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Original articles

# Gas turbine monitoring using neural network dynamic nonlinear autoregressive with external exogenous input modelling

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## Abstract

The main purpose of the present work is to propose an effective tool which allows to ensure the protection and the safety measures against the instability phenomena in a gas turbine based on the modelling of its dynamic behaviour. In order to provide an efficient diagnostic strategy for this type of rotating machine, a supervision system based on the development of artificial neural network tools is proposed in this paper. Where, the dynamic nonlinear autoregressive approach with external exogenous input NARX is used for the identification of the studied system dynamics, to monitor the vibrational dynamics of the operating turbine. This leads to establishing a solution for the different ranges of rotational speed and ensuring dynamic stability through the vibration indicators, determined by the proposed neural network approach. Also, offer a normalized mean square error on the order of  $3.8414e-3$  for the high-pressure turbine,  $1.29152e-1$  for the gas control valve and  $2.12090e-4$  for the air control valve. Furthermore, it permits the vibration monitoring and efficiently extracts the essentials of dynamic model behaviour, to effectively size the operating gas turbine system.

The obtained results of the application of the proposed approach on the gas turbine system presented in this paper proves its ability for the detection and the management on real-time of the eventual failures caused mainly by intrinsic vibrations. On the other side, these results prove clearly the effectiveness of the use of the artificial neural networks as a very powerful calculation tools in the modelling of complex dynamic systems.

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*Keywords:* Monitoring; Gas turbine; Artificial neural networks; Dynamic nonlinear autoregressive with external exogenous input modelling

## 1. Introduction

Recently, several researches have been developed for several industrial applications, using artificial intelligence techniques for decision support in diagnostic and monitoring systems. Among these techniques, the artificial neural

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networks due to its high capacity and speed of modelling, it gains much success and attention in several industrial applications because of its ability to solve non-linear problems by learning and by the flexibility of the technical solutions desired in the industry. The artificial neural networks approach makes possible the treatment of information in multiple ways and the imitation of the systems operation in several industrial systems. Because, these artificial intelligence tools are used for decision support in a very efficient and reliable way, due to the direct use of data from the monitoring variables. Indeed, artificial neural networks are used in several applications presenting better performances for monitoring, by their capacity and speed of learning.

A works synthesis on the applications of the artificial intelligences' methods such as; modelling, fault diagnosis and optimization, have made by Sina Faizollahzadeh Ardabili et al. in [3] during the period 2007–2017, they have shown that these approaches require a large volume of data with several input parameters to be applied.

Indeed, in 2020 Chenyue Xie et al. in [41] proposed models based on neural networks for the prediction of spectral and statistical properties of speed and temperature in instantaneous flow structures, they showed by an analysis of the results, that the neural networks model is more efficient than the mixed dynamic model. Dawei Zhao, et al. in [43] proposed a systematic research to compare the performances of the regression and the artificial neural network models in the prediction of the joints welded by points to monitor the dynamic power signature in the welding process, they have shown that the performance of prediction models based on artificial neural networks is reliable as a function of data quality. In 2019, Olcay Altıntaş et al. in [1] proposed a maintenance approach based on an artificial neural network for locomotive systems, by observing the lubricating oil of the engine, they show that the obtained results are very sufficient and this approach can be applied at low cost and with a real-time working mechanism. Jan-Hendrik Menke et al. in [20] have used artificial neural networks to monitor the energy distribution grids in electrical networks, they overcome the limits of existing conventional approaches by this intelligent network (smart power grids). In 2018 Pengcheng Zhuo et al. in [44] proposed a real-time fault diagnosis strategy for the gas turbine blade based on the hidden output feedback (OHF) using Elman neural networks, so as to manage the smooth running of the blades of a turbine based on the Elman neural network with hidden output feedback (OHF). Where in 2017 Mohammadreza Tahan et al. in [35,36], studied the performance of industrial gas turbine engines using a multi-network ANN model for real-time automatic diagnosis based on two back-propagation training algorithms, namely Levenberg–Marquardt and Bayesian regularization algorithms to form the optimal networks using a set of training data, applied to the detection of compressor flow drop and fouling in the axial compressor in an industrial 18.7 MW twin-shaft gas turbine engine. And Yu Zhang et al. [42] proposed the detection and diagnosis of faults applied for an industrial gas turbine system based on measurements from several groups of sensors. Specifically, the use of hierarchical clustering (HC) and self-organized map neural networks (SOMNN) for the detection of wear of bearing tilt pads and pre-chamber exhaustion at an early stage.

Whence, in 2016 Amozegar M. and Khorasani K. in [2] proposed a set of dynamic neural network identifiers for fault detection and isolation of gas turbine engines in order to monitor the health of the gas turbine engine, they used specifically a dynamic multilayer perceptron MLP and a dynamic radial basis function neural network RBF with a dynamic support vector machine SVM, for the precise identification of a system model to solving the FDI task. Also, Hamid Asgari et al. in [4] tested non-linear autoregressive models with external exogenous input (NARX) for the simulation of the start-up phase of a single shaft gas turbine, Marjani A. and Baghmolai A.M. in [19] proposed an analytical and numerical modelling of the gas transport network with a comparison of the results obtained by the artificial neural networks (ANN) and the fuzzy inference system (FIS), Grzegorz Nowak and Andrzej Rusin in [25] realized an artificial neurons system to control the heating process of a steam turbine and Nadji Hadroug et al. in [14] carried out an approach for fault detection in a gas turbine using adaptive neuro-fuzzy interference system (ANFIS) to control their dynamic behaviour, this approach uses the adaptive learning mechanism of neural networks and fuzzy inference techniques for the detection of turbine faults.

In 2015, Sina Tayarani-Bathaie S. and Khorasani K. in [32] proposed the faults detection and isolation in an aircraft gas turbine engine using a neural network bank based on the dynamics neural model DNM and the time delay neural network TDNN, for aircraft engine diagnostics and health monitoring. And El Hamzaoui Y. et al. in [7] have made an optimization of the operating conditions of a steam turbine using an inverse artificial neural network. In 2014, Sadough Vanini Z.N. et al. in [29] studied the detection and isolation of faults of a dual spool gas turbine engine using dynamic neural networks and multiple model approach for an aircraft jet engine, from which each dynamic neural networks DNN corresponds to a specific operating mode of the healthy engine or the faulty state of the aircraft jet engine. And Sina Tayarani-Bathaie S. et al. in [33] studied the dynamic neural network-based fault

diagnosis of gas turbine engines. They proposed a faults detection and isolation FDI scheme using dynamic neural networks DNN with infinite impulse response filter (IIR) applied to learn the input/output map of the aircraft jet engine faults in a dual spool turbo fan engine. In 2013, Nikpey H. et al. in [24] developed an optimal model based on artificial neural networks for micro turbine gas modelling and in 2012, Sanjay Barad G. et al. in [30] validated a neural network approach for a gas turbine monitoring with optimal mechanical performance. In 2011 Bartolini CM et al. in [5] applied artificial neural networks to the modelling of a micro turbines and Thomas Palmé et al. in [26] validated the model of a gas turbine by classifying data with artificial neural networks. In 2009, Fast M. et al. in [8] developed a multi-model approach for an industrial gas turbine using neural network techniques. In 2004 Joly R.B. et al. in [16] carried out a diagnostic system based on artificial neural networks applied to a high-throughput gas turbine.

Currently the industrial monitoring field based on diagnostic functions provides a set of solid tools to improve operations of the industrial equipment and to ensure the optimal ratio of cost/quality. One of the main applications in industrial plants of fault diagnosis is the vibration monitoring in rotating machines which is still a hot topic in most industrial sectors [12,38,44]. It is obvious that the design of the monitoring system will provide the necessary information for a diagnostic strategy for these machines to ensure their protection against instability and to evaluate their dynamic behaviour accurately. The conventional modelling approaches of this type of machine cannot present their dynamic behaviours accurately due to the highly nonlinear mathematical complexities of such systems [4,10,13,17,35], on the other side they are very costly procedures. Therefore, there is a great increased need for developing new approaches to ensure the precise modelling of the different internal phenomena of such systems. This is the case of gas turbines, which are subject to several unstable phenomena, which are often difficult to interpret because of the problems of their dynamic complexities and their operating environment [6,13,21]. Artificial neural networks can provide an interesting solution for monitoring problems with gas turbines. Indeed, this work shows that their memorization, learning and adaptation capacities represent very useful functions for the monitoring system of the examined turbine. However, the most important benefits that can be attributed to neural network monitoring of turbines is the modelling and estimation of vibration indicators by learning. This approach does not require explicit knowledge of complex mathematical models, but which requires reliable operating data, based on the use of developed artificial neural networks.

Indeed, the complexity of the vibratory behaviour and the non-linearity of gas turbine models increase the difficulty of setting up a real-time monitoring model for this type of rotating machine. To solve this problem of their real-time monitoring, this work offers a reliable diagnostic strategy based on dynamic nonlinear autoregressive modelling with external exogenous input (NARX) for the detection of malfunctions affecting a GE MS 3002 gas turbine, with a monitoring approach based on the generation of fault indicators, which contain information on anomalies and malfunctions of the gas turbine system to be monitored. This will allow better management of failures caused by vibrations, by detecting faults before they become critical and by describing the parameters linked to vibrations. This work focuses mainly on the application of the artificial neural networks approach for faults diagnosis in rotating machines, although many other works have been carried out on other industrial applications for the modelling and process control or information processing sciences to solve problems that are recognized as difficult such as optimization, classification, pattern recognition, diagnosis and decision-making. To develop such a supervision procedure, based on artificial neural networks, this work proposes a diagnostic strategy for the detection of malfunctions that may occur in a gas turbine of type GE MS 3002, based on dynamic nonlinear autoregressive modelling with external exogenous input (NARX). In order to monitor this gas turbine, a preliminary selection of a certain number of indicators originating from measurements and established permanently during the operation has been made.

In view of the complexity of the vibratory phenomena involved, the diagnosis of these phenomena requires an increasingly fine modelling of their behaviour. The dynamics of the gas turbine under consideration is studied and modelled using a dynamic nonlinear autoregressive approach with external exogenous input (NARX), which serves as an efficient database for models leading to improve the safety and the performance of such system, where the main aim is to prevent failures and to ensure maximum availability of this rotating machine.

