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MONITORING OF HIGH-SPEED SHAFT OF GAS TURBINE USING ARTIFICIAL NEURAL NETWORKS: PREDICTIVE MODEL APPLICATION

Mohamed Ben RAHMOUNE[1], Ahmed HAFAIFA[1], Kouzou ABDELLAH[1], XiaoQi CHEN[2]

[1] Applied Automation and Industrial Diagnostics Laboratory, Faculty of Science and Technology, University of Djelfa 17000 DZ, Algeria
e-mails : B.Rahmoune@univ-djelfa.dz, hafaifa.ahmed.dz@ieee.org, kouzouabdellah@ieee.org

[2] Department of Mechanical Engineering, University of Canterbury, Christchurch, New Zealand.
e-mail: xiaoqi.chen@canterbury.ac.nz

Abstract

The automatic engineering known a very rapid progress with the consequent development of numerical methods and computer systems, by the growth of computational capacity. In this context, this work proposes a strategy of predictive control of the high-pressure shaft speed of a gas turbine using artificial neural networks in order to monitor the vibratory behavior of this rotating machine. This approach makes it possible to ensure the stability of this turbine under real conditions and to detect any deviation of their dynamic behavior from the margin of safety. This approach makes it possible to include the control limitations on the turbine variables in the modeling step of the high-speed shaft speed controller.

Keywords: Monitoring, gas turbine, vibrations, artificial neural networks, predictive model.

1. INTRODUCTION

The increasing complexity of industrial systems requires the implementation of modern techniques, that enable the development of effective monitoring strategies with reasonable costs, which is practically impossible with conventional monitoring mechanisms.

Recently, the technological evolution in the fields of industrial computing and digital instrumentation, for the analysis of the monitoring systems of rotating machines, made it possible to implement new monitoring and maintenance strategies for these installations industrial [1, 2-6, 11 and 17]. The protection of these machines is ensured by the triggering of an alarm or by stopping the machine, if the amplitude of the vibration reaches values deemed excessive for the correct operation or integrity of the machine. In order to control the vibration dynamic behavior of the high-pressure shaft of a gas turbine, this work proposes to examine and illustrate the aptitude of the application of artificial neural networks in order to follow the operating condition of this rotating machine; This is part of the vibratory monitoring, taking the example of a GE MS 3002 gas turbine system.

To achieve these objectives, systems are used which are becoming more efficient as regards the choice of technology to adopt a desired behavior and to ensure a stable and safe operation of this industrial process.

Indeed, the proposed monitoring mechanism based on artificial neural networks makes it possible to demonstrate the symptoms of an anomaly, to find the origin of the anomaly and determine the corrective actions to be taken and especially for the vibratory failures. This proposed approach offer a best solution for increasing performance and improving the reliability of the rotating machine under consideration. Also, it ensures the durability of the equipment by avoiding sudden failures, which makes it possible to maintain the operation of the turbine and to keep the threshold of productivity at a stable level, in order to avoid any degradation of the studied system by the scheduling of preventive tasks.

This work proposes a strategy of a robust predictive controller of the high-pressure shaft speed of a gas turbine, using artificial neural networks. The controller design is made from the input-output model of the examined gas turbine. From this, an equivalent representation of variables state is derived, which depends only on past outputs and inputs (known values) and to use the proposed controller algorithm in the feedback system state.

2. GAS TURBINE MONITORING USING ARTIFICIAL NEURAL NETWORK ALGORITHM

The strategy of predictive model applied to the high-pressure shaft speed of the examined turbine based on artificial neural network techniques, allows the development of a fault diagnosis procedure, designed to detect and locate vibration defects of this machine and allows to make a localization and identification of the vibration failure by the model of system to be monitored. In this section of our work, the artificial neural network approach is proposed to describe the dynamic behavior of the turbine shaft, which can be characterized by deterministic relationships between causes and vibration effects.

