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ARMAX-BASED IDENTIFICATION AND DIAGNOSIS OF VIBRATION BEHAVIOR OF GAS TURBINE BEARINGS

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Abstract:

Parametric identification approaches play a crucial role in the control and monitoring of industrial systems. They facilitate the identification of system variables and enable the prediction of their evolution based on the input-output relationship. In this study, we employ the ARMAX approach to accurately predict the dynamic vibratory behavior of MS5002B gas turbine bearings. By utilizing real input-output data obtained from their operation, this approach effectively captures the vibration characteristics of the bearings. Additionally, the ARMAX technique serves as a valuable diagnostic tool for the bearings, enhancing the quality of identification of turbine variables. This enables continuous monitoring of the bearings and real-time prediction of their behavior. Furthermore, the ARMAX approach facilitates the detection of all potential vibration patterns that may occur in the bearings, with monitoring thresholds established by the methodology. Consequently, this enhances the availability of the bearings and reduces turbine downtime. The efficacy of the proposed ARMAX approach is demonstrated through comprehensive results obtained in this study. Robustness tests are conducted, comparing the real behavior observed through various probes with the reference model, thereby validating the approach.

Keywords**:** System identification, ARMAX, parametric estimation, gas turbine, vibration modelling.

Nomenclature and abbreviations

AIC	Akaike's information criterion
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
ARMAX	Auto Regressive Moving Average with eXogenous input
ARX	Autoregressive with Extra Input
FL	Fuzzy logic
FPE	Final prediction error
HP	High-pressure turbine
LP	Low-pressure turbine
MIMO	Multiple Input, Multiple Output
MSE	Mean Square Error
NRMSE	Normalized Root Mean Square Error
OE	Output Error
SISO	Single Input, Single Output
$A(q)$	System state vector
$B(q)$	Command vector
$C(q)$	Observation vector
a_i, b_i, c_i	Polynomial weighting coefficients
$G(q)$	Transfer function
g	Natural number
$H(q)$	Dynamic disturbance function
k	Discrete time
N	Number of samples taken is the
n_a	Degrees of the polynomial $A(q)$
n_b	Degrees of the polynomial $B(q)$
n_c	Degrees of the polynomial $C(q)$
n_k	Dead time in the process
q	State operator
S	Number of estimated parameters
$u(k)$	Input signal
u_1	HP rotor speed Input
u_2	LP rotor speed Input
$V_N(\theta)$	Criterion function
$\dot{V}(\vec{\theta})$	Gradient of $V_N(\theta)$
$\ddot{V}(\vec{\theta})$	Hessian of $V_N(\theta)$
$y(k)$	Output signal
y_1	Vibration model on bearing #1 of HP rotor
y_2	Vibration model on bearing #3 of LP rotor

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θ	Estimator
$e(k)$	White noise perturbation with zero mean
$\hat{y}(k)$	Output predictor of $y(k)$
$\sigma(k)$	Variance
$\varepsilon(k)$	Error of prediction
$\nu(k)$	Stochastic disturbance signal
λ	Sample time

1. INTRODUCTION

Monitoring and identifying vibration behavior present significant challenges in modern installations utilizing gas turbines. The ability to establish protective measures and alarm levels for these devices is crucial in preventing failures. Consequently, companies relying on such systems face the major challenge of maintaining desired performance levels while ensuring proper control of these rotating machines.

In this context, this study proposes the development of a dedicated vibration model for the bearings of an MS5002B gas turbine, utilizing the ARMAX structure guided by operational data. This approach serves as an effective solution for real-time monitoring of the vibratory dynamics of the turbine, aimed at ensuring optimal operation and minimizing turbine downtime.

Vibration monitoring is imperative for most installations with rotating equipment to minimize preventive maintenance and extend equipment lifespan. Recent works have focused on diagnostic approaches for rotating machines, integrating vibration analysis based on input-output data. For example, the work of Benrabeh Djaidir et al. [4] proposed an approach for detecting the vibration faults of a turbine through the behavior analysis of the input/output operating data of the rotating machine. This enables the improvement of vibration diagnosis strategy with better detection precision in real-time applications. Madhavan S. et al. [11] provided guidance on the detection of failures caused by turbine shaft blade vibration to maximize the energy delivered by the machine while reducing vibration problems. Saeed R.A. et al. [24] integrated the concept of artificial intelligence for the diagnosis of turbine faults using ANN artificial neural network models and ANFIS adaptive neuro-fuzzy inference systems, ensuring intelligent vibration analysis and improved efficiency in detecting failure occurrences due to vibration. Abdelhafid Benyounes et al. [1] proposed a comparative study of modeling and control of a gas turbine, exploring fuzzy techniques, neural networks, and the ANFIS structure. Sanjay Barad et al. [25] developed an intelligent configuration for monitoring the mechanical state of a gas turbine, based on the use of neural networks, leading to improved monitoring performance and precision. Sidali Aissat et al. [28] identified the operating parameters of a gas turbine using a fuzzy multi-model approach and exploited operating data for the prediction of the operating state dynamics of the machine.

However, Sadough Vanini Z.N. et al. [23] applied artificial intelligence techniques to diagnose faults in a double-body turbine, specifically utilizing artificial neural networks for fault detection and isolation. Merouane Alaoui et al. [13] proposed a method for analyzing the stability and vibration bifurcation of a gas turbine based on operating data, allowing for the prediction of vibration indices and highlighting their stability at the bifurcation points in high-speed operating regimes. Shoyama Tadayoshi [26] conducted a detailed analysis of bearing vibration phenomena, studying nonlinear bifurcations and ensuring overall stability. Sidali Aissat et al. [27] employed a multi-model approach for the identification of turbine variables, using decoupled states to detect defects through residue generation based on parity space. Merouane Alaoui et al. [14] proposed a turbine monitoring strategy using a generalized predictive adaptive control structure for turbine speed monitoring, which demonstrated a good response time and efficiency in regulating turbine parameters.

