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GAS TURBINE VIBRATION MONITORING BASED ON REAL DATA AND NEURO-FUZZY SYSTEM

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Abstract

The gas turbine is considered to be a very complex piece of machinery because of both its static structure and the dynamic behavior that results from the occurrence of vibration phenomena. It is required to adopt monitoring and diagnostic procedures for the identification and localization of vibration flaws in order to ensure the appropriate operation of large rotating equipment such as gas turbines. This is necessary in order to avoid catastrophic failures and deterioration and to ensure that proper operation occurs. Utilizing an approach that is based on spectrum analysis, the purpose of this study is to provide a model for the monitoring and diagnosis of vibrations in a GE MS3002 gas turbine and its driven centrifugal compressor. This will be done by utilizing the technique. Following that, the collection of vibration measurements for a model of the centrifugal compressor served as a suggestion for an additional method. This method is based on the neuro-fuzzy approach type ANFIS, and it aims to create an equivalent system that is able to make decisions without consulting a human being for the purpose of detecting vibratory defects. In spite of the fact that the compressor that was investigated has flaws, this procedure produced satisfactory results.

Keywords: Vibration analysis, Gas turbine, Centrifugal compressor, Neuro-Fuzzy system, ANFIS

List of Acronyms

ANFIS: Adaptive Neuro-Fuzzy Inference System
FFT: Fast Fourier Transform
GE: General Electrical
HP: High-Pressure
LP: Low-Pressure
ANN: Artificial Neural Networks
AI: Artificial Intelligence
ES: Expert Systems

1. INTRODUCTION

There are a variety of applications for gas turbines in industry; however, one of the most common uses for gas turbines is in the oil business, where they are extensively used to ensure safe gas transportation in extremely long gas pipes. Because of the growing complexity of industrial installations and the severe operational limitations they face, the value that these supervisory tactics provide to the operation of industrial systems has increased [1-15].

Typically, programmable logic controllers are given process control settings, and real data (measurements, alerts, faults, operational status feedback, etc.) is used to monitor vibration in rotating machinery.

The development of the gas turbine and its success have been dependent on the enhancement of its technical performance. High safety requirements, reduced operating costs, the control of equipment availability, and improved reliability give system maintenance a key role.

It should be possible to act only in the event that faulty components are present, reduce the amount of time required for repairs, and produce a diagnosis that is both accurate and straightforward, despite the complexity of the apparatus. This necessitates the unavoidable application of preventative maintenance, which is one of the strategies that is now enjoying the greatest level of popularity in the sector.

The latter has become a real profession with its own concepts and methodology. Among the factors that have favoured this type of maintenance, we can mention automation, diagnosis, and industrial monitoring.

Diagnosis can be seen as an attempt to explain abnormal system behaviour by analysing its relevant

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characteristics. It is reasoning leading to the identification of the cause of an anomaly from the information revealed by observations (measurement, sign, symptom).

In this environment, many different research communities in automation and artificial intelligence have created numerous different ways for fault identification and diagnosis. It is generally agreed that using methods and strategies from artificial intelligence (AI), like expert systems (ES), artificial neural networks (ANN), and fuzzy logic, can be a good way to make reliable monitoring systems [16-21].

In this direction, vibration analysis has become an essential tool for any maintenance department to ensure effective monitoring of machines whose failures or degraded operation present a major risk for the safety of personnel, production, or the quality of the finished product [22-24].

The aim of the work is to find methods of monitoring and diagnosis in order to increase safety and guarantee the continuity of production and operation in industrial sectors by taking the example of a gas turbine.

In this work, we examined real vibration measurements of the GE MS 3002 gas turbine and its driven centrifugal compressor using FFT and wavelet transform to analyze and noise the real vibration signals, which were obtained by vibration sensors on site.

We proposed an intelligent expert system based on the ANFIS approach [19]. The expert system exploits neuro-fuzzy self-learning based on real vibration data (without faults) to create an equivalent system capable of making decisions without consulting a human being to estimate and identify vibration faults on the centrifugal compressor using residual signal generation. The results obtained were satisfactory, and we were able to detect faults using our model.

2. INDUSTRIAL APPLICATION

In this work, the vibration behaviour of a gas turbine that was installed at the gas center of TIMZHERT, which is located in Hassi R-Mel, in the south of Algeria, was investigated [15]. The analysis of observed signals was used to determine the vibration behaviour.

