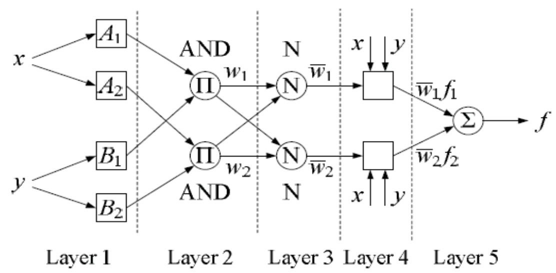



Fig. 1. Network structure of ANFIS model [25]

Layer 1. Generates the membership grades:

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

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

Where $\mu_{A_i}$ and $\mu_{B_i}$ can be any membership functions.

Layer 2. Generates the firing strengths.

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

Layer 3. Normalizes the firing strengths.

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

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

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

Where, and are the so-called consequential parameters.

Layer 5. Output calculation

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

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*

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 [29].

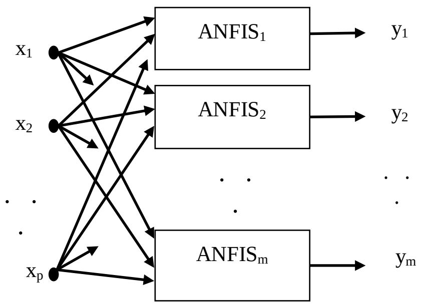



Fig. 2. Architecture of the MANFIS network [29]

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.

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

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

## IV. PROPOSED SYSTEM FOR THE PREDICTION OF THREE INTERDEPENDENT PARAMETERS

In this section we propose a system capable of performing the prediction of three interdependent parameters. This prediction system could be applicable in cases where the planning of maintenance activities is dependent on three key parameters. These parameters being themselves dependent on each other.

*A. Structure of our proposed system*

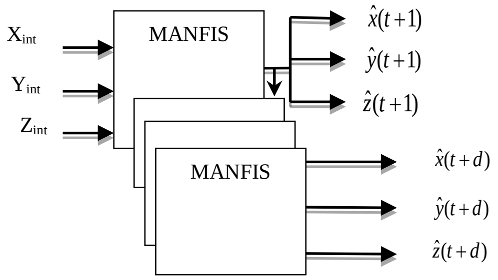



Fig. 3. Prediction system of three interdependent parameters

For this 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:

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

$$Y_{int} = [y(t-3) \quad y(t-2) \quad y(t-1) \quad y(t)]^T \tag{12}$$

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

For this 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. 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 [30]. Although widely used in the field of climate predictions, we have found it interesting to validate our system whose application is in the field of industrial maintenance.

*C. 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 our prediction system with three interdependent parameters. 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 [31] and taken over by [24].

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 (16). We have tested eleven horizons of prediction (d varying from 1 to 20).

$$A = \begin{pmatrix} x_1 & y_1 & z_1 \\ \vdots & \vdots & \vdots \\ x_k & y_k & z_k \end{pmatrix} \quad (14)$$

$$\hat{A} = \begin{pmatrix} \hat{x}_1 & \hat{y}_1 & \hat{z}_1 \\ \vdots & \vdots & \vdots \\ \hat{x}_k & \hat{y}_k & \hat{z}_k \end{pmatrix} \quad (15)$$

$$\forall k \in [1, K], \qquad RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left[A(k) - \hat{A}(k)\right]^2} \quad (16)$$

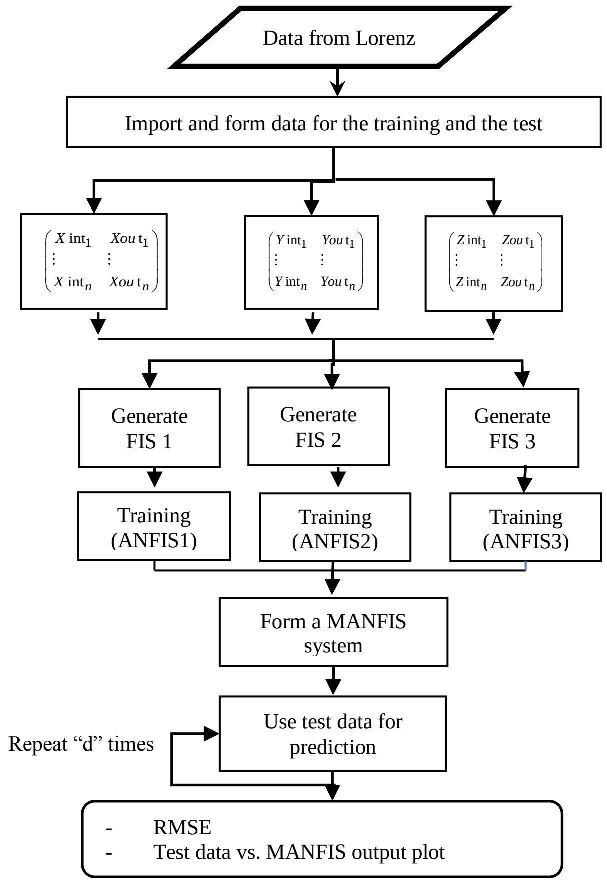



Fig. 4. Process deployed in the prediction system of three interrelated parameters