Numerous other studies have focused on controlling, modeling, diagnosing, monitoring, and evaluating the vibration behavior of rotating machinery. This work contributes to the understanding and control of vibration-related problems, such as the developments made by Yasser Chiker et al. [30], who studied the dispersibility of nanofillers on vibrational dynamics and their influences on composite materials. Combescure D. and Lazarus A. [6] employed finite element techniques to model a rotating machine and analyze its vibration behavior, predicting the influence of vibrations on turbine operation and improving efficiency. Mohamed Benrahmoune et al. [15] proposed strategies for estimating fault monitoring and fault identification factors for gas turbines using smart tools like deep learning, fuzzy logic, neuro-inference, and artificial neural networks. They also performed dynamic learning of a neural network for gas turbine monitoring, employing a neural architecture based on external exogenous input [17].

Identification methods are frequently used to determine the characteristics of complex dynamic models representing various physical phenomena. Recently, artificial intelligence has been applied in fault diagnosis, discussing recent advances in model-based fault diagnosis for dynamic system behavior. Mateo Daniel Roig Greidanus and Marcelo Lobo Heldwein [12] developed a fault-tolerant control strategy for gas turbines to improve their online monitoring. Choayb Djeddi et al. [5] implemented a robust approach for detecting faults affecting a turbine using a fuzzy neuro-inference configuration, ensuring high protection of the machine. Nadji Hadroug et al. [22] implemented an advanced turbine fault detection framework based on the fuzzy concept for the identification of symptom-fault correlations. Muhammad Mujtaba Syed et al. [19] devised an advanced approach for diagnosing gas pipeline faults, especially for transient behaviors.

Mohsen Shabanian and Mohsen Montazeri [18] developed a fault diagnosis algorithm with a neuro-fuzzy structure applied to a complex nonlinear system. Weipeng Sun et al. [29] proposed model estimation and nonlinear characterization approaches for gas turbines and rotor bearing systems.

Several researchers have also developed applications on turbine reliability. Nadji Hadroug et al. [21] studied the modeling of reliability and availability indices of a gas turbine using an adaptive neuro-fuzzy inference representation. Ahmed Zohair Djeddi et al. [2] estimated the reliability of a gas turbine by minimizing the risk of failures and conducted a comparative study between usual reliability distributions. Ahmed Zohair Djeddi et al. [3] improved the availability and maintainability of a gas turbine using long-term memory networks based on deep learning and exploiting failure data.

This article presents a parametric identification technique that monitors the vibration behaviors of MS5002B gas turbine bearings using the ARMAX approach and real-time operational data. The goal is to predict vibrations in the high-pressure and low-pressure turbine rotor bearings through optimal multi-input-multi-output estimation. To evaluate the developed model's quality, performance tests using criteria such as RMSE, FPE, and MSE are proposed. Residual analysis, including residual autocorrelation and cross-correlation tests, is also performed. The implementation of the ARMAX approach involves acquiring and filtering turbine operating data, followed by the identification process to develop vibration behavior models for the examined turbine bearings. The tests and validation results demonstrate satisfactory performance, illustrating the efficiency of estimating and detecting the studied turbine's vibratory behavior.

2. GAS TURBINE SYSTEM

The performance of gas turbines depends on the operating conditions, such as climate and load. To ensure proper operation and increase their lifespan, it is important to understand the effects of these conditions on the gas turbines. In this paper, we propose to use an ARMAX model to identify and predict the vibration behaviors of the MS5002B gas turbine bearings in discrete time. This gas turbine is installed in the Hassi R'Mel gas center in southern Algeria. It is a two-shaft internal combustion turbine that consists of a gas generator and a power turbine. The gas generator includes an air compressor, a combustor and a high-pressure (HP) turbine that drives the air compressor. The power turbine includes a low-pressure (LP) turbine that drives a centrifugal compressor to produce the useful power. The two shafts are not linked, so they can operate at different speeds to adapt to the load variations required by the centrifugal compressor. Figure 1 shows the MS5002B gas turbine system and Table 1 summarizes its characteristics.

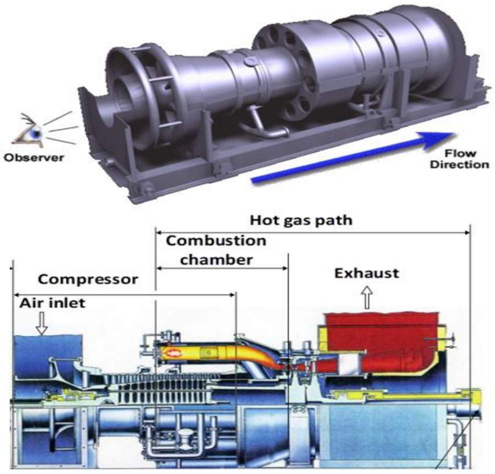

Fig. 1. MS5002B Gas turbine

Table 1. MS5002B turbine specifications

Design parameters (ISO conditions)	
Cycle	**Simple**
Pressure Ratio	6 – 8
Exhaust Temperature	517.2 °C
Exhaust Flow	124.3 Kg/s
Number of turbine stages	02
Rated power	28336.6 Kw
Heat Rate	12468.3 Kj/Kwh
Turbine efficiency	28.8 %
shaft speed	5100 rpm HP and 4903 rpm LP

The MS5002B gas turbine under study consists of two shaft lines, each equipped with a separate power turbine known as a free turbine. These two rotors operate independently, allowing them to function at different speeds to accommodate the required load variations for the centrifugal compressor. The first rotor encompasses the axial compressor and the high-pressure (HP) turbine, as illustrated in Figure 2. This rotor compresses the air and delivers it to the pressurized combustion chambers. The second rotor, the low-pressure (LP) turbine, as depicted in Figure 3, is responsible for driving the centrifugal compressor as a load. The LP turbine shaft is supported by two bearings, namely bearings #3 and #4, forming the low-pressure turbine shaft.

Fig. 2. HP high pressure turbine shaft

Fig. 3. LP Low Pressure Turbine Shaft

The vibration and rotation speed data of the turbine rotor are collected by various sensors installed on the turbine. These sensors produce analog signals that are converted into digital signals by an analog-digital converter. The vibration signals are measured at bearings #1 and #3 using velocimeters, as shown in Figure 4. The rotation speed signals are measured using magnetic speed sensors, as shown in Figure 5.