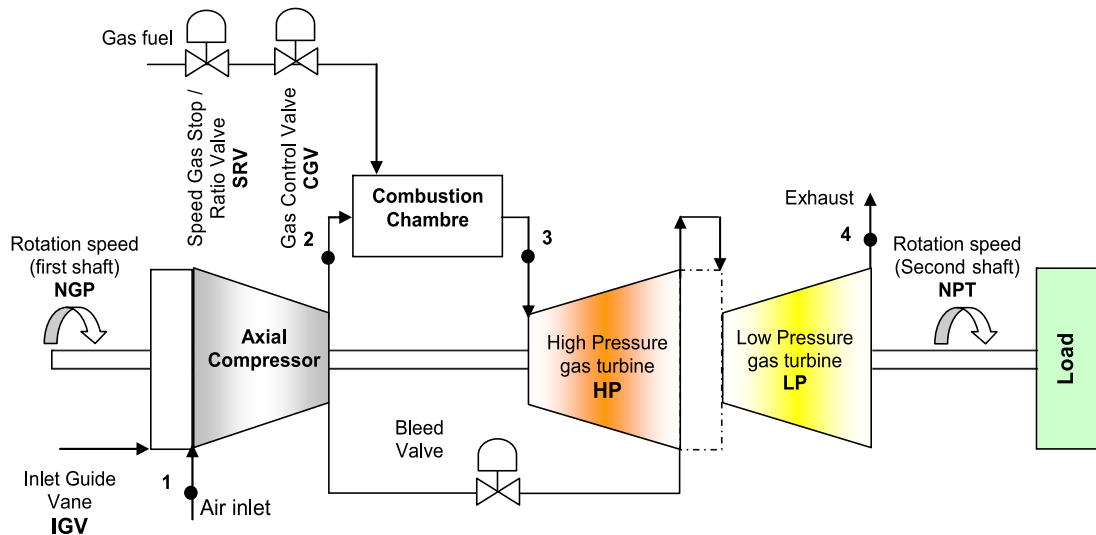
## 2. Gas turbine investigations

The studied gas turbine in this work is a GE MS 3002 model with double shaft and a single cycle, it consists of an axial compressor of 15-stages with 6 combustion chambers that are arranged at (90°) from the axial direction

**Table 1**

MS 3002 Gas turbine technical characteristics.

Manufacturer: General Electric	Power Turbine: 80- 9400 CV
Model: MS 3002	Fuel consumption rate (100% HP on 27C): 2.84 m <sup>3</sup> /s
Serial No: 244370	Max exhaust temperature: 516.6 C
HP Speed and axial compressor: 7100 rpm	Exhaust gas pressure: 1.009. 3 bars
N° axial compressor stage: 15	Starting system: turbo stator
Number of wheels HP wheel (s): 01	Direction of rotation: anticlockwise
Speed LP: 6500 rpm	Number of shafts: 02 Twin shaft

**Fig. 1.** Two shaft gas turbine.

of high pressure turbine (HP) has a single stage which is the first and in the second stage there is the low pressure turbine which drives the load. These technical characteristics of the studied gas turbine are presented in Table 1. This turbine is installed at the gas compression station in Hassi Massoud at the south of Algeria, it compresses and injects more than 24 million cubic metres per day of gas. It is used within the main desert gas network which contains a gas-lift loop with a length of 180-kilometre and a reinjection gas line with length of 28-kilometre which transports the gas to the pipeline for other energetic applications in Algeria.

Indeed, a gas turbine is a machine which transforms the calorific energy into the mechanical energy, this transformation is carried out by the operational basic elements of the gas turbine [6,11,13,15,21,34]. Due to its excellent performance, it knows a large use in many industrial applications, its efficiency is greater than 35% when it is alone and it is greater than 55% when it is used in a combined cycle. The case study of the present paper is concentrating on the most widespread application of the gas which is the gas transportation industry as shown in Fig. 1, this rotating machine is composed of three main elements:

- Axial compressor,
- Combustion chamber,
- Power turbine.

The gas turbine is generally defined by its type of one shaft or of two shafts, by the type of the driven machine if it is fixed or mobile and also by the nature of its thermodynamic cycle, simple or with recovery.

In industrial applications, the major problems of instability encountered in rotating machine are the wear of their fins or blades (especially the fixed fins and the movable fins) Fig. 2. These fins are the most expensive elements in the compressor, the main causes of this wear can be summarized as follows [5,14,18,21–23,31,37]:



Fig. 2. Wear of the axial compressor fins.

- The phenomenon of erosion caused by poor air filtration,
- The increase of the temperature to high thresholds (1200 °C)
- The phenomenon of vibration which is practically caused by:
  - 1- Misalignment of one shaft with respect to the other (compressor shaft and turbine shaft);
  - 2- Poor balancing of the fins (incorrect mounting of the fins) or of the rotor;
  - 3- Cold start-up (starting the machine at low temperature lubricating oil),
  - 4- Start without rotor turns,
  - 5- Closing of the anti-pumping valve at start-up of the launching turbine.

The optimal compression ratio required in the axial compressor is ensured by the 15-stages of this compressor, in order to improve the efficiency and the stability of the turbine this ratio is increased per stage. Therefore, the rotational speed of the rotor has to increase to the stability limit of the machine [9,27,39,40,42]. However, the two-shaft gas turbine presented in this work has the advantage, that the first rotor (compressor rotor) has a low mass inertia to reduce the acceleration and the deceleration time of this rotor. On the other hand, the second rotor of the free turbine has a high mass inertia which allows to give to the rotor the function of a steering wheel. It will act as an energy store which stabilizes the rotation speed and avoids a possible runaway in case of eventual load drop.

To improve the stability response and the thermal efficiency of the studied gas turbine plant and to ensure a more accurate control of its operation with better efficiency, the dynamics of the gas turbine under investigation is modelled using a non-autoregressive Linear dynamics approach with external exogenous input (NARX), this will serve as an efficient database for models leading to improved security and performance of this system. Where the main aim is to predict the failures and to ensure a maximum availability of this rotating machine. To do this, the studied gas turbine is modelled based on its characteristics, firstly the compressor section is modelled using the ambient pressure and temperature ( $P_a$  and  $T_a$ ) of the inlet air valve *IGV* (Inlet Guide Vane).

The model of the *IGV* (Inlet guide vane) is obtained based on the model of the  $B_v$  (Bleed vanne) with the ambient pressure and temperature of the inlet and the delay on the response of the *IGV*, where the ambient temperature  $T_a$  is considered equal to  $T_1 = T_a = 293.15K$  and the inlet pressure of the compressor  $P_1$  is given as follows:

$$P_1 = P_a - \Delta P_a \quad (1)$$

With  $P_a$  is the atmospheric pressure of the turbine installation area,  $\Delta P_a$  is the pressure drop in the admission channel.

The model of the *IGV* (Inlet guide vane) is presented by the data matrix in the following form:

$$IGV(n) = [IGV(n-1) \quad P_a(n) \quad T_a(n) \quad B_v(n)] \quad (2)$$

where, the model of the combustion gas control valve *GVC*(Gas Valve Control) is obtained by using the temperature and pressure at the compressor outlet  $T_2$  and  $P_2$ , the fuel gas flow  $F_g$  and the delay of the *GVC* estimated response

as follows:

$$P_2 = P_1 \tau \quad (3)$$

where  $\tau$  is the compression ratio.

Hence, the temperature of the compressor output is expressed as follows:

$$T_2 = T_1 \left( \frac{P_2}{P_1} \right)^{\frac{(\gamma-1)}{\gamma}} \quad (4)$$

The isentropic exponent  $\gamma$  is defined as follows:

$$\gamma = \frac{C_{p(T_1-T_2)}}{C_{p(T_1-T_2)} - r} \quad (5)$$

where  $C_{p(T_1-T_2)}$  defines the average specific heat of the air between temperatures  $T_1$  and  $T_2$ .

The values of the combustion fuel gas flow  $F_g$  and the bleed valve  $B_v$  are the actual values taken from the presented gas turbine in this work. However, the combustion fuel gas control valve  $GCV$  of the gas turbine will be modelled using the data matrix:

$$CGV(n) = [CGV(n-1) \quad IG V(n) \quad P_2(n) \quad T_2(n) \quad F_g(n)] \quad (6)$$

This allows to model the dynamics of the high pressure turbine  $HP$ , using the model of the bleed valve  $B_v$ , with the air inlet valve (IGV) in the compressor, the flow rate of the combustion gas  $F_g$  and the fuel gas control valve  $GCV$  as well as the response delay of the speed shaft  $HP$  which is given by the data matrix:

$$HP(n) = [HP(n-1) \quad IG V(n) \quad CGV(n) \quad F_g(n) \quad B_v(n)] \quad (7)$$

To achieve the modelling the of the studied gas turbine dynamics, the data matrices of  $IGV(n)$ ,  $CGV(n)$  and  $HP(n)$  are used in the elaboration of the NARX model variables of the turbine, it allows to monitor this gas turbine and to predict the failures, to ensure the maximum availability and better efficiency of the studied gas turbine.

### 3. Artificial neural networks models

Neural networks are increasingly popular in various fields of engineering sciences with the multiplication of information sources and the growth of computing tools of industrial computing, the use and the evaluation of models based on artificial neural networks in industrial environment become an easy task [14,20,40,41]. Where these techniques of artificial intelligence present themselves as a solution which allows to solve the problems of complexities and nonlinearities of these industrial systems. Indeed, the function of diagnosing of dysfunctions of the presented gas turbine is carried out using a dynamic nonlinear autoregressive system with external exogenous input (NARX) based on a dynamic neural network structure, this system is represented mathematically as follows [28,43]:

$$y(n+1) = f \left( \begin{array}{c} y(n), \dots, y(n-d_y+1), \dots, \\ u(n), u(n-1), \dots, u(n-d_u+1) \end{array} \right) \quad (8)$$

with  $u(n)$  represents the inputs,  $y(n)$  represents the outputs of the NARX model,  $n$  is a unit of time,  $d_u \geq 1$  and  $d_y \geq 1$ ,  $d_u \leq d_y$  are the input memory and output memory orders of the neural networks corresponding to the measured variable delay and  $f(\cdot)$  is its activation function.