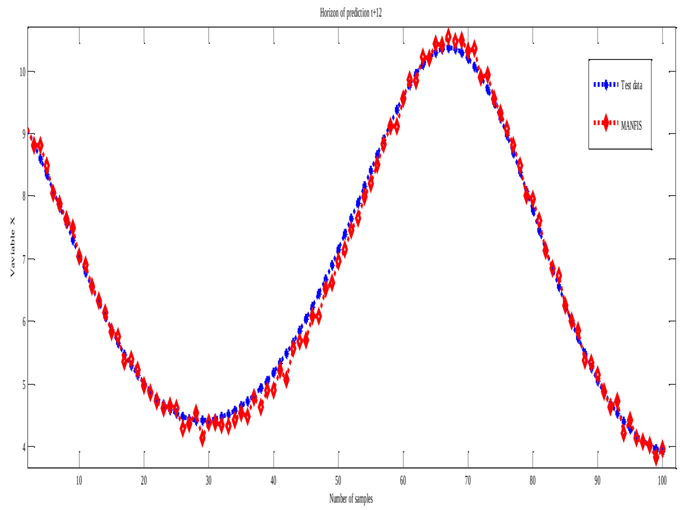
## V. RESULTS AND ANALYSIS

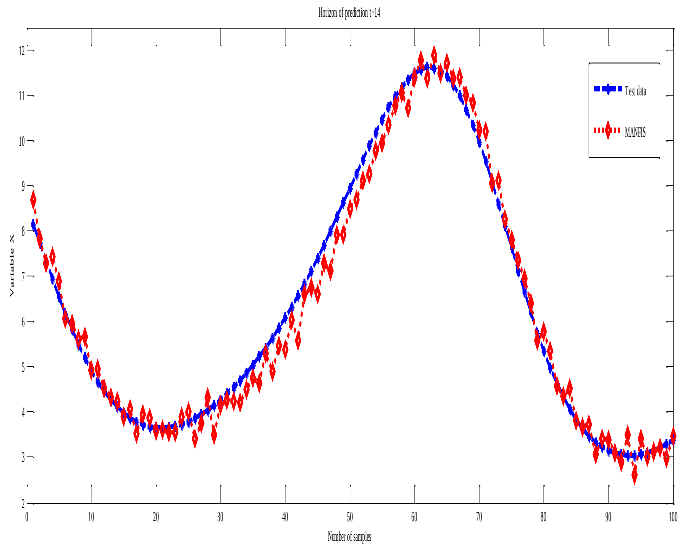
Table II presents the RMSE values obtained at different horizons of prediction.

TABLE II. RMSE AT DIFFERENT HORIZONS OF PREDICTION

| Horizon of prediction | RMSE test set |
|---|---|
| t +1 | 0.0003 |
| t+2 | 0.0018 |
| t+4 | 0.0109 |
| t+6 | 0.0330 |
| t +8 | 0.0761 |
| t+10 | 0.1463 |
| t+12 | 0.2468 |
| t+14 | 0.3766 |
| t+16 | 0.5310 |
| t+18 | 0.7019 |
| t+20 | 0.8802 |

Figs. 5 to 7 show a comparative analysis of the predictions obtained by the MANFIS system compared to the test data. Analysis of these curves shows that the selection of inputs provides acceptable accuracy in the short and medium term.