Fig. 4. Position of the vibration velocimeter sensor

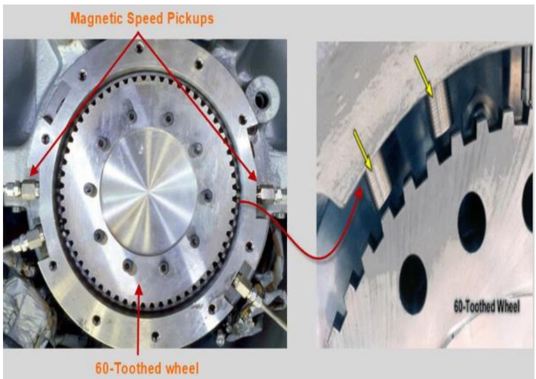

Fig. 5. Position of the magnetic speed sensor

Practically, the vibration alarm levels of the studied MS5002B turbine are presented in Table 2, serving as critical measurements for the ongoing monitoring of this rotating machine. These indices play a crucial role in the analysis of vibration signals, offering one of the most effective methods for preventing breakdowns and failures of gas turbines. Regular measurements of vibration levels are carried out periodically for the MS5002B turbine, as an increase in vibration level signifies a significant deterioration factor.

However, it should be noted that these vibration level measurements may not always provide precise information about the exact location of turbine faults. Instead, they are useful in determining the levels at which the highest vibration amplitudes occur. Nevertheless, by obtaining a robust parametric representation of the vibration model through reliable data acquisition, it becomes possible to identify the sources responsible for turbine vibrations accurately.

Table 2. MS5002B Turbine Vibration Alarm Levels

Vibration	**Alarm level**	**Danger level**
Bearing #1 (BB1)	12.7 mm/s	25.4 mm/s
Bearing #3 (BB4)	12.7 mm/s	25.4 mm/s

The vibrations of the MS5002B turbine result from various phenomena and faults, including external forces such as friction, unbalance, misalignment, bearing failure, gear teeth, and other sources that generate vibrations. These vibrations pose significant operating risks to the turbine rotor, which are then transmitted to the bearings. To detect and analyze vibration anomalies associated with the MS5002B turbine bearings, we present their types in Table 3, which cover a wide operating range. In the next section, we propose a state equation model based on the ARMAX model. This model enables us to monitor the vibrations of these bearings and track changes in vibration levels affecting bearing #1 and bearing #3 of the turbine. By doing so, we can assess the turbine's condition and identify any faults.

Table 3. Type of MS5002B turbine bearings

Bearing N°	**Kind**	**Type**
#1	Journal	Elliptical
	Thrust (active)	Tilting pad (six pads)
	Thrust (inactive)	Tapered land
#2	Journal	Elliptical
#3	Journal	Tilting-pad (five pads)
#4	Journal	Tilting-pad (five pads
	Thrust	Tilting-pad (eight pads
	Thrust	Tilting-pad (four pads

The following part presents an estimation study of the state model parameters based on the ARMAX approach, with a view to its application for the development of the MS5002B turbine bearing vibration model. These estimates from ARMAX models with the input/output variables of turbine operation are very similar to the profiles of the vibration data affecting this rotating machine.

3. ARMAX MODEL

The identification and modeling of the dynamics of complex industrial systems play a crucial role in their management. These models are derived from the relationships between various physical quantities that describe the system's behavior and interactions among different variables. Parametric identification approaches offer significant value as they aim to estimate the parameters of mathematical models using the system's operational data. In this study, we focus on the identification of vibration behavior in a turbine by employing the ARMAX model. The goal is to develop a reliable approximation of the rotor bearing behavior in a gas turbine, where the model parameters are adjusted based on the operational data of the rotating machine. Within this context, this section presents the identification of model variables using the ARMAX approach, which will later be utilized for predicting the behavior of the examined turbine rotor bearings.

Indeed, the AutoRegressive model with Adjusted Mean and eXogenous variables denoted ARMAX is an input-output model of a system, is often given in a more compact form in discrete time as follows:

$$y(k) = G(q)u(k) + H(q)e(k) \tag{1}$$

where $y(k)$ are the system outputs, $u(k)$ are the inputs and $e(k)$ are the noises.

In this study, the identification of the parameters of a turbine model is proposed using the ARMAX structure of a discrete dynamical system given by a transfer function [1, 7, 8-9, 20], of the following general form:

$$G(q) = \frac{B(q)}{A(q)} \tag{2}$$

With:

$$\begin{cases} A(q) = 1 + a_1 \cdot q^{-1} + \ldots + a_{n_a} \cdot q^{-n_a} \\ B(q) = b_1 + b_2 \cdot q^{-1} + \ldots + b_{n_b} \cdot q^{-n_b+1} \end{cases} \tag{3}$$

This ARMAX model comprising noises in the input and on the output of the system, these disturbances are represented by the stochastic signal $v(k)$, itself being generated with a dynamic $H(q)$, also by the stochastic signal $e(k)$ of white noise type. With a normal distribution variance at zero mean σ_2, as shown in Figure 6, which illustrates the block diagram of the ARMAX model. Hence, this form of ARMAX model has a dynamic for the noise signal and the input of the system, which can be written in the following form:

$$H(q) = \frac{V(q)}{E(q)} = \frac{1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-n_c}}{1 + a_1 q^{-1} + \ldots + a_{n_a} q^{-n_a}}) = \frac{C(q)}{A(q)} \tag{4}$$

Therefore, the system representation in the form of states becomes:

$$y(q) = \frac{B(q)}{A(q)} u(q) + \frac{C(q)}{A(q)} e(q) \tag{5}$$

This representation of formula (5) can be represented in vector form as follows [7, 16]:

$$\begin{aligned} y(l) + a_1 y(l-1) + \ldots + a_{n_a} y(l-n_a) = \\ b_1 u(l-n_k) + \ldots + b_{n_b} u(l-n_k-n_b+1) \\ + c_1 e(l-1) + \ldots + c_{n_c} e(l-n_c) + e(l) \end{aligned} \tag{6}$$

Where $u(l)$ and $y(l)$ are the input and output, respectively, $e(l)$ is the zero-mean white noise disturbance of the variance σ_2, n_a, n_b and n_c are the degrees of the polynomials, respectively $A(q)$, $B(q)$ and $C(q)$, n_k is the dead time of the process.