Using the model of Eq. (8) and the data matrices of (2), (6) and (7), the NARX model of the turbine variables is given in the following form:

■ The Inlet guide vane IGV:

$$IGV(n+1) = f \left( \begin{array}{cccc} IGV(n) & IGV(n-1) & \dots & IGV(n-d_{IGV}+1) \\ Pa(n) & Pa(n-1) & \dots & Pa(n-d_{Pa}+1) \\ Ta(n) & Ta(n-1) & \dots & Ta(n-d_{Ta}+1) \\ Bv(n) & Bv(n-1) & \dots & Bv(n-d_{Bv}+1) \end{array} \right) \quad (9)$$

■ The combustion fuel gas control valve CGV:

$$CGV(n + 1) = f \begin{pmatrix} CGV(n) & CGV(n - 1) & \dots & CGV(n - d_{CGV} + 1) \\ IG V(n) & IG V(n - 1) & \dots & IG V(n - d_{IGV} + 1) \\ P_2(n) & P_2(n - 1) & \dots & P_2(n - d_{P_2} + 1) \\ T_2(n) & T_2(n - 1) & \dots & T_2(n - d_{T_2} + 1) \\ F_g(n) & F_g(n - 1) & \dots & F_g(n - d_{F_g} + 1) \end{pmatrix} \quad (10)$$

■ The high-pressure turbine HP:

$$HP(n + 1) = f \begin{pmatrix} HP(n) & HP(n - 1) & \dots & HP(n - d_{HP} + 1) \\ IG V(n) & IG V(n - 1) & \dots & IG V(n - d_{IGV} + 1) \\ CGV(n) & CGV(n - 1) & \dots & CGV(n - d_{CGV} + 1) \\ F_g(n) & F_g(n - 1) & \dots & F_g(n - d_{F_g} + 1) \\ Bv(n) & Bv(n - 1) & \dots & Bv(n - d_{Bv} + 1) \end{pmatrix} \quad (11)$$

The dynamic neural network structure used in this work is a multilayer architecture with an input layer and masked layers and an output layer with a sigmoid-type activation function, given by:

$$f_1 = \frac{2}{1 + e^{-2\alpha}} - 1 \quad (12)$$

The linear activation function for the output layer is presented as follows:

$$f_2 = x \quad (13)$$

The retro-propagation algorithm is used in the learning step and the learning rules are used to minimize the mean squared error given by the following equation:

$$E = \frac{1}{2} \sum_i (d_i - y_i)^2 = \frac{1}{2} \sum_i \left( d_i \sum w_{ij} x_j \right)^2 \quad (14)$$

where the weight change  $w_{ij}$  by an amount  $\Delta w_{ij}$  must be proportional to the error gradient given by:

$$\Delta w_{ij} = -\eta \frac{dE}{dw_{ij}} = \eta \sum_i (d_i - y_i) x_i \quad (15)$$

The weighted sum of the inputs of dynamic neural networks can be calculated using the following expression:

$$a_j = \sum_{j=1,n} w_{ij} x_j \quad (16)$$

From this equation the values of the activation function can be calculated and the state of neuron can be obtained, their values will be used in the upcoming neurons of the system expressed by the following equation:

$$y_i = \varphi(a_i - \theta_i) \quad (17)$$

The gradient descent algorithm is used to calculate the derivatives of the turbine system variables with respect to all its inputs, in order to calculate the outputs of the neurons of the hidden layer, the following expressions are used:

$$u_j = f_1 \left( \sum_{i=1} w_{ij}^1 x_i + w_{kj}^1 x_k + b_j^1 \right) \quad (18)$$

$$y_k = f_2 \left( \sum_{i=2}^N u_i + b_k^2 \right)$$

where  $f_1(v) = \frac{2}{1+e^{-2v}} - 1$ ,  $f_2(v) = v$  are respectively the sigmoid and linear activation functions of the output and input layer of neural networks,  $k$  is the index of the output layer,  $i$  is the index of the input layer,  $j$  is the index of the layer,  $w_{kj}$  is the synaptic weight between the hidden layer and the output layer,  $w_{ji}$  is the synaptic weight between the input layer and the hidden layer,  $w_{ki}$  is the synaptic weight between the output layer and the input layer (feedback term),  $x_i$  is the connection between the input layer and the hidden layer,  $x_j$  is the connection between the hidden layer and the output layer,  $b_j^1$  is the connection between the output layer and  $b_j^1$  is the input layer and is the bias of the neuron  $j$ .



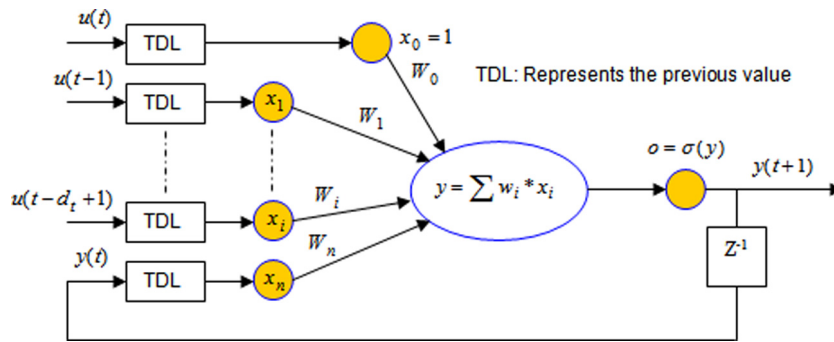


Fig. 3. Nonlinear dynamic autoregressive with external exogenous input (NARX) with neural network architecture.

The established model by the dynamic nonlinear autoregressive system with external exogenous input (NARX) is shown in Fig. 3, with output feedback to the input to minimize the cost function, This allows to predict the future value of outputs  $y(t)$  from the previous value of  $y(t)$  and  $x(t)$ . Once the network is completed, it is necessary to provide future estimations over a prediction horizon  $N$ , where the predictions are recursively executed until the desired forecasted horizon is reached, these networks are evaluated in terms of Normalized Mean Squared Error (NMSE) which is expressed as follows:

$$NMSE(N) = \frac{1}{N \cdot \sigma_x^2} \sum_{n=1}^N (x(t+1) - \hat{x}(t+1))^2 \quad (19)$$

In this paper, the gas turbine model based on dynamic non-linear dynamics with external exogenous input (NARX) is explored and tested on the real obtained onsite data of the studied gas turbine. This investigated approach allows to propose a new gas turbine monitoring procedures which provided an effective diagnostic tools that can be applied for the diagnosis of failures in the rotating machines, using the operating data and the information collected onsite during its operation.

#### 4. Diagnosis based on artificial neural networks

The diagnostic procedure in an industrial system determines the type, the amplitude, the location and the time of detection of the fault. Where the diagnostic function succeeds the detection of faults and includes the phases of isolation and identification of the faults. Recently, developments have been made in the use of modern diagnostic methods for monitoring industrial systems [1,20,28,29,35]. These methods are based on the insertion of the artificial intelligence techniques into various industrial applications. Among these approaches, artificial neural networks are used to monitor these processes, taking into account their computational and modelling capabilities.

To establish the link between symptoms and typical situations of the studied gas turbine, it is necessary to establish a relation between a set of characteristic values taken during their operation at a given instant on the process and the typical situations known a priori. Using the dynamic neural network approach, it will be a matter of triggering the rules of the knowledge base using the observed facts, based on a model established by the dynamic non-linear autoregressive system with external exogenous input (NARX), which will deal with the analysis of indicators of failures given by the difference between the measurement and its estimation. This method can be presented as shown in Fig. 4. The difference in error signal is considered as an indicator of behavioural anomalies given by the residuals which are obtained by comparing the behaviour of the system model with that of the real system. These fault indicators will be presented in the next section and implemented in the results section.

##### 4.1. Residuals generation

The complexity of the vibratory behaviour of a gas turbine increases the difficulty to set up a model for real-time monitoring for this kind of machine. However, the effectiveness of artificial neural networks techniques is used to address the gas turbine real-time monitoring problem. This approach is based on various digital modelling tools

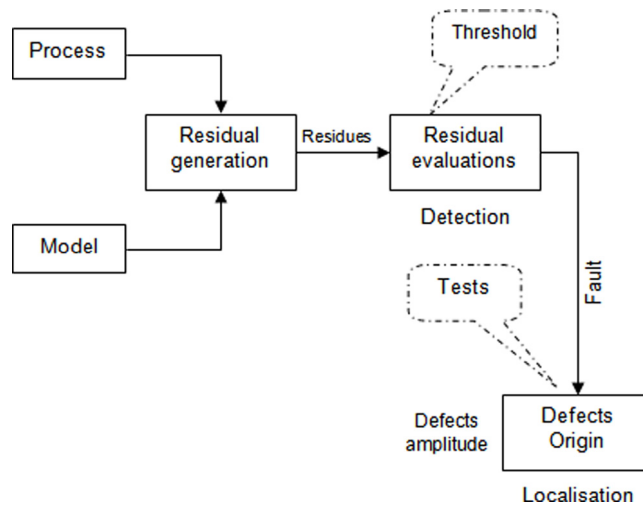


Fig. 4. Fault indicators analysis.

using real data. In order to guarantee the supervision and monitoring of the vibration behaviour of the examined turbine, artificial neural networks are applied to experimental input/output data for the modelling of this turbine. However, monitoring of model-based systems consists of generating fault indicators, which contain information on the anomalies and malfunctions of the system to be monitored.

The concept is to measure the difference between the behaviour observed on the variables of the gas turbine and the behaviour of models obtained by artificial neural networks, given by [14,15]:

$$r(k) = y(k) - \hat{y}(k) \tag{20}$$

where  $y(\cdot)$  turbine output variables,  $\hat{y}(\cdot)$  estimated variables

The residue  $r(\cdot)$  in the presence of faults will deviate significantly from the zero value and will be identical to zero when the system is operating normally. In practice, the measurements made on the system are most often marred by measurement noise, so the vector of residues is then written:

$$r(k) = y_m(k) - \hat{y}(k) \tag{21}$$

where  $y_m(\cdot)$  is the measured system output.

In this work, the turbine model contains two inputs and one output; The first input is the variation of the air inlet valve *IGV* (Inlet guide vane), which is a function of the ambient pressure and ambient temperature of the compressor section, given by Eq. (1). This input will be used in turbine modelling by the data matrix  $IGV(n)$  and the second input is the variation of the fuel gas control valve *CGV* is obtained using the temperature, and the pressure at the output given by Eq. (3) will be used in turbine modelling by the data matrix  $CGV(n)$ . The output given by the variation of the speed of rotation of the HP shaft, given by the data matrix  $HP(n)$ , is strongly linked to the vibrations of the five bearings installed on the rotor of the examined turbine.