2.1. ARTIFICIAL NEURAL NETWORK ALGORITHM

In order to improve the performance of the proposed control strategy, that is to say the evolution of its outputs as a function of that of its inputs. Artificial neural networks are suitable for this type of problem as an effective supervisory tool, among the various types of artificial neural networks, multi-layer networks, which are very popular and currently used in several industrial applications [7-8, 14-15 and 18]. In this work, the artificial neural networks approach was used to model the parameters of the rotation speed as input variables and their measurements are accessible by sensors which provide their quantities in real time. The structure of the proposed multilayer neural networks is shown in Figure 1.

In the case under consideration, the algorithm code, taking into account the parameters of the examined turbine and their operating environment, is responsible for performing supervised learning from a data base that has been carried out and well adapted in the framework learning by the multi-layer perceptron for the control of the studied turbine. This is to optimize the best parameters for the used artificial neural networks.

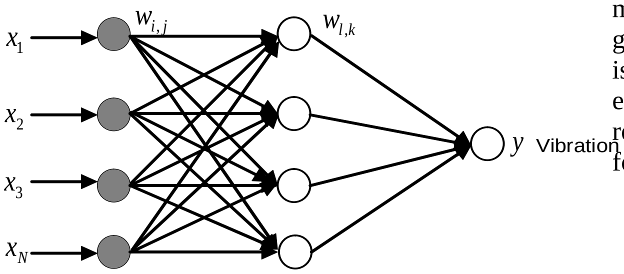

Fig. 1. Structure of multi-layer artificial neural networks [20]

The step of modelling using neural networks use the retro-propagation of the gradient is performed by a supervised learning algorithm. This algorithm aims at making associations between pairs of vectors (input data, desired output). Indeed, the basic idea of this algorithm is to minimize the quadratic error criterion with respect to the connection weights, once the weights are updated according to the error, layer by layer from the output layer, is given by the following formula:

$$E = \frac{1}{2}\sum_{i=1}^{M}\left(yd_i - y_i\right)^2 \qquad (1)$$

The predictive controller inputs with the neural network structure is given by:

$$u_k = \sum_{u=1}^{n} w_{ki}x_i = w_{k1}x_1 + w_{k2}x_2 + ... + w_{kn}x_n \qquad (2)$$

where $x_i\,(i = 1,2,....,n)$ are the input signals from n external neurons transmitted to the neuron k, w_{ki} is the weight between i and k neuron.

The multi-layer neural network proposed for this application uses a sigmoid function, linear in the hidden layer and the output layer defined by the following equation:

$$\begin{aligned} u_j &= f_1\Big(\sum_{i=1} w_{ij}^1 x_i + b_j^1\Big) \\ y_k &= f_2\Big(\sum_{l=1}^{N} w_{lk}^2 u_1 + b_k^2\Big) \end{aligned} \qquad (3)$$

with f_1, f_2 the hidden layer activation and output layer function.

The retro-propagation algorithm uses the learning rule to minimize the quadratic error with respect to the connection weights given by the following equation [19, 21]:

$$E = \frac{1}{2}\sum\left(d_i - y_i\right)^2 = \frac{1}{2}\sum\Big(d_i \sum w_{ij}x_j\Big)^2 \qquad (4)$$

The change of the weight w_{ij} with an amount of Δw_{ij} must be proportional to the gradient error given by:

$$\Delta w_{ij} = -\eta\,\frac{dE}{dw_{ij}} = \eta \sum_i \left(d_i - y_i\right)x_i \qquad (5)$$

The objective of the retro-propagation algorithm is to minimize the mean square error by calculating network output error using the gradient and then modifying the weights in the opposite direction of gradient. For the stopping criterion of this algorithm is to use a validation set from the real data of the examined system. From the equations 4 and 5, the retro-propagation algorithm written in the following form:

$$E_{app}(w) = \frac{1}{2}\sum_{k\in E_{app}}\sum_{j=1}^{m}\left|y_j(x_k, w) - d_{jk}\right|^2 \qquad (6)$$

where d_{jk} and $j^{ème}$ are the desired output elements, d_k is the output of the network of the element input x_k of $k^{ème}$ training set.

The objective of this error given by the gradient retro-propagation learning algorithm is to find the set of weights, ensuring an output of the neural network which follows as much as possible the desired reference value. Subsequently, learning will be supervised from neural networks from a data base, to suit the predictive control strategy of the examined gas turbine.