From equation (6), the representation of a system with a single input and a single output SISO, conceding the effects of disturbances resulting from a filtered white noise, the representation of a system in the form of states becomes :

$$A(q) = B(q)u(l-n_k) + C(q)e(l) \tag{7}$$

With:

$$C(q) = 1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-n_c} \tag{8}$$

Such that q^{-1} is the shift operator, given by:

$$q^{-g} x(k) = x(k-g)\ ;\ g \in N \tag{9}$$

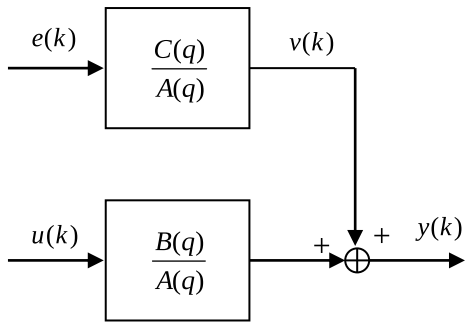

Fig. 6. Structure of the ARMAX model

Modeling and identification based on the structure of the ARMAX model shows the effectiveness of the models developed for the vibrations of the rotor bearings of the studied turbine, which is based on the analysis of actual behavior observed and that of reference models. Practically, in the ARMAX models, the noise signal $e(k)$ and the control signal $u(k)$ are subject to the same dynamics, because these disturbances are directly linked to the control input of the system. Hence, from model (5), it is possible to predict the future value of the output $y(k)$ using the previous measurements of the signals $u(k)$ and $e(k)$. Therefore, it is easier to calculate these predictions using computer hardware with different discrete values of different turbine signals.

The most commonly used parametric estimation models can all be summarized in the general form of output error models ARMA, ARX and OE with exogenous variables in ARMAX form, in Table 4, which is used to represent in the form synthetic and coherent a set of system data in the form of reliable models. Based on discrete-time linear parametric estimation with minimization of prediction error and modeling flexibility in the presence of disturbances.

Table 4. Parametric estimation methods

Model	**Representation of states equations**	$\boldsymbol{G(q,\theta)}$	$\boldsymbol{H(q,\theta)}$
ARX	$A(q)y(k) = B(q)u(k) + e(k)$	$\frac{B(q)}{A(q)}$	$\frac{1}{A(q)}$
ARMAX	$A(q)y(k) = B(q)u(k) + C(q)e(k)$	$\frac{B(q)}{A(q)}$	$\frac{C(q)}{A(q)}$
OE, Output Error	$y(k) = \frac{B(q)}{F(q)}u(k) + e(k)$	$\frac{B(q)}{F(q)}$	1

The ARMAX structure is a method for identifying the parameters of systems based on their operating data. It aims to establish mathematical models that can describe these systems accurately. Therefore, it can be a useful tool for prediction and analysis in real time or offline applications. However, it requires a good data acquisition process on this equipment.

For the development of the ARMAX model approach, one begins with the acquisition of the data of the operating inputs/outputs, then the choice of the structure of the ARMAX model used. Subsequently, the estimation of the model parameters will be made based on the validation tests of the identified turbine model parameters. Firstly, the ARMAX process for $x(k)$ is determined, then the series $y(k)$ is filtered and the order (delay) of the system transfer function is determined. Then the vector $C(q)$ of the rest system dynamics is determined to arrive at the final estimate of the model parameters, as shown in the flowchart in Figure 7 below.

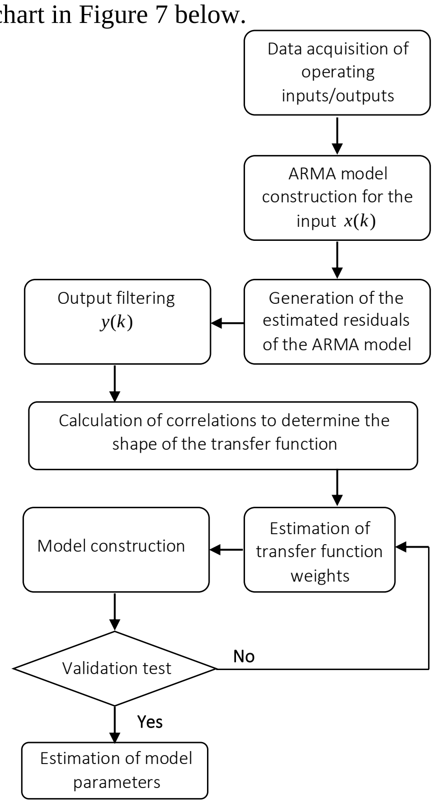

Fig. 7. Flow chart of the proposed ARMAX approach

The general form of the predictor $\hat{y}(k)$ of the output $\hat{y}(k)$ is given by:

$$\hat{y}(l,\theta) = \frac{B(q)}{C(q)}u(l) + \left[1 - \frac{A(q)}{C(q)}\right]y(l) \tag{10}$$

Where:

$$C(q)\hat{y}(l,\theta) = B(q)u(l) + [C(q) - A(q)]y(l) \tag{11}$$

Adding $[1 - C(q)]\hat{y}(l,\theta)$ to both sides of this expression gives:

$$\hat{y}(l,\theta) = B(q)u(l) + [1 - A(q)]y(l) + [C(q) - 1][y(l) - \hat{y}(l,\theta)] \tag{12}$$

Such as:

$$\varepsilon(l,\theta) = y(l) - \hat{y}(l,\theta) \tag{13}$$

And if we introduce the two vectors:

$$\vec{\phi}(l,\theta) = \begin{bmatrix} -y(l-1)\ldots -y(l-n_a) \\ ,u(l-1)\ldots u(l-n_b), \\ \varepsilon(l-1,\theta)\ldots \varepsilon(l-n_c,\theta) \end{bmatrix}^T \tag{14}$$

With:

$$\vec{\theta} = \left(a_1\ldots a_{n_a}, b_1\ldots b_{n_b}, c_1\ldots c_{n_c}\right)^T \tag{15}$$

Then, the predictor equation (12) can be rewritten as follows:

$$\hat{y}(l,\theta) = \vec{\phi}(l,\theta)^T \cdot \vec{\theta} \tag{16}$$

Where, the prediction error $\varepsilon(l)$ for the ARMAX model can be described as follows:

$$\varepsilon(l,\theta) = [C(q,\theta)]^{-1}[A(q,\theta)y(l) - B(q,\theta)u(l)] \tag{17}$$

The criterion function is sometimes called a cost function and is defined by:

$$V_N(\theta) = \frac{1}{N}\sum_{l=0}^{N-1} \varepsilon^2(l,\theta) \tag{18}$$

Where N is the taken number of samples.