Indeed, the input/output data matrices  $IGV(n)$ ,  $CGV(n)$  and  $HP(n)$  collected on the examined turbine will be used to predict models of turbine variables using artificial neural networks; and then in a direct way will be used for generation of the residues, considering the difference of the quantities measured and modelled, these residues will be presented in the results sections.

### 5. Investigation results

In this section, proposed procedures based on artificial neural networks have been applied for the monitoring of the presented gas turbine of type GE MS 3002, shown in Fig. 5, the aim was to detect and to isolate failures in this turbine system by applying the dynamic nonlinear autoregressive model with exogenous external input (NARX). Experimental results have been illustrated for each component of the gas turbine GE MS 3002 on real-time testing

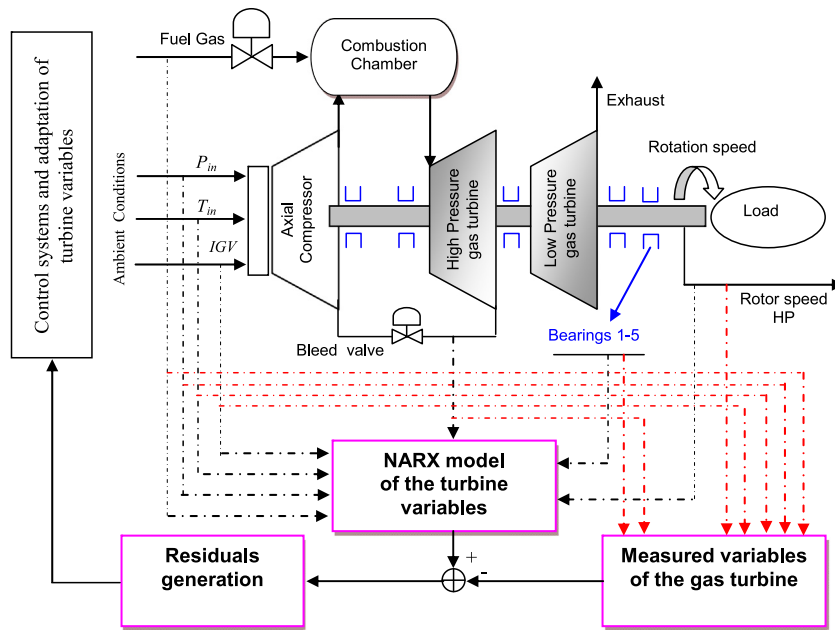


Fig. 5. Gas turbine monitoring structure.

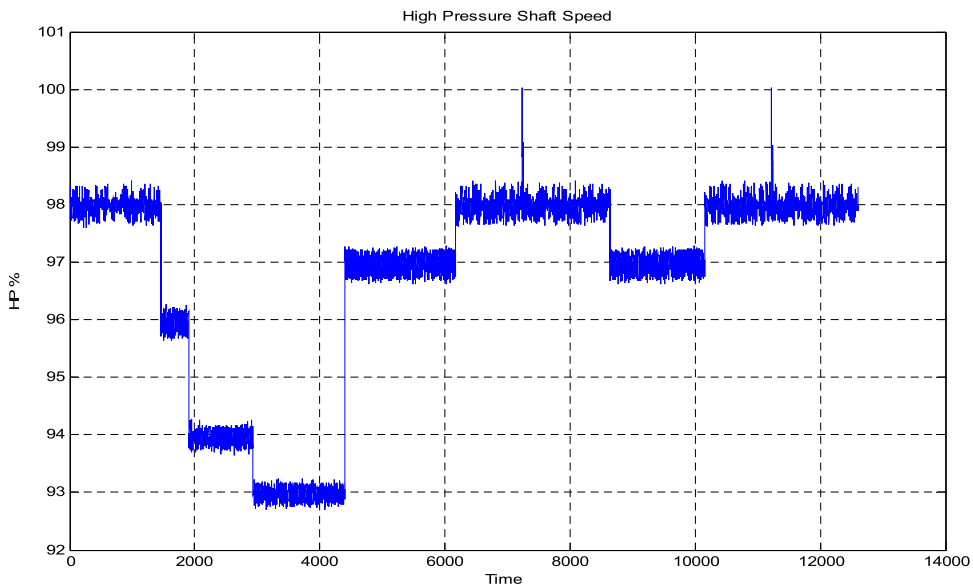
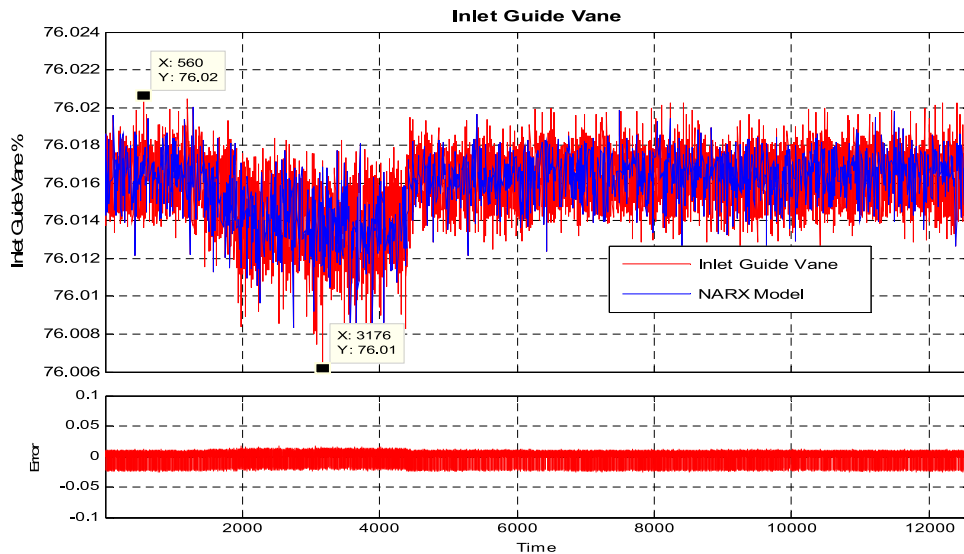


Fig. 6. High pressure turbine RPM variation.

using the proposed diagnostic system, firstly the structure of models obtained has been analysed. Then the results of the tests have been carried out on this application according to the required specifications,

The operating components of the studied gas turbine have been modelled using the proposed NARX system. In this gas turbine system, the axial compressor is driven by the shaft speed of the high-pressure turbine HP. This is controlled by the IGV air input which is itself controlled its motorized valve, to adjust the amount of area at the inlet of the axial compressor. On the other side, the gas control valve GCV adjusts gas turbine combustible at the inlet of the combustion chamber. Furthermore, the bleed valve at the inlet of the low-pressure turbine BP shaft adjusts the flow of combustible gas after the combustion chamber. Fig. 6 shows the variation of the rotation speed of the high-pressure turbine with two critical points at times 7000 s and 11000 s.



**Fig. 7.** Variation of air control valve IGV model with its NARX model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Fig. 7** shows the variation of the NARX neuronal model of the IGV air control valve, this valve opens and closes in percentage %, where the dynamic neural network uses the objective function  $E$  given in the previous section which minimizes the error on the model. The curve in red is the opening percentage of the IGV valve and the curve in blue is the NARX model output, the error response is shown below in the same figure. The test carried out on the IGV air control valve show the variation of the NARX neural model between 76.01% and 76.02%, which corresponds to the actual variation of the IGV air control valve. The sensitivity to changes in dynamics and actual variation in the opening and closing of the IGV air control valve is clearly shown by the result in this figure. **Fig. 8** shows the performances obtained for the NARX model of the air control valve, these performances are presented as a function of error between the referential signal and the output of networks by the average square error criterion which is at the order of  $10^{-4}$ , this performance is satisfactory, it is obtained with 13 iterations, in terms of mean square error, as shown in **Table 2** and **Fig. 9** shows their associate residual variation.

The main idea of this work remains the employ of neural networks in order to set up a model for gas turbine process variables useable directly in the control. Consequently, the robustness of the proposed model is demonstrated by the stability of the obtained models, since neural modelling cloaks the complex mathematical equations of the turbine system. **Fig. 10** shows the variation of the GCV gas control valve model with its NARX model is between 64.72% and 76.19% depending on the measured data, according to this figure, the proposed model correctly predicts the evolution of opening and closing of the GCV gas control valve. **Fig. 11** shows the validation performances obtained by the NARX model; this figure highlighted the good model performance with a prediction error of the order of  $10^{-1}$ . The values of the MSE given in **Table 2** for the NARX model validation show that the best optimization is obtained with a practically 44 iterations and **Fig. 12** shows their associate residual variation.

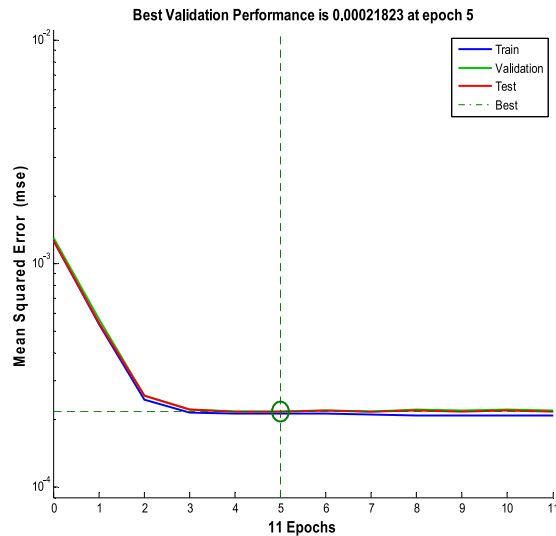
**Fig. 13** shows the model variation of the (HP) high pressure turbine shaft with its NARX model, with fluctuations between 92.86% and 99.94%, the number of iterations has become big, on account to the dynamics of rotation of the turbine shaft, but even if these iterations have increased, according to this figure, the network is still able to correctly predict the evolution of the variation of the HP high pressure shaft. **Fig. 14** shows the validation performances obtained by the NARX model, at the start of the learning, validation and test sequences, the state of the NARX predictor is initialized to zero, the mean square error obtained with the NARX predictor is around  $10^{-3}$  with 375 iterations, which constitutes a much better performance, as it is shown in **Table 2** and **Fig. 15** shows their associate residual variation.

To exploit the NARX neural model developed in this work, we need to build a learning, validation and testing base, using a set of data that allow us to fix the weights of network connections. Once these weights are calculated,

**Table 2**

Performances of NARX model of the examined gas turbine variables.