The four main bearings of the MS-3002 gas turbine hold both the high-pressure (HP) and low-pressure (LP) rotors in place. Bearings are labeled with the numbers 1, 2, 3, and 4.

2.1. Centrifugal compressor (the load)

In a centrifugal compressor, the air flow is radial from the impellers, and the air passes through diffusers from one stage to the next before being discharged. Compressors can be in suction, discharge, or flow control, depending on process requirements. A centrifugal compressor can operate from a couple thousand RPM to over 20,000 RPM, depending on the compressor size and manufacturer. Speeds of 100,000 rpm can be achieved in the aviation and aerospace industries.

Table 1. Specifications of the examined turbine

Parameter	Value or symbol
Designer: General Electric	GE
Type	MS 3002
HP speed axial compressor	7100 rpm
N°. floor wheel (s) HP	01
N°. axial compressor stage	15
BP speed	6500 rpm
N°. BP wheel	01
Turbine power 80%	9400 CV

Fig. 1. Actual photo of the Centrifugal Compressor of the DP-STAH base

2.2. Wavelet transforms

The wavelet transform allows a localization in time and frequency. The wavelet transforms $TO(a,b)$, is defined as the dot product between $\Psi_{a,b}(t)$, and the signal $s(t)$ according to the following equation [20]:

$$TO(a,b) = |a|^{-1/2} \int_{-\infty}^{+\infty} s(t)\Psi^{*}\left(\frac{t-b}{a}\right) dt \qquad (1)$$

- A complex wave can be broken down into its component sinusoids and studied using the Fourier transform.
- The Fourier transform is used to identify what those sinusoidal components are for a particular wave.
- The discrete Fourier transform is going to be the method that we employ here.

Convolutions between wavelets and data can be computed simultaneously via the convolution theorem.

Since the wavelet transform necessitates a more in-depth examination in the frequency domain, a separate review is necessary for the spectrum analysis and its various variants, as well as its link to other transforms and special functions and, to a much greater extent, its specificity in a variety of applications [20].

2.2. ANFIS architecture

The ANFIS architecture is a form of adaptive networking that makes use of supervised learning algorithms when it comes to the learning process.

This architecture performs a function that is analogous to the Takagi-Sugeno fuzzy inference system model. The fuzzy reasoning procedure for the Takagi-Sugeno model and the ANFIS architecture is depicted in Figure 2. Assume that there are only two inputs, x and y, and one output, f, for the sake of simplicity. Following is an explanation of the two principles that were utilized in the "If-Then" procedure for the Takagi-Sugeno model: [19]:

$$Ruler\ 1 = if\ x\ is\ A_1\ and\ y\ is\ B_1\ Then\ f_1 = p_1x + q_1x + r_1$$

$$Ruler\ 2 = if\ x\ is\ A_2\ and\ y\ is\ B_2\ Then\ f_2 = p_2x + q_2x + r_2$$

Where A_1, A_2 and B_1, B_2 are the membership functions of each input x and y, while p_1, q_1, r_1, and p_2, q_2, r_1, are linear parameters in part as a consequence of Takagi - Sugeno fuzzy inference model.

The fuzzy inference procedures that are used for the development of the areas of data that are categorized by the neural networks [19] are used to acquire the optimization variables of the gas turbine that was under study.

The ANFIS architecture can be broken down into five distinct layers, as seen in figure 3. While the other layers each have a fixed node, the first and fourth layers each have an adaptable node. A concise explanation of each layer can be found in the subsequent section:

- **Layer 1:** each node of this layer adapts to a parameter of the function.