Indeed, the sought estimator $\hat{\theta}_N$ of θ must therefore minimize the function V_N, we obtain:

$$\hat{\theta}_N = arg \min_{\theta} V_N(\theta) \tag{19}$$

In this parametric identification study, the Gauss-Newton optimization algorithm is used as a method to find the best model parameters. This Newton-Raphson search algorithm is exploited to obtain the optimal parameters of the estimator $\hat{\vec{\theta}}_N$ and to minimize the criterion function $V_N(\theta)$, generally this function is given as following [10, 15]:

$$\hat{\vec{\theta}}_N^{(i+1)} = \hat{\vec{\theta}}_N^{(i)} - \lambda_N \cdot \left(\ddot{V}_N\left(\hat{\vec{\theta}}_N^{(i)}\right)\right)^{-1} \cdot \dot{V}_N\left(\hat{\vec{\theta}}_N^{(i)}\right) \tag{20}$$

Where $\dot{V}(\vec{\theta})$ is the gradient of $V_N(\theta)$ is given by:

$$\dot{V}_N(\vec{\theta}) = -\frac{1}{N}\sum_{l=0}^{N-1} \psi(l,\vec{\theta})\varepsilon(l,\vec{\theta}) \tag{21}$$

With:

$$\psi(l,\vec{\theta}) = \frac{1}{C(q)}\vec{\phi}(l,\vec{\theta}) \quad (22)$$

$$\psi(l,\vec{\theta}) = \left[\frac{\partial\hat{y}}{\partial a_1}\cdots\frac{\partial\hat{y}}{\partial a_{n_a}},\frac{\partial\hat{y}}{\partial b_1}\cdots\frac{\partial\hat{y}}{\partial b_{n_b}},\frac{\partial\hat{y}}{\partial c_1}\cdots\frac{\partial\hat{y}}{\partial c_{n_c}}\right]^T \quad (23)$$

Thus, the Hessian of the function $V_N(\theta)$ is given by:

$$\ddot{V}_N(\vec{\theta}) = \frac{1}{N}\sum_{l=0}^{N-1}\psi(l,\vec{\theta})\,\psi(l,\vec{\theta})^T - \frac{1}{N}\sum_{l=0}^{N-1}\dot{\psi}(l,\vec{\theta})\,\varepsilon(l,\vec{\theta})^T$$

$$= \frac{1}{N}\sum_{l=0}^{N-1}\psi(l,\vec{\theta})\,\psi(l,\vec{\theta})^T - M(\vec{\theta}) \quad (24)$$

From where:

$$M(\vec{\theta}) = \frac{1}{N}\sum_{l=0}^{N-1}\dot{\psi}(l,\vec{\theta})\varepsilon(l,\vec{\theta})^T \quad (25)$$

Nevertheless, the main disadvantage of the Newton-Raphson algorithm is that the second-order term $M(\vec{\theta})$ of $\ddot{V}(\vec{\theta})$ is difficult to calculate. Therefore, to reduce and simplify the calculation, it is necessary and efficient to neglect the term $M(\vec{\theta})$.

So, when we neglect the second-order term $M(\vec{\theta})$ in the Hessian matrix $\ddot{V}(\vec{\theta})$, the use of the Gauss-Newton algorithm will be easily done. Thus, equation (17) becomes:

$$\hat{\vec{\theta}}^{(i+1)} = \hat{\vec{\theta}}^{(i)} - \lambda_N\cdot\left(\ddot{V}_N\left(\hat{\vec{\theta}}^{(i)}\right)\right)^{-1}\cdot\dot{V}_N\left(\hat{\vec{\theta}}^{(i)}\right) \quad (26)$$

With:

$$\ddot{V}(\vec{\theta}) \approx \frac{1}{N}\sum_{l=0}^{N-1}\psi(l,\vec{\theta})\psi(l,\vec{\theta})^T \quad (27)$$

Where λ is the step, generally considered a positive decreasing function.

After the determination of the model parameters with the proposed ARMAX structure, the validation of this model is carried out using the robustness tests of this algorithm, as it is shown in Figure 3. However, the identification is carried out by minimizing a quality criterion which characterizes the difference between the behavior of the system given by the various measures, and that of its reference model.

To assess the convergence of the proposed ARMAX approach, the Akaike Information Criterion (AIC) is used to measure the model quality. This performance criterion is based on the calculations of the final prediction errors (FPE), given by the following formula:

$$FPE = V_N(\hat{\theta}_N)\cdot\left(\frac{1+\frac{S}{N}}{1-\frac{S}{N}}\right) \quad (28)$$

where N is the number of samples and S is the number of estimated parameters.

Similarly, to ensure that the model parameters are well adjusted, a testing process based on the determination of the normalized root mean square error (NRMSE) will be carried out. Hence, the measures of the difference between the real variables and their estimates are defined by the following goodness-of-fit formula:

$$fit(\%) = 100\left(1 - \frac{\|y_{measured} - y_{predicted}\|}{\|y_{measured} - \bar{y}_{predicted}\|}\right) \quad (29)$$

As well, the root mean square error is used to test the quality and performance of model parameters, which is defined by:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\varepsilon^T(t).\varepsilon(t) \quad (30)$$

In the next section, the ARMAX approach is applied to identify the model parameters of an MS5002B gas turbine, fitted by a recursive least squares procedure. This in order to evaluate the output quantities which represent the different speed variations and the vibration variations of the studied bearings of this rotating machine. To do this, the implementation steps of the ARMAX approach is shown in Figure 7, with parametric identification of the transfer function using turbine observation data, in order to monitor and detect their malfunctions.