	Target value	Mean square error	Regression R
Performance of NARX model of IGV air control valve			
Training	8828	2.16103e-4	4.41184e-2
Validation	1892	<b>2.08650 e-4</b>	4.51141e-2
Testing	1892	2.13941e-4	4.73218e-2
Performances of the NARX model of the CGV gas control valve			
Training	8828	1.37210e-1	9.80678e-1
Validation	1892	<b>1.2690e-1</b>	9.81975e-1
Testing	1892	1.37684e-1	9.80511e-1
Performances of the NARX model of the HP high pressure turbine shaft			
Training	8828	5.4034e-3	9.99115e-1
Validation	1892	<b>3.33270e-3</b>	9.98882e-1
Testing	1892	9.16117e-3	9.98566e-1

**Fig. 8.** NARX Model Performance of air control valve IGV.

the network is functional and it can carry out the task of modelling turbine variables without modifying the weights, depends on input and output data from the turbine system.

However, [Table 2](#) presents the distribution of turbine data used in this modelling in three categories; 70% of the data for network training, 15% for validation, and the remaining 15% for testing neural network performance with the result of the cost function of modelling results. The results drawn in this work show that the neural networks explored by the estimation of the turbine variables examined were perfectly modelled using the proposed NARX model system, something that allows to present its dynamic behaviour and ensuring optimal operation of the turbine.

The obtained results show that the neural networks which has been explored for the estimation of the variables of the studied gas turbine examined have been perfectly modelled using the proposed NARX system to present the dynamic behaviour of this studied machine ensuring its optimal operation. These results show that the modelling of the studied gas turbine based on the NARX approach which has been proposed in this paper is proved to be a very powerful tool for the diagnosis of failures, however its effectiveness is depending on the acquired data content and quality that can contribute positively in obtaining improved models of the studied gas turbine system. As it is

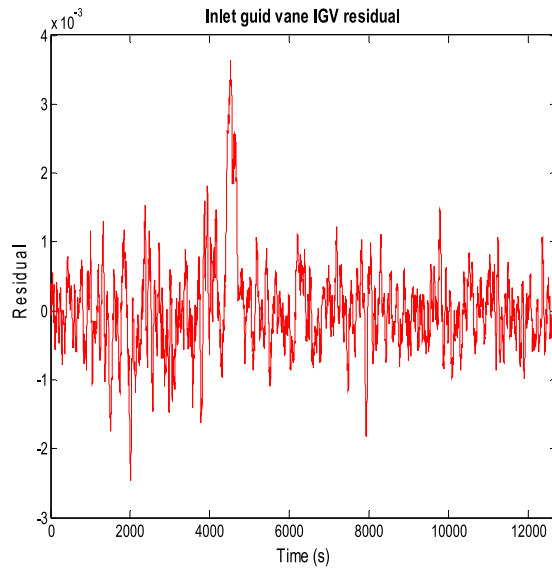


Fig. 9. Residual variation of the air control valve IGV.

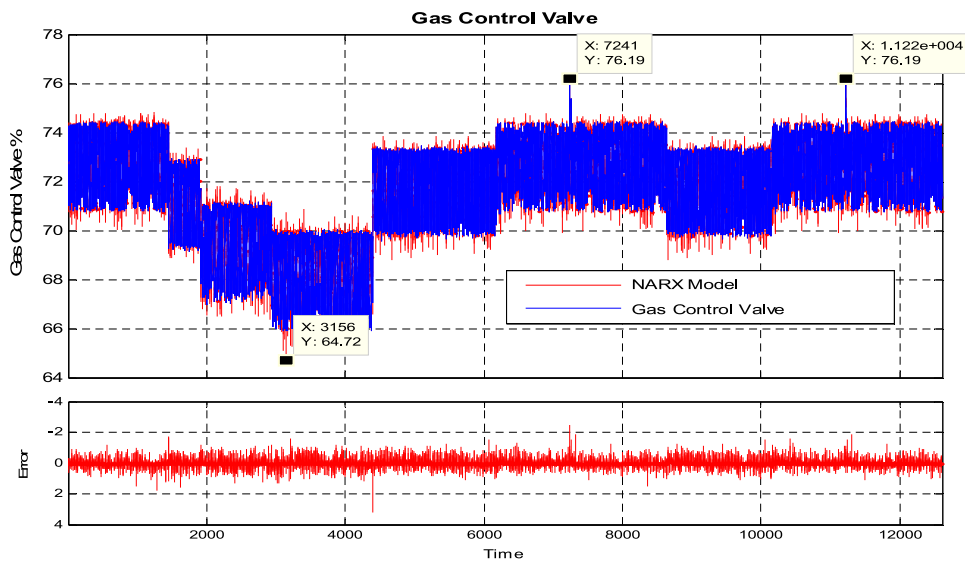


Fig. 10. Variation of model of combustion control gas valve CGV with its model NARX.

shown in Fig. 16, the test model of the HP high-pressure turbine shaft with its NARX model provides the most suitable practical monitoring tools for the modelling of the studied gas turbine MS 3002 presented in this paper.

To validate the proposed neural model in this work, it aims to increase the modelling capacities of the vibratory behaviour of examined gas turbine. In order to study the vibratory behaviour of this turbine, the vibration neural model of the bearings N° (01, 02, 03, 04 and 05) are shown in Figs. 17A, 18A, 19A, 20A and 21A, to get better management of the failures caused by the vibrations in the five bearings. This allows to describe the parameters related to the vibrations and represents the state of the vibratory motion. To obtain the best model of turbine bearings, the NARX model allows to compare the predictive capacity of the multiple regression and the neural network, known by its capacity to treat nonlinear relations with the values predicted by the real models, shown in Figs. 17B, 18B, 19B, 20B and 21B, compared with the observed values of the operating data of the studied turbine.

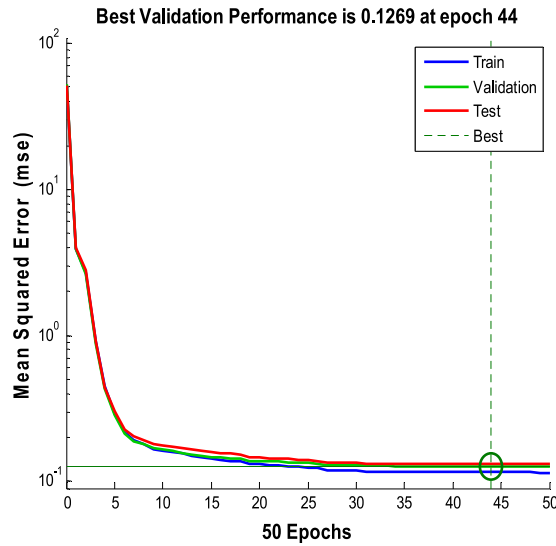


Fig. 11. NARX model performance of the gas control valve CGV.

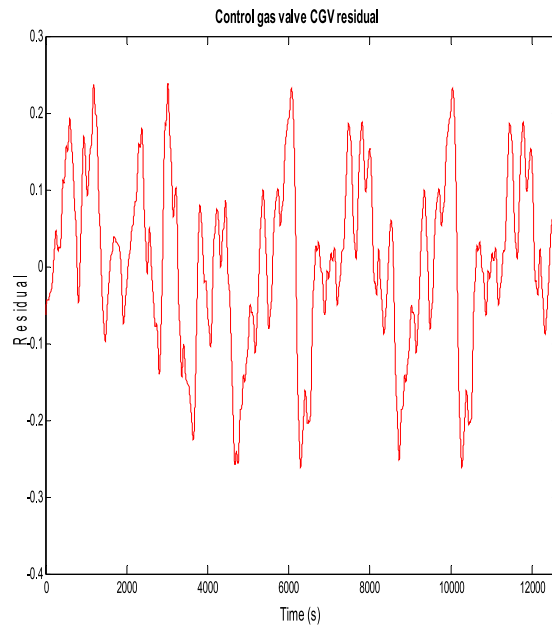


Fig. 12. Residual variation of the combustion control gas valve CGV.

Fig. 17A shows the output of the NARX vibration model of the bearing N° 1 and Fig. 17C shows their associate residual variation, note that the neural model is identical with the amplitude of vibration of this bearing, with two critical points; the first at time 7257 s with an amplitude of 69.67  $\mu\text{m}$  and the second at time 11124 s with an amplitude of 69.67  $\mu\text{m}$ . This response is stable periodically predicted by the NARX model, confirmed by the prediction error between the actual behaviour and that NARX model in the same figure. In order to validate this proposed neural model, Fig. 17B shows the predicted dynamic vibration behaviour of the HP rotor bearing 1 of the examined turbine.

Fig. 18A presents the output of the NARX vibration model of the bearing N° 2 and Fig. 18C shows their associate residual variation, which correctly tracks the actual vibration behaviour in this bearing, with two critical

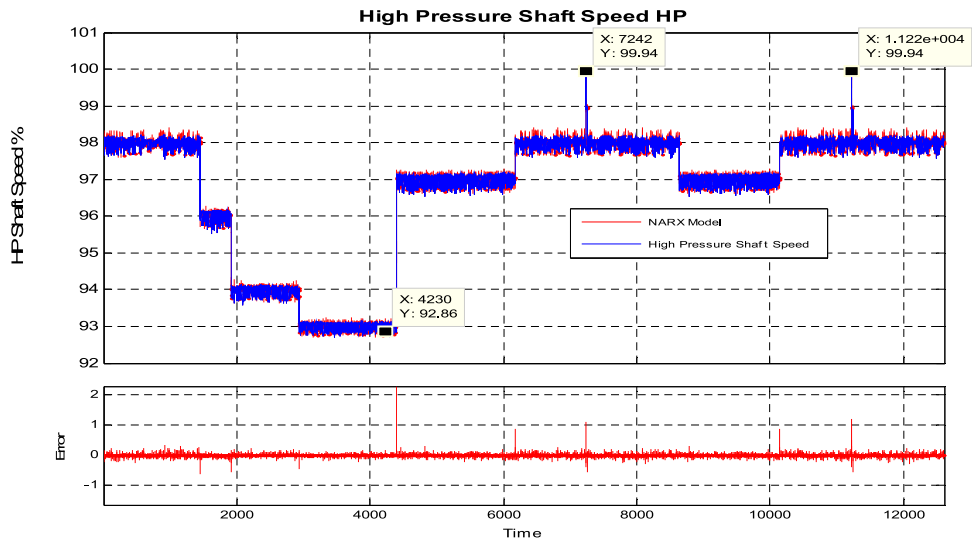


Fig. 13. Model variation of the HP high-pressure turbine shaft with its NARX model.