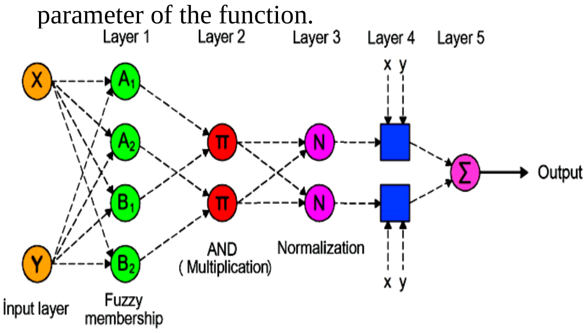

Fig. 3. ANFIS Architecture

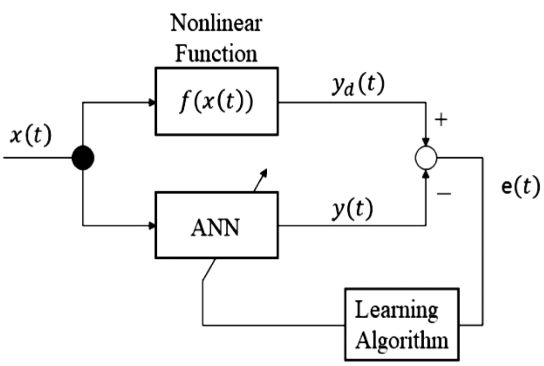

Fig. 4. Back propagation neural network with a nonlinear function

Figure 4 is a diagram structure of the backpropagation algorithm. The key of backpropagation algorithm is that the error between the desired output $y_d(t)$ and the output $y(t)$ of the neurons is fed back to the network to optimize the weights in each neuron to minimize the error [19,20].

Each point in the input space is assigned a membership value (or degree of membership) between 0 and 1 according to a curve called a membership function, also called a degree of membership function (DMF). Sometimes the term "universe of conversation" will be used to describe input space.

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{x-c_i}{2a_i}\right)\right]$$

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}} \qquad (3)$$

$$O_{1,i} = \mu_{Ai}(x), \quad i = 1,2$$

$$O_{1,i} = \mu_{Bi-2}(y), \quad i = 3,4$$

Degrees of membership functions for fuzzy sets Ai and Bi are denoted by $\_\mu_{Ai}$ and μ_{Bi-2}. $\{a_i, b_i, c_i\}$ are parameters of a membership function that can alter the form of the membership function. Parameters at this level are sometimes referred to as "base" parameters.

- **Layer 2:** Each node in this layer is fixed or non-adaptive, and the circular node is labelled as $\prod$. The signal entering a node is multiplied by whatever is going in, and the product is sent on to the next node as the output. The strength of each rule's execution is represented by a node in this layer. The output is obtained by using the T-norm operator with generic performance, such as AND, in the second layer.

$$O_{2i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \ i = 1,2 \qquad (4)$$

Where w_i is the output that represents the firing force of each rule.

- **Layer 3:** The circular node in this layer is designated as N, indicating that it is non-adaptive and therefore fixed. The normalized shot resistance is the end outcome [19,20].

$$O_{3i} = w_i = \frac{w_i}{\sum_i w_i} \qquad (5)$$

- **Layer 4:** Each node in this layer is a single-output adaptive node, with a node function defined as

$$O_{4i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (6)$$

Where w_i is the normalized firing force of the previous layer (third layer) and$(p_i x + q_i x + r_i)$ is a node parameter. The parameters of this layer are called consequent parameters.

- **Layer 5:** The output is calculated as the total of all inputs from the preceding node at this fixed or non-adaptive node. A circular node in this layer is denoted by Σ.

$$O_{4i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

3. RESULTS AND DUSCUSSION

3.1. Radial measurement of the Centrifugal Compressor

Our first case study is the vibration monitoring of the centrifugal compressor. The radial vibrations represent this component of shaft vibration. This vibration component is measured with two proximity sensors (X, horizontal) and (Y, vertical) oriented perpendicular to the shaft center with an angular phase shift of 90°±. This measurement gives a complete view of the shaft vibration and the radial position within the bearing set; see Figure 5.