4. RESULTS AND DISCUSSION

During the inspection conducted on the MS5002B gas turbine under study, the vibratory behavior of this rotating machine was investigated. The process of identifying turbine parameters involved utilizing a dataset of vibration signals collected on-site following a maintenance operation. These data were employed in the ARMAX modeling steps discussed in the previous section, enabling the successive identification of vibration modeling parameters for the studied turbine bearings.

Furthermore, by implementing actual turbine operating data, a comparison can be made between the estimated models derived from the ARMAX structure and the observed behavior of these bearings. Consequently, the error serves as a metric for evaluating and testing the accuracy of these models, as demonstrated in the case studies conducted on the ARMAX models.

Indeed, these actual operating data of the examined turbine were explored to identify the parameters of the ARMAX model with multi-input and multi-output MIMO structure of the turbine system. In this case, the input variables chosen in this identification are; The HP high pressure turbine rotor rotational speed u_1 and the LP low pressure turbine rotor rotational speed u_2. As well as the output variables are; The vibration variation in the vertical direction y of the bearing #1 of the high pressure turbine HP rotor y_1 and the vibration variation in the vertical direction y of the bearing #3 of the low pressure turbine LP rotor y_2.

To do this, the filtered HP high pressure turbine rotor speed variation signals are shown in Figure 7 and Figure 8 shows the LP low pressure turbine rotor speed variation. These signals are used to identify the ARMAX vibration model parameters of MS5002B turbine bearings #1 and #3.

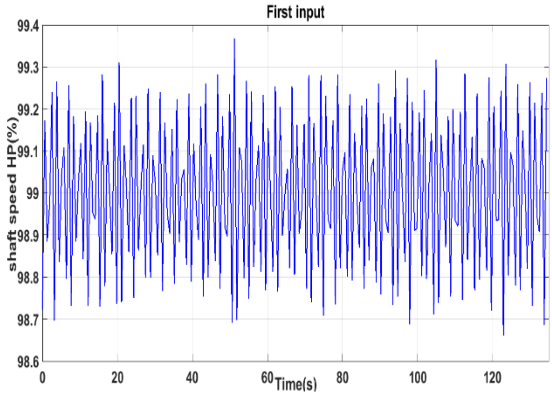

Fig. 7. HP high pressure turbine rotor speed variation

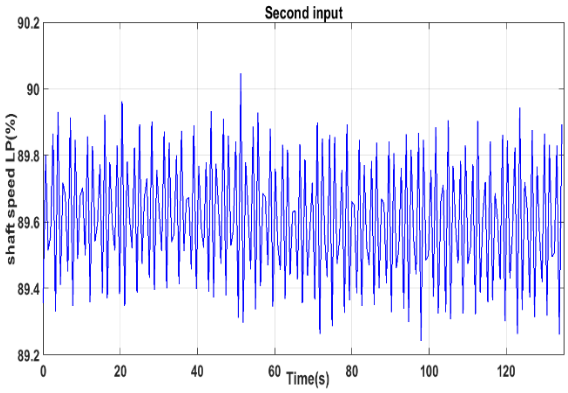

Fig. 8. LP Low pressure turbine rotor speed variation

To ensure maximum turbine availability with good real-time monitoring with the proposed ARMAX identification approach, via vibration data collect and process to develop fault indices in the vibration box. This can be used to minimize turbine downtime as well as to minimize maintenance costs, with scheduled scheduling of maintenance overhaul actions. However, these measurements of turbine operating data recorded on bearings #1 and #3 allow the identification of the output variables of this rotating machine. This makes it possible to implement the parameter estimation method of the ARMAX model with acceptable identification accuracy, in relation to the desired turbine behaviors.

Hence, the results obtained are shown by Figure 9 which shows the vibration variation of bearing #1 of the HP high pressure turbine rotor y_1 and by Figure 10 which shows the vibration variation of bearing #3 of the LP low pressure turbine rotor y_2. In these results a comparison is presented between the actual measurements and the vibration prediction outputs on bearings #1 and #3. This shows a better fit for these two outputs y_1 and y_2 with a prediction rate equal to 73.78% and 88.25% respectively. This confirms the good efficiency of the parameter estimation approach of the ARMAX model applied to the MS5002B gas turbine.

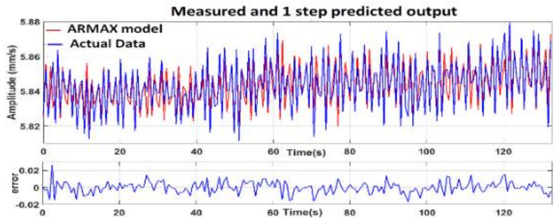

Fig. 9. Variation of vibration of bearing #1 of the HP high pressure turbine rotor

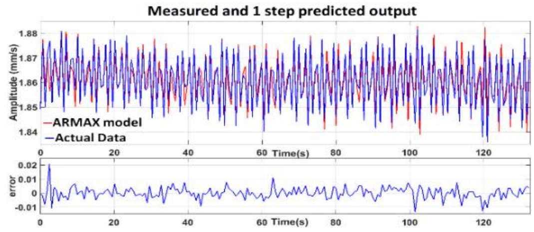

Fig. 10. Variation of vibration of the bearing #3 of the low pressure turbine LP rotor

In order to test the robustness of the developed ARMAX model, validation tests were carried out by analyzing the residuals according to the following two hypotheses:

- Test of the residual autocorrelation function,
- Cross-correlation test between past input and residual.

The quality of the estimated model can be assessed if the autocorrelation function is located in the confidence interval composed of two straight lines. Hence, Figure 11 shows the analysis of the two functions of residual autocorrelation and intercorrelation of the vibration variation of the bearing #1 of the HP high pressure turbine rotor y_1. These results show that the prediction error is inside the confidence region, which confirms that the obtained model is reliable.