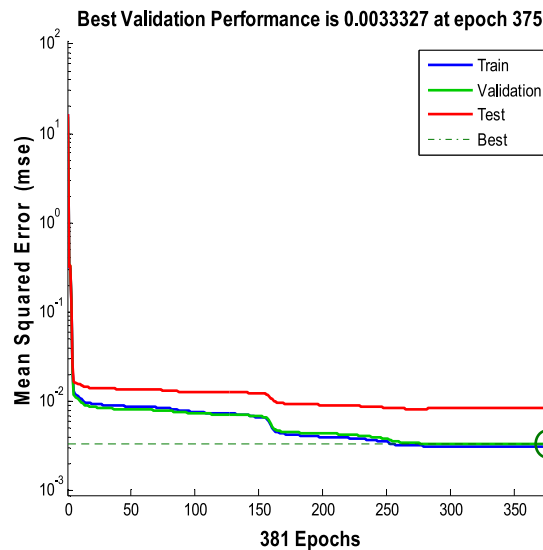


Fig. 14. NARX model performance of the HP high pressure turbine shaft.

points; the first at time 7257 s with an amplitude of 88.77  $\mu\text{m}$  and the second at time 11124 s with an amplitude of 88.82  $\mu\text{m}$ , these amplitudes are big than the amplitudes in the first bearing N°01. Fig. 18B gives the shape of vibration prediction in the bearing N° 2 and makes it possible to analyse the vibratory phenomenon on this bearing of rotor HP of the turbine, this confirms that the higher the rotation speed, the more the vibration effect becomes preponderant.

Fig. 19A presents the output of the NARX vibration model for the case of the third bearing N° 03 and Fig. 19C shows their associate residual variation, with two critical points; the first at time 7257 s with an amplitude of 73.17  $\mu\text{m}$  and the second at time 11124 s with an amplitude of 73.17  $\mu\text{m}$ . Hence, Fig. 19B shows the results after neuronal modelling of the vibration behaviour in the bearing N° 03 of rotor HP, possible instabilities of the rotor on this bearing can be induced in the case of higher rotation, which ascend by the difference between the actual behaviour in blue and that of the NARX model in red in this figure. This allows to confirm that the approach of



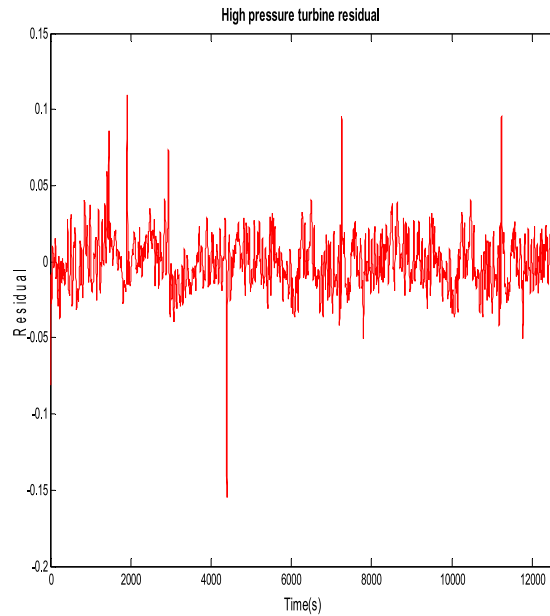


Fig. 15. Residual variation of the high-pressure turbine HP shaft.

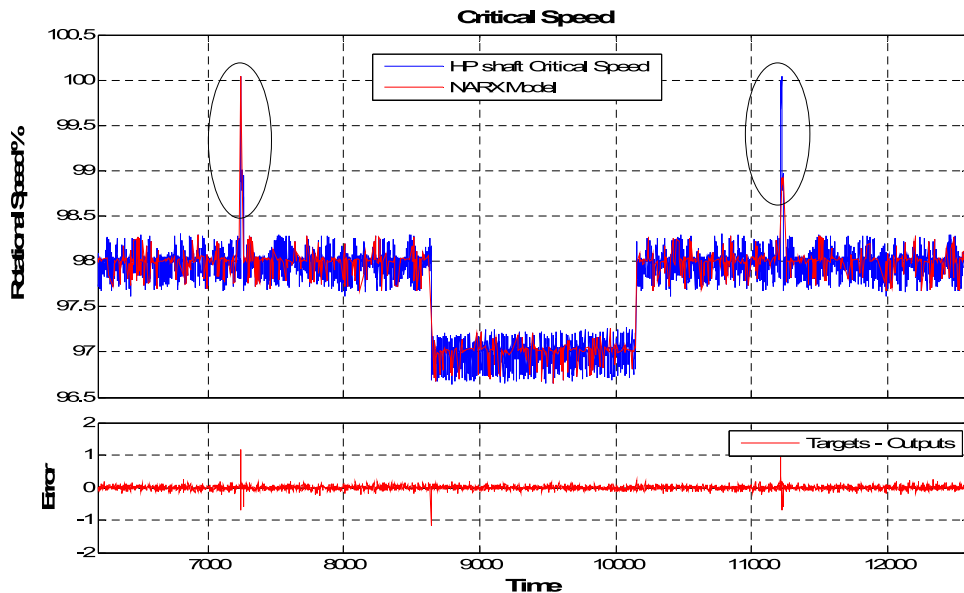


Fig. 16. Model variation of the HP high pressure turbine shaft with its NARX model on two critical points in 7000 s and 11000 s.

NARX modelling adopt in this work has shown its interest in state predictors of turbine model variables compared to conventional approach, which are usually presented in the literature, these modelling results by neural networks are particularly parsimonious and more precise than other conventional approaches.

To model the dynamic behaviour of the HP rotor at bearing 04, the amplitudes of its vibrations under different rotation conditions and excitations are presented in Fig. 20A of the output of the NARX vibration model of this bearing and Fig. 20C shows their associate residual variation. Indeed, the natural frequencies of the rotor change according to its rotation speed, which confirmed by this figure, where the critical speeds are determined at two

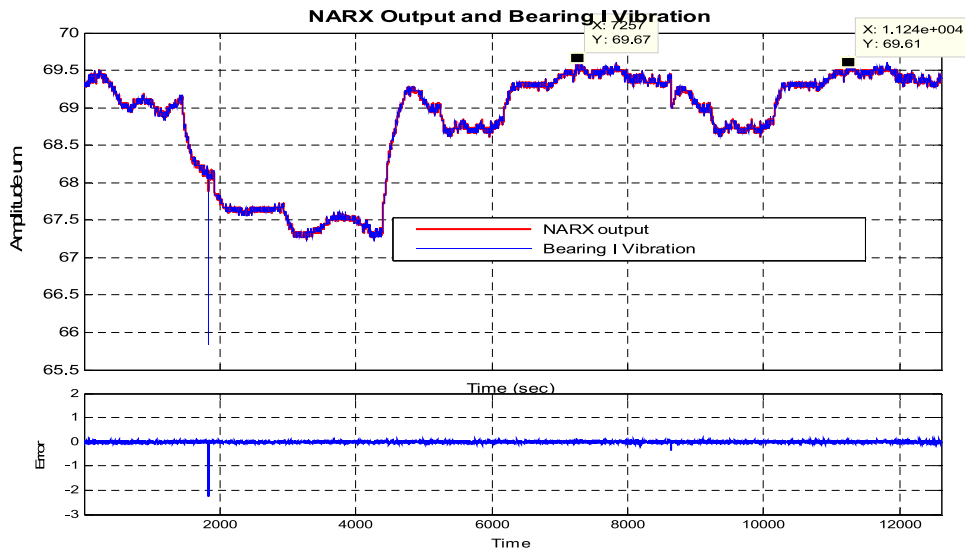


Fig. 17A. Neural model variation of the bearing N° 01 vibration.

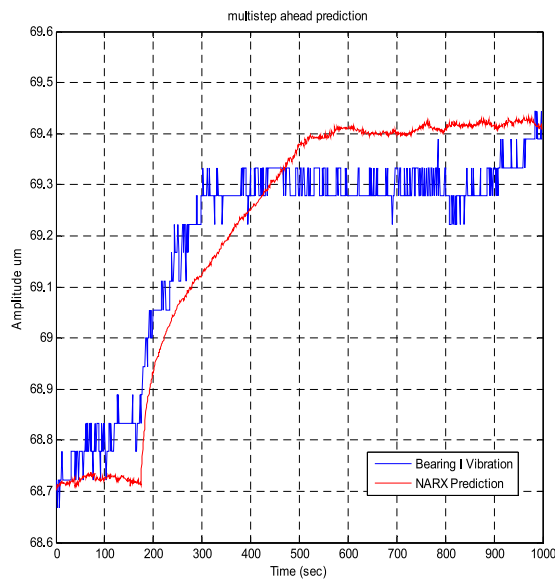


Fig. 17B. Neural prediction of the bearing N° 01 vibration.

critical points; the first at time 7242 s with an amplitude 79.44  $\mu\text{m}$  and the second at time 11122 s with an amplitude of 79.44  $\mu\text{m}$ . The results obtained from the NARX vibration model in the bearing N° 04, is satisfactory, let us examine the real variation of vibration of this bearing with the NARX model. However, the bearings can be damped against dynamic vibrations of the turbine rotor, as shown in Fig. 20B, in practice, the rotational speeds are fixed far from critical areas by the operator of the machine, the bearing allow absorption of excessive vibration from the turbine rotor. Here, the use of neural networks makes it possible to arrive at an approximator which to provide a good estimate of the turbine output at bearing N° 04, this neural approach has reduced the computation time to an extreme during the phase of using this model in the monitoring of the examined turbine.