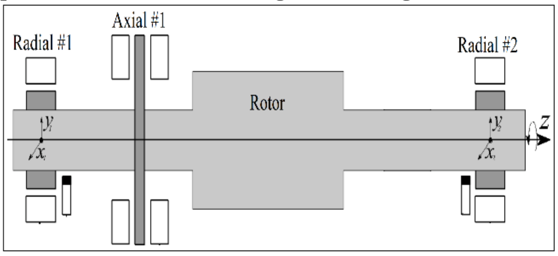

Fig. 5. Measurement points on the centrifugal. compressor

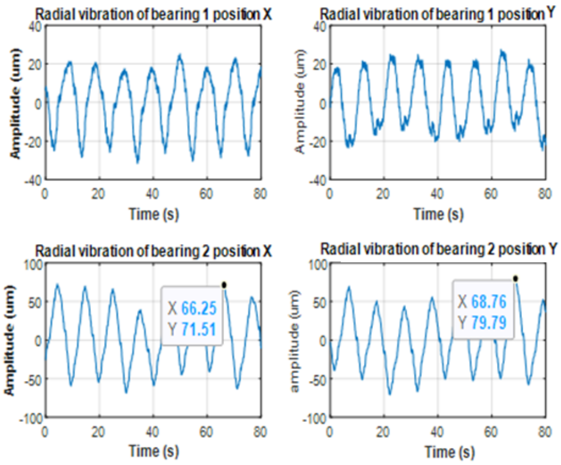

Fig.6. Vibration signals at the two bearings of the centrifugal compressor

The figure 6, shows the vibrations measured on bearing 1 (X, Y position) and bearing 2 (X, Y position) of the centrifugal compressors over a period of time (s) as a function of the amplitude in (µm).

This table summarizes the alarm thresholds indicated in their monitoring system:

Table 2. Alarm thresholds

	Vibration seismic (velocity probe)	Radial direction proximity probes	Axial direction proximity probes
Warning threshold (pre-alarm)	12.5 mm/s	70 µm	1 mm
Threshold of Danger (trip)	25 mm/s	90 µm	1.2 mm

Two alarm thresholds for displacement have been defined by the GENERAL ELECTRIC (GE). company. The alert threshold (pre-alarm) is 70 µm, and the danger alarm threshold is 90 µm.

We notice that the vibration on our figure in radial direction position X of bearing 1 clearly exceeds the threshold of alert (pre-alarm). To detect the presence of a defect or not, we used the Fourier transform (FFT):

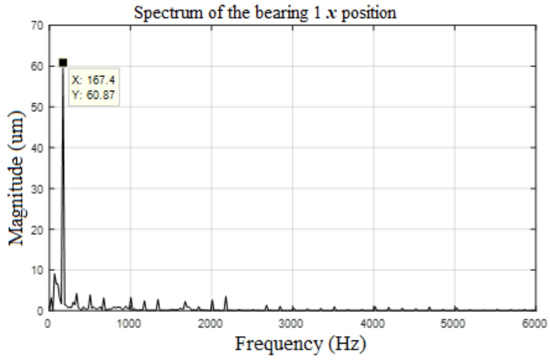

Fig. 7. Spectrum of the bearing 1 of the centrifugal compressor

The dynamic behaviour and displacement of the rotor shown in Figure 7 at level bearing 1 (horizontal radial direction) rotate at 10049 rpm. We note a very important peak at the first order for the frequency of rotation (167.48 Hz); a strong unbalance, misalignment, blade rub, and gearbox wear lead to harmonics. In order to be sure of our diagnosis concerning an unbalanced fault or not, we measured the change of position of a rotor in the axial direction in relation to the thrust bearing using two proximity sensors.

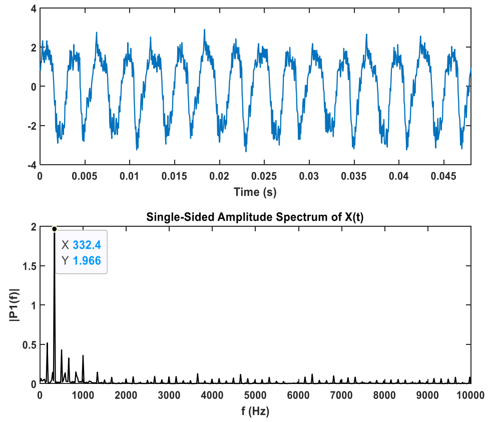

Fig. 8. Vibration signal and spectrum of the bearing 1

Figure 8 represents the vibration at the thrust bearing of the centrifugal compressor in the axial direction. We notice that there is no exceeding of the warning threshold. The following spectrum serves as an illustration of this:

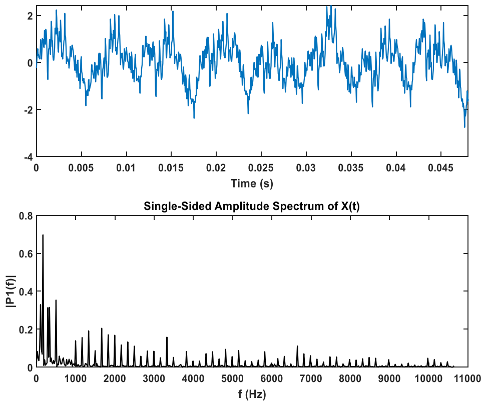

Fig. 9. Vibration signal and spectrum of the thrust bearing 2

The two-shaft turbine is mechanically more complex than the single-shaft turbine. However, it provides better efficiency at partial load, is particularly well suited to driving a compressor, which is taken over when the speed is increased, and can operate over a wide speed range. Also noteworthy is the reduced power of the starting motor, which drives only the first shaft.

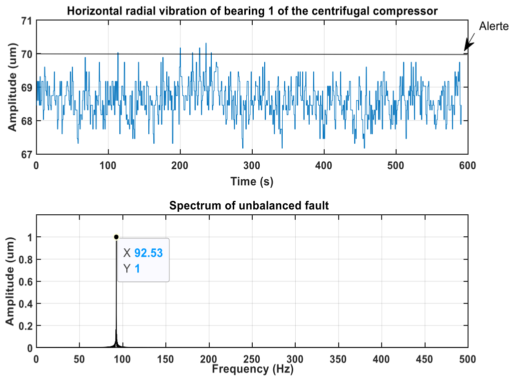

Fig.9. Horizontal radial vibration of bearing 1of the CC

3.2. Variation of the HP and LP rotor speed

This table summarizes the speed measurements of each rotor constituting the gas turbine and the driven load:

Table 3. Table that summarizes the speeds of our measurements at each part of the system

	Turbine HP	Turbine BP	Multiplier BP rotor coupling	Multiplier rotor coupling with CC
Speed (rpm)	7041 rpm	5833 rpm	5818 rpm	10049 rpm
Rotation frequency (Hz)	117.35 Hz	97.21 Hz	96.96 Hz	167.48 Hz

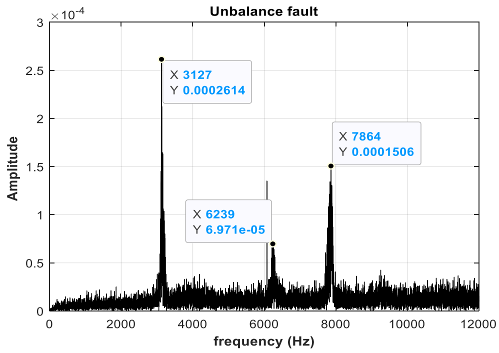

Fig. 10. Spectrum at stage 1, of the HP turbine

Using the wavelet application to remove the noise, we obtain the following diagram:

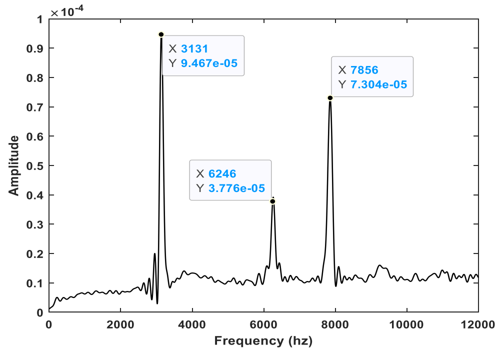

Fig.11. Wavelet application spectrum

This figure 10 shows a spectrum of wavelet coefficients over a frequency band [0:12000 Hz]. The rotation frequency f_r = 117.35 Hz for a speed of 7041 rpm of the HP rotor, and in our spectrum, the first important peak that is clearly seen is 3131 Hz, which corresponds to 26 x the rotation frequency. So we are very far from detecting a defect on the machine because the majority of the main defects do not exceed order 3 to 4 of the rotation frequency.