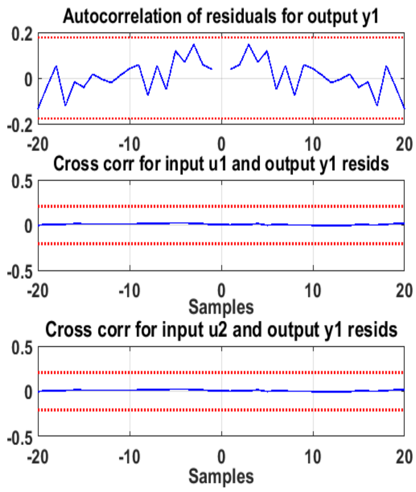

Fig. 11. Validation of vibration model of the bearing #1

Considering the results obtained for the vibration variation of bearing #3 of the LP low pressure turbine rotor y_2, shown in Figure 12, the behavior of the vibration model prediction error is very acceptable for a full load service of turbine examined. Hence, the level of vibration in this bearing #3 does not reach the alarm thresholds recorded for the turbine.

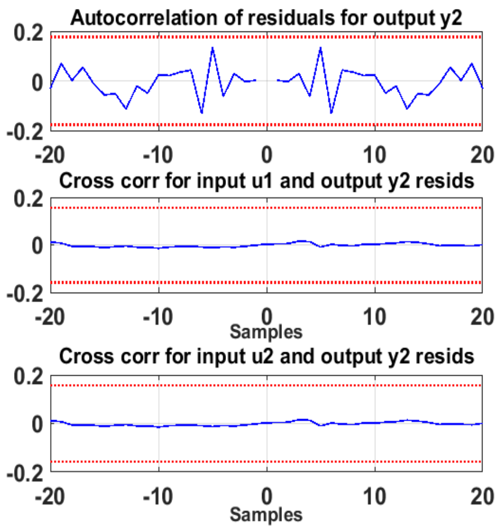

Fig. 12. Validation of vibration model of the bearing #3

Moreover, additional validation tests were conducted during the turbine startup phase and throughout its establishment to assess the robustness of the developed ARMAX model in this study. For this case study, all the data used for model identification was collected on-site through various measurements performed on the turbine shaft to determine the ARMAX model.

Figure 13 illustrates the speed variation of the low-pressure (LP) turbine rotor during the startup phase until the stable operating phase, representing the established turbine speed. A closer look is given to the transition zone from the dynamic regime to the stable regime within the time interval of 260-280 seconds. This zoomed-in view provides a more accurate representation of the system, which carries a high risk of transitioning towards instability. It is within this critical zone that the ARMAX model is trained using operating data from the startup phase to the stable operating regime, ensuring comprehensive learning of the system dynamics.

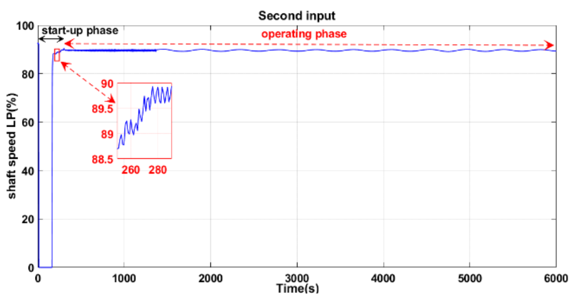

Fig. 13. Speed variation of the low pressure turbine LP rotor during the start-up phase to the established operating regime

Additionally, Figure 14 presents a comparison between the signals predicted by the ARMAX model and the measured signals during a test conducted on a sample of data collected over a time interval of up to 6000 seconds. The graph demonstrates a close alignment between the measured and predicted signals for the bearing case #3 of the low-pressure (LP) rotor, with an error below 0.03. This level of error is considered acceptable and indicates a high degree of accuracy in the predicted signals.

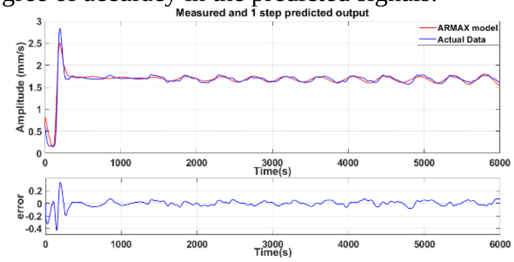

Fig. 14. Comparison produced between the predicted signals via the ARMAX model and the measured signals for the case of bearing #3 of the LP rotor

Furthermore, during the startup phase, specific tests were conducted to evaluate the ARMAX model's response to different inputs, focusing on the variation of the high-pressure (HP) turbine rotor speed, as depicted in Figure 15.

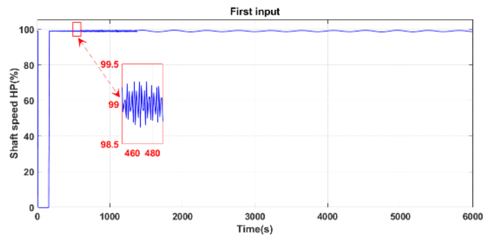

Fig. 15. Speed variation of the HP high pressure turbine rotor during the start-up phase until the operating phase

To further investigate the comparison between the measured and predicted signals for the bearing case #1 of the HP rotor, Figure 16 illustrates the predicted vibration amplitude in relation to the measured signal during both transient and steady states. The graph confirms that the output signal predicted by the ARMAX model closely aligns with the measured signal on the HP turbine rotor, validating its ability to accurately capture the behavior of the studied turbine.

Based on the results obtained from utilizing the ARMAX model under various turbine operating conditions, including normal and extreme scenarios during the startup phase, the performance is deemed satisfactory when compared to the measured signals in both transient and steady states.