The development of a neural model makes it possible to estimate the vibration evolution of HP rotor bearings from turbine input/output measurements and the operating conditions of this rotating machine, allowing the influence

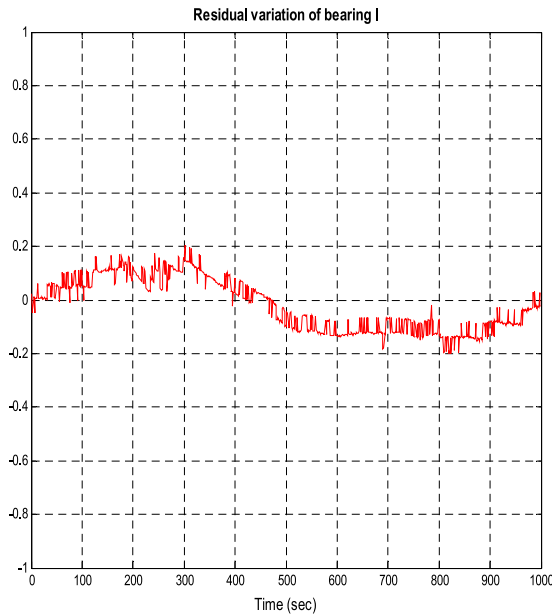


Fig. 17C. Residual variation of vibration in the bearing N° 01.

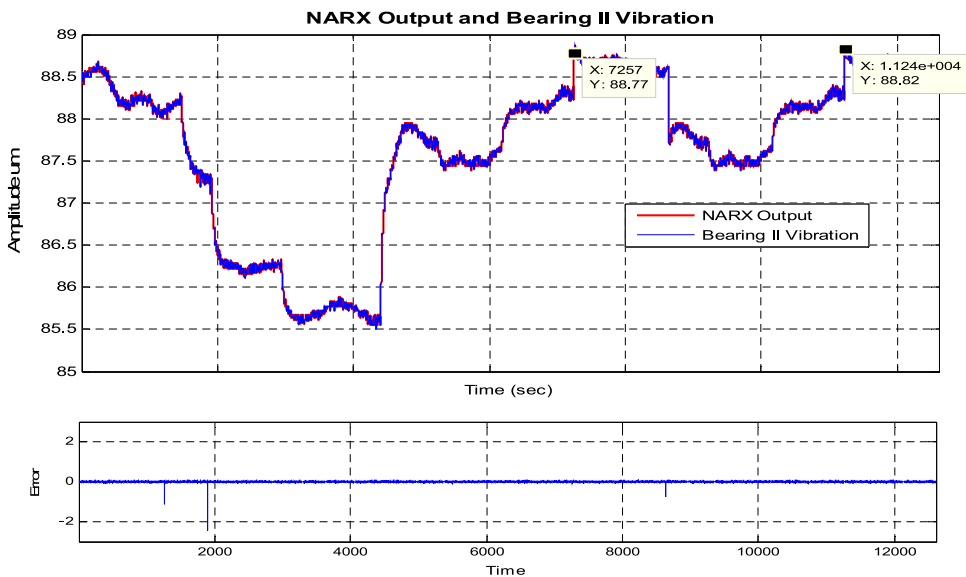
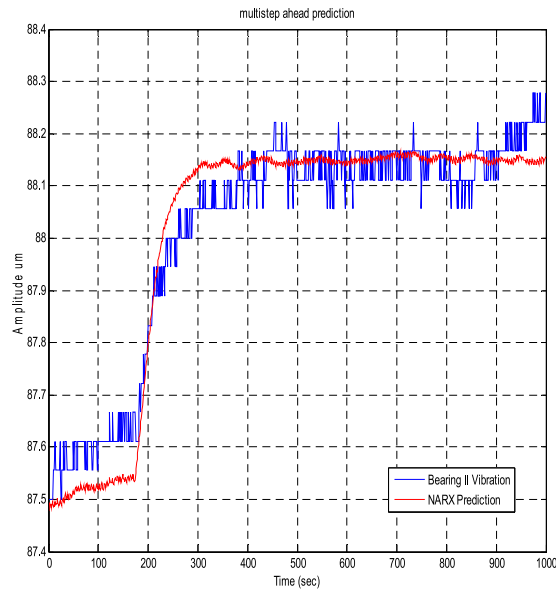


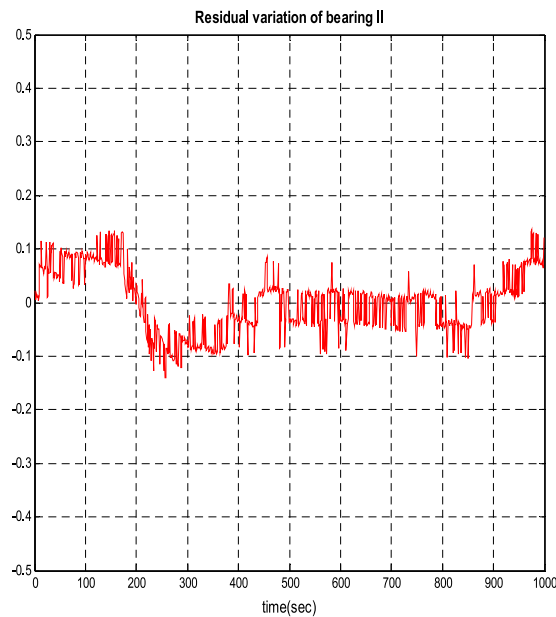
Fig. 18A. Neural model variation of the bearing N° 02 vibration.

of speeds to be determined reviews of dynamic rotor characteristics. After validating the developed NARX model, the last case is shown in Fig. 21A of output variation of the NARX vibration model of the fifth bearing and Fig. 21C shows their associate residual variation, with two critical points; the first at time 7242 s with an amplitude of 80.28  $\mu\text{m}$  and the second at time 11122 s with an amplitude of 80.28  $\mu\text{m}$ .

The validation of vibration modelling in the fifth bearing is ensured by a comparison between the curves from the real model with the proposed neural model, as shown in Fig. 21B, these results are interesting and allow to represent the functioning of the examined turbine rotor. This figure shows that the critical speed plays an important



**Fig. 18B.** Neural prediction of the bearing N° 02 vibration.



**Fig. 18C.** Residual variation of vibration in the bearing N° 02.

role in determining the number of neurons necessary for a satisfactory prediction of the turbine parameters and that the error can be optimized by choosing the correct configuration of the NARX network.

The obtained results show clearly that the use of the NARAX neural has allowed to increase the capability of the prediction of the five bearings models where each bearing has been tested independently. The degradations analysis and interpretation in the studied gas turbine components are based on real series of measurements and observations of abnormal phenomena obtained onsite. This allows the modelling of the degradations causes based on the evaluation of the neuronal models of these components. The proposed approach which is based on the neural

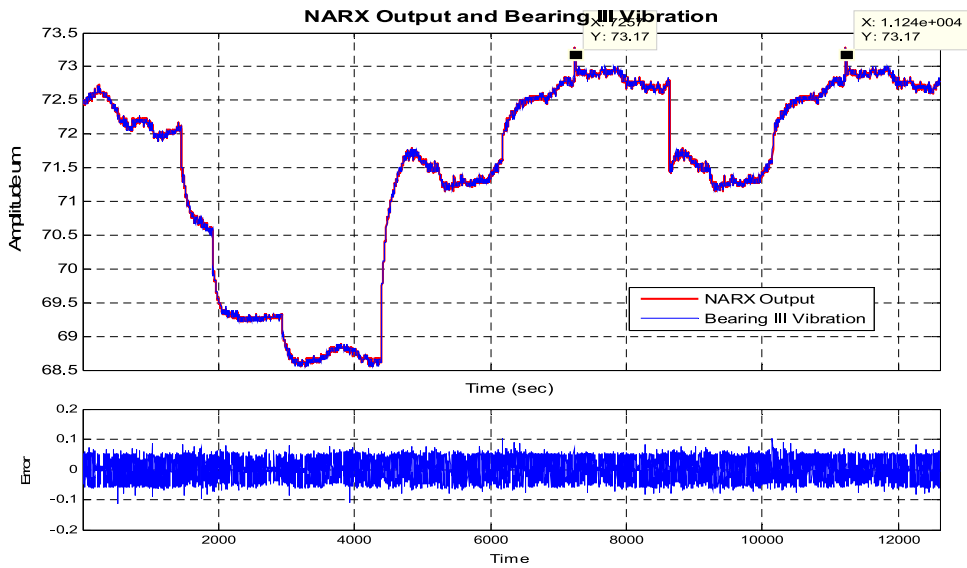


Fig. 19A. Neural model variation of the bearing N° 03 vibration.

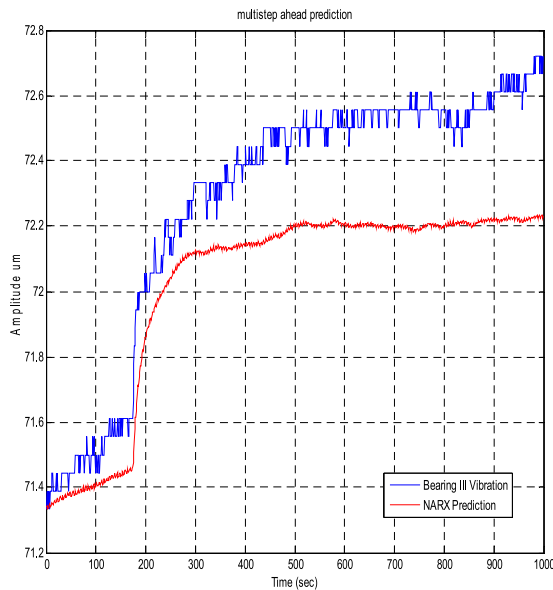


Fig. 19B. Neural prediction of the bearing N° 03 vibration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

modelling of vibration defects allows to provide access to the dynamical behaviour analysis of the turbine under study, where the nature of the anomaly can be identified precisely and their severity on the normal operation can be estimated.

## 6. Conclusion

The main objective of the present work is the modelling of the gas turbine components using a dynamic nonlinear autoregressive approach with external exogenous input NARX, which gives the ability to identify the dynamic

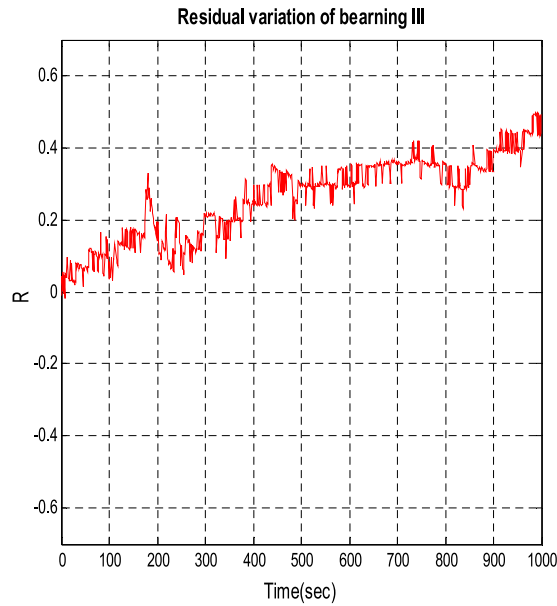


Fig. 19C. Residual variation of vibration in the bearing N° 03.