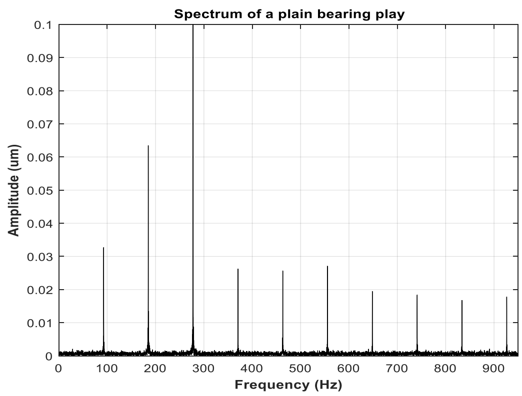

Fig. 12. Spectrum at bearing, 1 of the HP turbine

3.3. Monitoring of the centrifugal compressor based on ANFIS

In this section, we will construct a model and prediction based on the neuro-fuzzy system type ANFIS. Earlier, we mentioned that this system has the ability to automatically generate models based on fuzzy rules that are based on the inference model of Takagi Sugeno.

The modelling of our system is based on input and output data. The input is a vibratory signal of level 1, without defects, or the machine works in good condition according to time. The input is represented by 1024 samples, and the ANFIS model uses this input to generate a single output. The input is fuzzified by three fuzzy sets of Gaussian types (Figure 13). The output is represented as a figure.

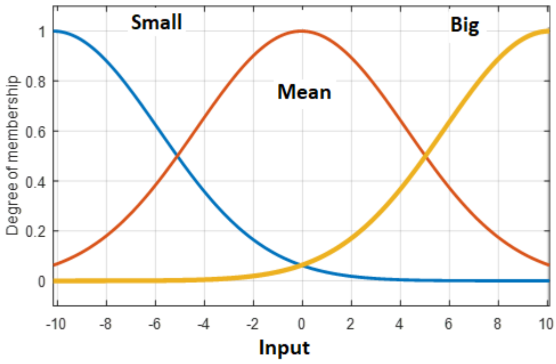

Fig. 13. Gaussian membership functions

The estimation performance of our ANFIS system with the input used was tested under three groups: the training group, which is used for supervised learning (Figure 14), the test group (Figure 15), and validation, and the results of these last three are all cumulated in Figure 16.

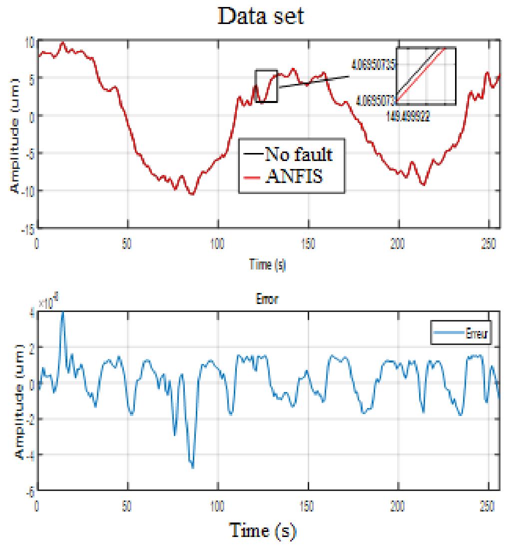

Fig. 14. Data test

Figure 16 shows the fault-free vibration signal output of the centrifugal compressor bearing 1 compared with the ANFIS model output. We notice that the error between the two is too small (error = 10^{-8} µm), so our learning was successful.

To characterize the prediction system performed, we calculate the residual. This residual is the difference between a measured output signal and the proposed ANFIS model estimate. It is given by the following relationship (fig. 17).