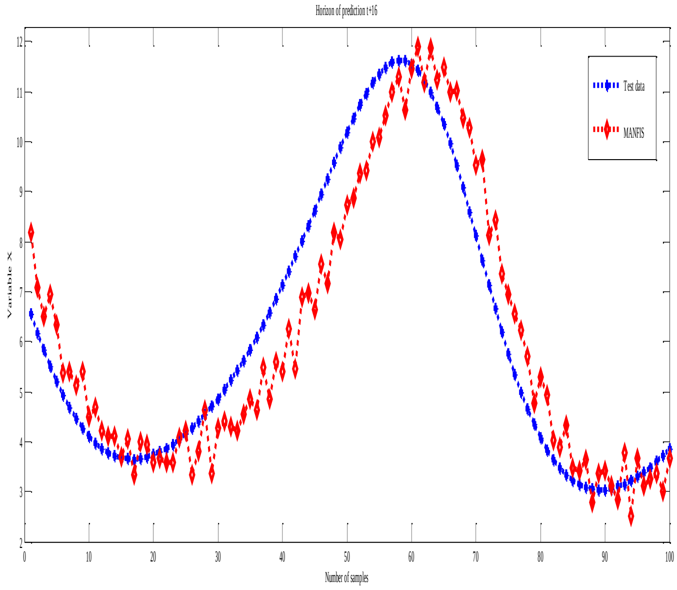



Fig. 5. Results of prediction of variable X at different horizons of prediction

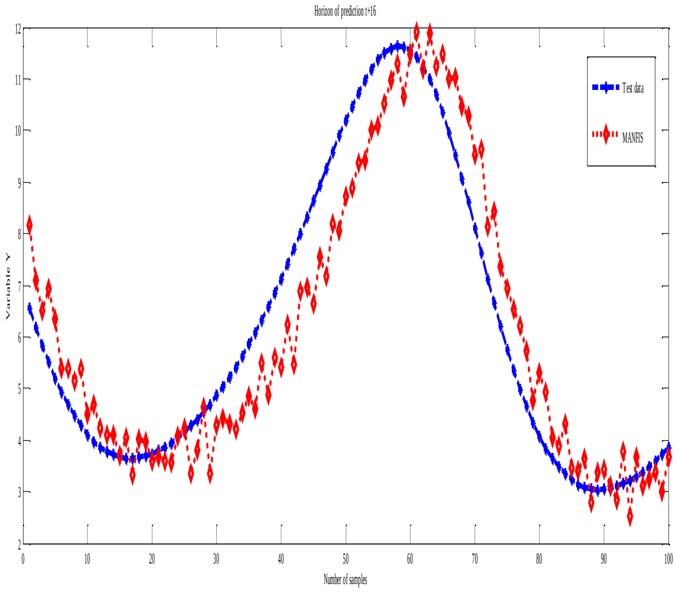
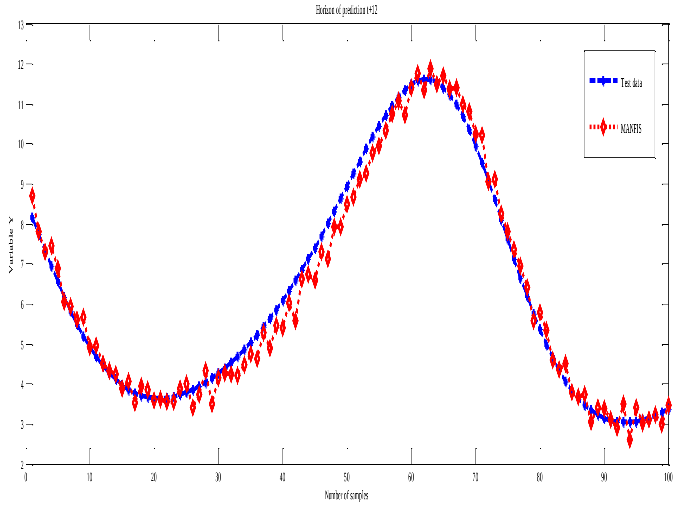
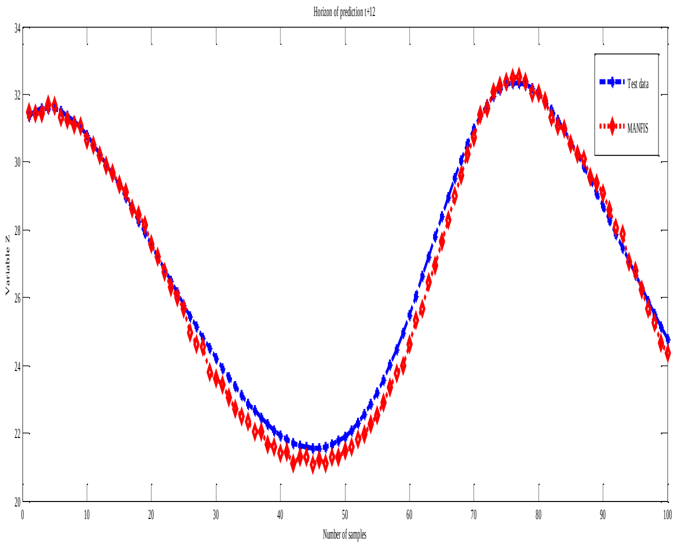
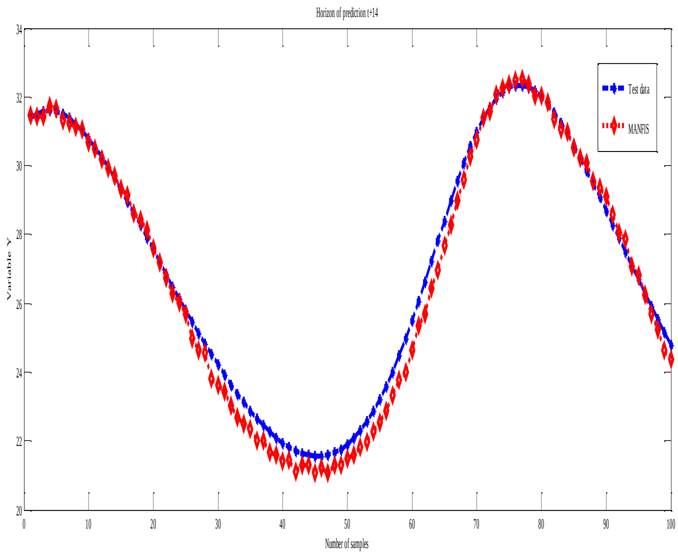
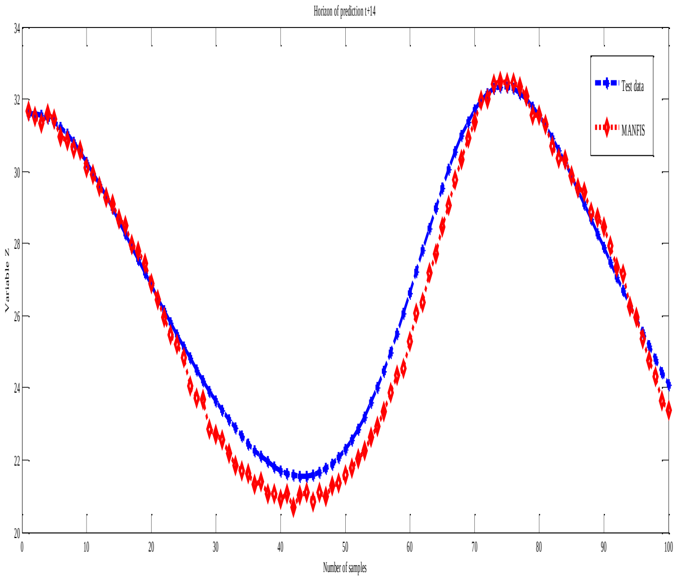