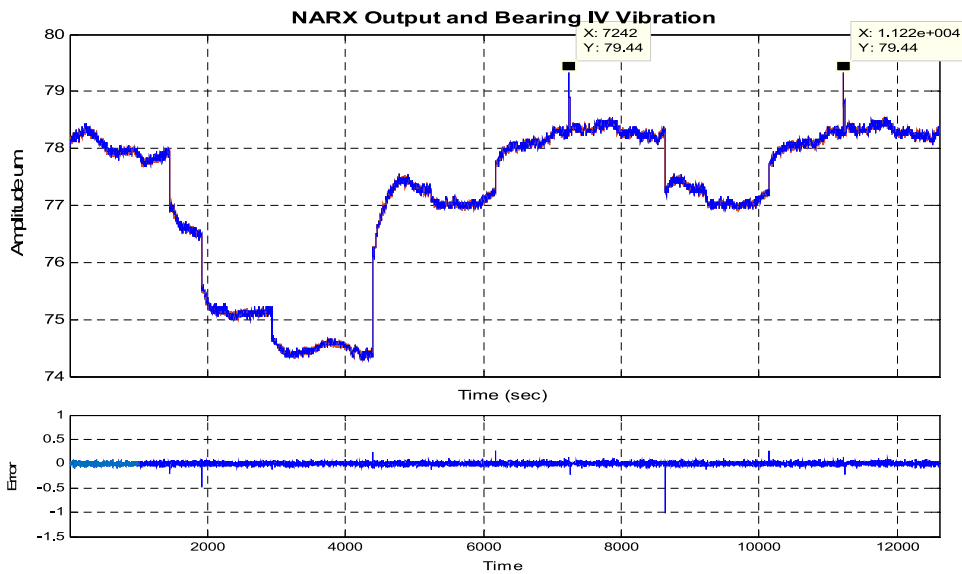


Fig. 20A. Neural model variation of the bearing N° 04 vibration.

behaviour of this turbine under good predictions. This brought some methodological elements to the monitoring practice of rotating machines, the obtained results from the study carried out on a gas turbine system reflecting their dynamic behaviour. These results based on a proposed diagnostic approach were tested then validated with convergent prediction errors towards zero. This approach made it possible to model the acts of degradation by vibration of the components of the examined gas turbine and to estimate and plan the duration of malfunction of this gas turbine system. The dynamic behaviour of the turbine system is determined by the proposed NARX model, where the critical speeds of five rotor bearings have been calculated and the associated vibration amplitudes under different excitations have been analysed. Indeed, the study of five cases of rotor bearings made it possible to

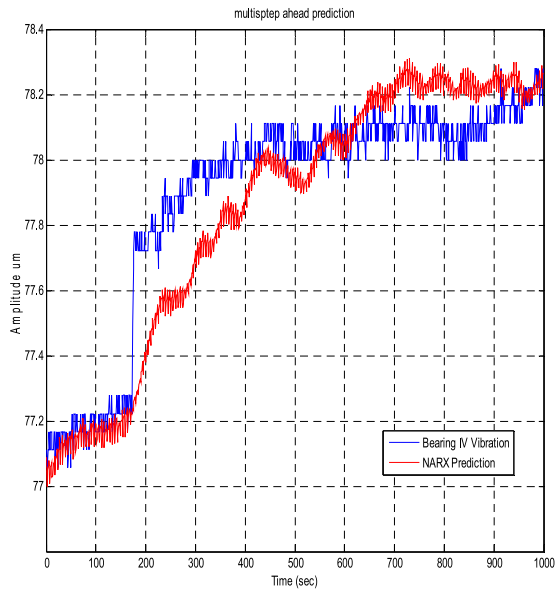


Fig. 20B. Neural prediction of the bearing N° 04 vibration.

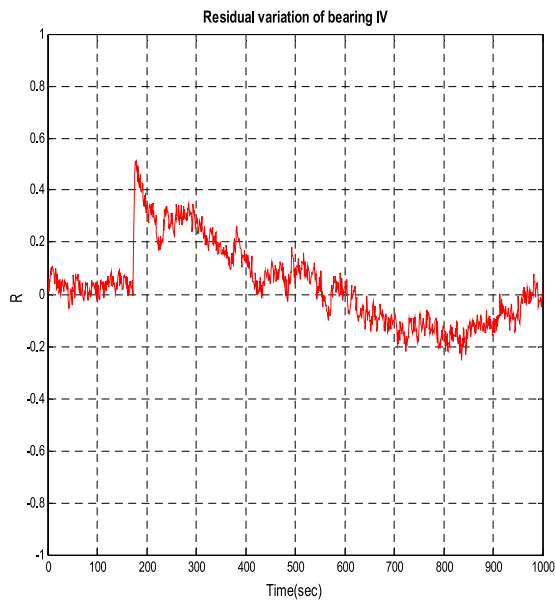


Fig. 20C. Residual variation of vibration in the bearing N° 04.

show the advantages and artificial neural networks in modelling their vibrational behaviour, given the performances obtained linked to the validation values given by the mean square error MSE obtained for the examined turbine variables; High Pressure Shaft HP equal to  $3.33270e-3$ , Gas Control Valve CGV equal to  $1.2690e-1$  and the Inlet Guide Vane IGV equal to  $2.08650e-4$ . Although the obtained results are satisfactory in terms of forecast error, depending on the influence of the number of turbine input/output data used in this modelling. The obtained model with the proposed approach allows to ensure an effective diagnostics strategy for this type of rotating machine and provides a very powerful tool for the maintenance needs, especially in the petroleum industry where the main aim is

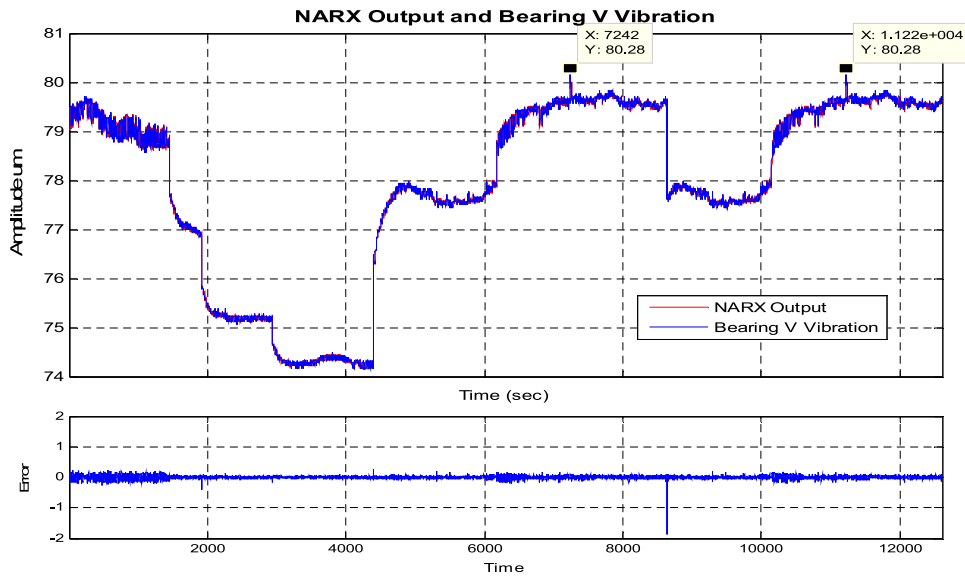


Fig. 21A. Neural model variation of the bearing N° 05 vibration.

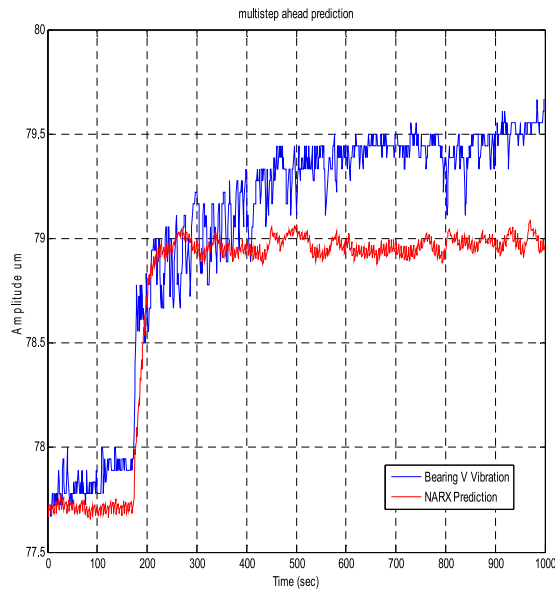


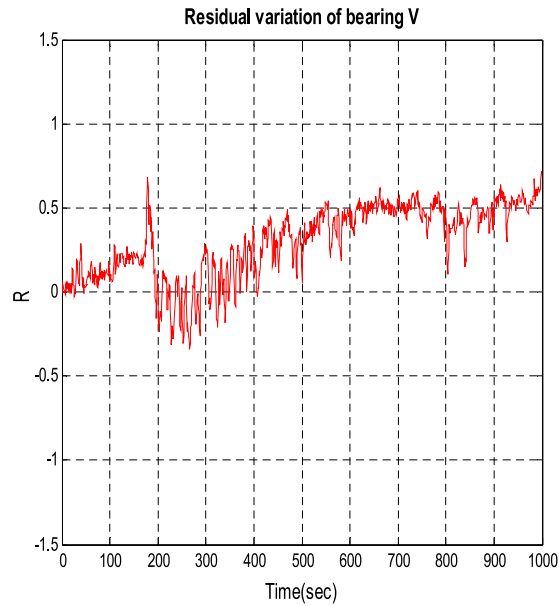
Fig. 21B. Neural prediction of the bearing N° 05 vibration.

to ensure a competitive quality and cost of operation. The obtained results allow to better manage the failures caused by the vibrations in the studied gas turbine and show the efficiencies of the artificial neural networks approach as very powerful tool for the modelling of the complex dynamic systems.

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**Fig. 21C.** Residual variation of vibration in the bearing N° 05.

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