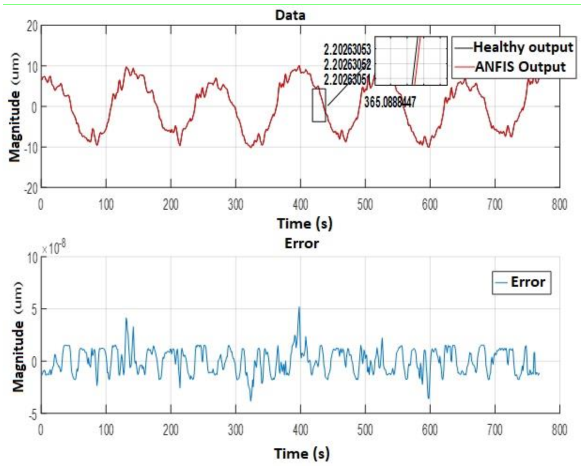

Fig. 15. Data training

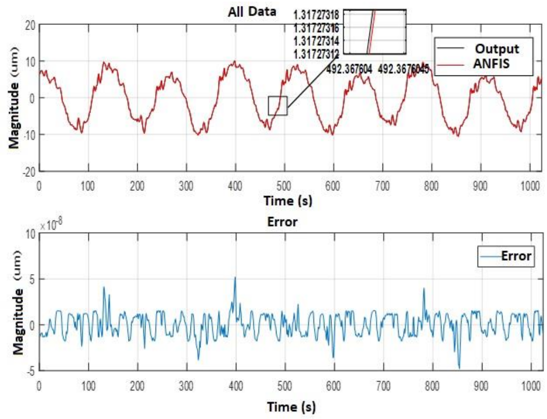

Fig. 16. Estimation of the output of the faultless signal with the ANFIS output and the error between them

$$R(k) = Y_{estimate}(k) - Y_{measure}(k) \quad (8)$$

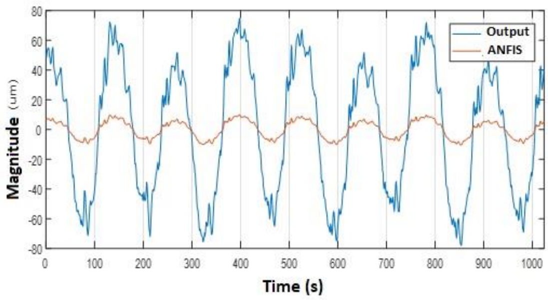

Fig. 17. Vibration signal measured with the output signal of the ANFIS model

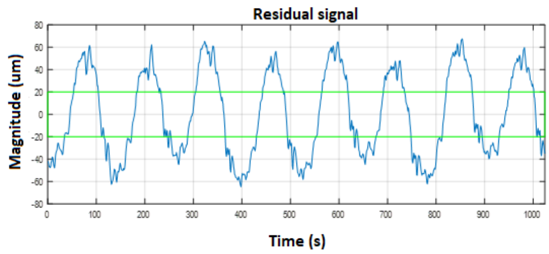

Fig. 18. The residual between the actual measured signal and the output signal of the ANFIS model

Figure 18 shows the residual between the signal measured on bearing 1 of the centrifugal compressors and the output signal of our ANFIS model; all values that are outside the interval [-20, +20] are faults. In order to define the detection of faults on bearing 1 of the centrifugal compressors, as shown in Figure 19.

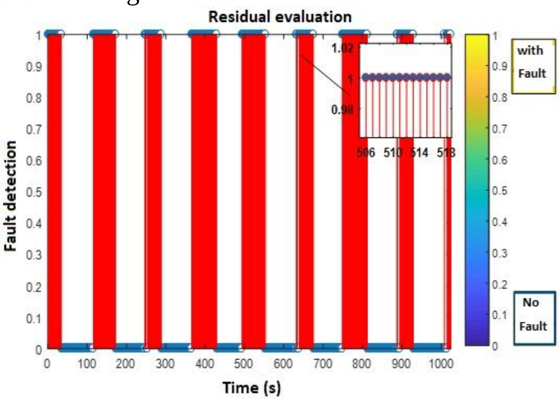

Fig.19. The evaluation of the defects on the examined system

Figure 19 shows the evaluation of the defects; the values that are equal to 1 express that there is a defect; on the other hand, the values that are equal to zero express that there is no defect.

4. CONCLUSION

In this paper, we have examined real vibration measurements of the GE MS 3002 gas turbine and its driven centrifugal compressor using FFT and wavelet transform to analyze and noise the real vibration signals, which were obtained by vibration sensors on site.

Several faults were detected at the centrifugal compressor, at the BP turbine, and at the HP turbine. We proposed an intelligent expert system based on the ANFIS approach. The expert system exploits neuro-fuzzy self-learning based on real vibration data (without defects) to create an equivalent system capable of making decisions without consulting a human being to estimate and identify the vibration defects on the centrifugal compressor using residual signal generation. The results obtained were satisfactory, and we were able to detect faults using our model.

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Author contributions: *Research concept and design, B.N.; Collection and/or assembly of data, D.B.; Data analysis and interpretation, H.N.; Writing the article, I.E.T.; Critical revision of the article, C.N.; Final approval of the article, C.N.*

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Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

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