Fig. 6. Results of prediction of variable Y at different horizons of prediction



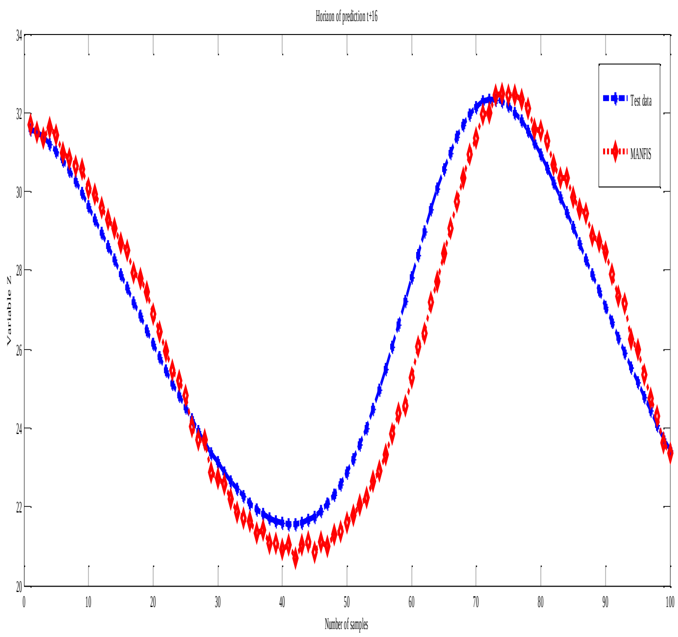



Fig. 7. Results of prediction of variable Z at different horizons of prediction

## VI. CONCLUSION

The industrial prognostic occupies today a place of choice in industrial maintenance. However, the planning of the maintenance of real industrial systems very often depends on the evolution of several interdependent parameters. This remark proves that the work reported in this paper deals globally with the definition of a prognostic system capable of predicting the evolution of three interdependent parameters.

For the setting up of this system the selection of the inputs and the cascading of the MANFIS systems have been implemented. This cascading allowed the incrementation of the variable time, an important element for the planning of the maintenance activities. The evaluation of the prediction indicators allowed us to conclude that the system offers satisfactory values of the RMSE for short and medium interval of time.

Although we have obtained acceptable prediction accuracy for short and medium term.

This work can be extended along several axes. First we can improve accuracy of prediction system without increasing the complexity of the prediction algorithm. In addition to improving accuracy, we could integrate the operating conditions and the future maintenance actions to this multi-parameter model.

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