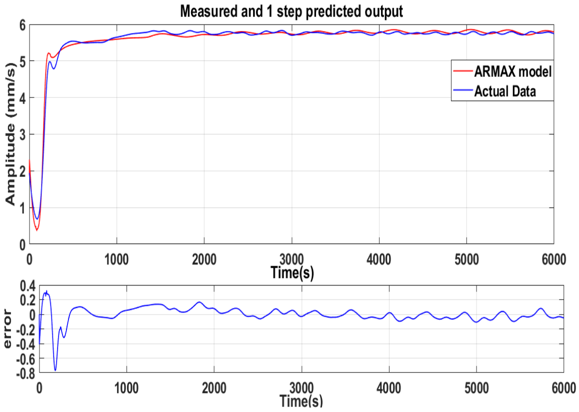

Fig. 16. Comparison produced between the signals predicted via the ARMAX model and the signals measured for bearing case #1 of the HP rotor

Moreover, in order to observe the behavior and assess the precision of vibration capture on bearings #1 and #3, rigorous validation tests were conducted by subjecting the ARMAX model to real-time scenarios that replicate the operating conditions it would encounter in practical applications. These tests involved comparing the model's predictions with reference data and performing statistical analyses to evaluate its accuracy under different circumstances. Through these rigorous validation tests, potential weaknesses or limitations of the ARMAX model were identified, allowing for necessary adjustments or improvements to be made. Consequently, the results obtained using the ARMAX model structure consistently demonstrate its superior performance and reliability in practical applications. The robustness of the ARMAX model developed in this study was successfully validated through tests conducted during the startup phase and until the commissioning of the turbine.

The results of the validation tests carried out of the two models ARMAX and ARX are presented in Table 5, it is clear that the estimated adjustment values of the ARMAX model developed could represent [73.78; 88.25] % of the data used, while the model ARX could represent only [69.78; 85.94] %. Also, the structure of the ARMAX model has a lower FPE than that of the ARX structure, which shows the effectiveness of the ARMAX approach on the ARX model.

Finally, the results of the structure of the ARMAX model are obtained for the bearing #1 and bearing #3 vibration variation model in the form of a state representation, with a multi-input and multi-output MIMO structure. Hence, the vibration variation model of the bearing #1 of the HP high pressure turbine rotor y_1 is expressed by:

$$A(q)y_1(k) = A_i(q)y_i(k) + B(q)u(k) + C(q)e_1(k) \quad (31)$$

What is given:

$$A_1(q) = 1 - 0.3695q^{-1} - 0.6458q^{-2}$$
$$A_2(q) = 0.3968q^{-1} - 0.3494q^{-2}$$
$$B_1(q) = 0.07306q^{-9} - 0.0766q^{-10}$$
$$B_2(q) = -0.08075q^{-9} + 0.08466q^{-10}$$
$$C(q) = 1 - 0.4582q^{-1} - 0.3013q^{-2} - 0.2207q^{-3}$$

Table 5. ARMAX and ARX models estimation validation results

Models output		Vibration model of HP bearing #1 y_1	Vibration model of LP bearing #1 y_2
Best fit %	ARMAX	73.78	88.25
	ARX	69.78	85.94
FPE	ARMAX	9.915×10^{-10}	
	ARX	11.755×10^{-10}	
MSE	ARMAX	6.487×10^{-5}	
	ARX	7.052×10^{-5}	
ARMAX Order	n_a= [2 2;2 2] n_b= [2 2;2 2]	n_c=[3;3] n_k= [9 9;9 9]	
ARX Order	n_a= [2 2;2 2]	n_b= [2 2;2 2] n_k= [1 1;1 1]	

As for the vibration variation model of the bearing #3 of the low pressure turbine rotor LP y_2 is expressed as follows:

$$A(q)y_2(k) = -A_i(q)y_i(k) + B(q)u(k) + C(q)e_2(k) \quad (32)$$

What is given:

$$A_1(q) = 1 - 0.1032q^{-1} - 0.8792q^{-2}$$
$$A_2(q) = -0.3073q^{-1} + 0.3017q^{-2}$$
$$B_1(q) = 0.06633q^{-9} - 0.06508q^{-10}$$
$$B_2(q) = -0.07322q^{-9} + 0.07184q^{-10}$$
$$C(q) = 1 - 0.7291q^{-1} - 0.06297q^{-2} - 0.0706q^{-3}$$

These state representations of vibration models of bearings #1 and #3 based on the ARMAX approach are an effective means for monitoring the operation of the turbine studied, because the analysis of vibration behavior makes it possible to identify their causes and to accurately deduce their location in real time. This allows you to make good decisions to carry out maintenance interventions before these vibrations become critical.

5. CONCLUSION

In this work, we have estimated the parameters of the vibration model of the bearings of an MS5002B gas turbine using an ARMAX model approach. We have focused on the high-pressure (HP) turbine bearing #1 and the low-pressure (LP) turbine bearing #3, using the real data from their operation. We have shown that the ARMAX approach can provide better predictions of the vibration models of these bearings, compared with the actual behavior of the HP and LP rotors of the turbine, even in the presence of measurement noise. We have validated our approach using various performance criteria, such as RMSE, FPE and MSE, and residual analysis with autocorrelation and cross-correlation tests. The results were very satisfactory and demonstrated the efficiency of the ARMAX approach for estimating and detecting the vibration behavior of the turbine. Moreover, we have determined the vibration monitoring thresholds using this approach, which can help to identify faulty bearings and their causes quickly. This can improve their availability and reduce turbine downtime. Furthermore, we have integrated the ARMAX model into a decision-making mechanism for monitoring this rotating machine. This can enhance the state assessment of vibrations of these bearings and ensure the continuity of production of the installation. The ARMAX approach has also opened up some future directions for this work. It would be interesting to test and develop other techniques and compare them with the ARMAX method, to improve the quality of parameter estimation. It would also be useful to extend this method to nonlinear models in a temporal context, to better capture the signatures of vibratory phenomena. Additionally, it would be worthwhile to study models with distributed parameters, to enrich and increase the consistency of the predicted outputs with the measured outputs. This may increase the fidelity of the identified model to represent the turbine output variables.

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Author contributions: *research concept and design, Y.M., M.G.; Collection and/or assembly of data, Y.M., M.G., A.H.; Data analysis and interpretation, Y.M., B.S.K., M.G., A.H., A.I.; Writing the article, Y.M., M.G.; Critical revision of the article, B.S.K., M.G., A.H.; Final approval of the article, B.S.K., M.G., A.H., A.I.*

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