2.2. GAS TURBINE PREDICTIVE MODEL

The objective of the predictive control model (MPC) is to use this model to predict the behavior of the system and choose the best decision in the sense of a certain cost while respecting the constraints of operation. In this section, the MPC will be applied to a MS 3002 gas turbine, this turbine is characterized by four subsystems, the axial compressor, the combustion chamber, the high pressure turbine and the low pressure turbine, as shown in Figure 2, where the parameters of this system are the fuel flow W_f inject into the combustion chamber and controlled by the stop ratio valve SRV and the gas control valve CGV, as well as the pressure P_2 and temperature T_2 at the inlet of the turbine.

The fuel flow rate is considered as input from the predictive control model and the high-pressure shaft rotation speed HP as output, with the variation in fuel flow W_f depends on the temperature T_2 and pressure P_2 at the outlet of the compressor. This allows the gas control valve CGV and the gas shut-off valve SRV to be operated.

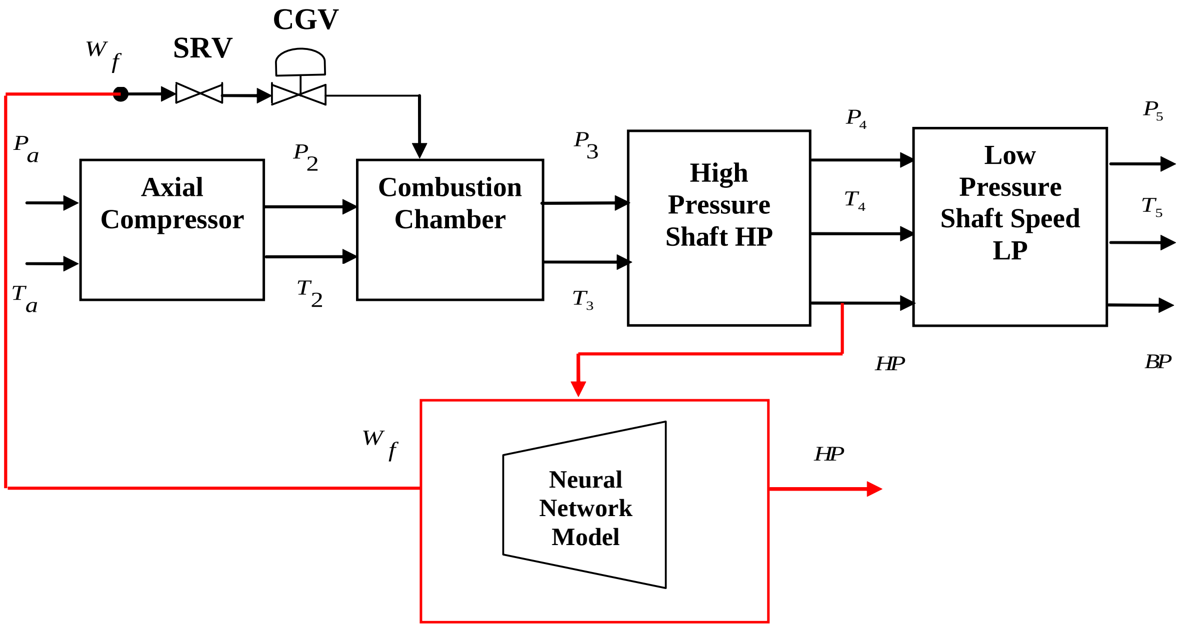

Fig. 2. Predictive control model of a gas turbine

The pressure and the temperature at the outlet of the compressor (P_2 and T_2) are defined by the following equation:

$$P_2 = P_1.\tau$$
$$T_2 = T_1 \left(\frac{P_2}{P_1}\right)^{\frac{(\gamma-1)}{\gamma}} \quad (7)$$

where τ is the gas compression ratio, $\gamma = \dfrac{C_{p(T_1-T_2)}}{C_{p(T_1-T_2)} - r}$ is the isentropic exponent of gas with $C_{p(T_1-T_2)}$ defines the average specific heat of the air between temperatures T_1 and T_2.

The variation of the rotor HP characterized by temperature T_3 and pressure P_3, fuel flow rate W_f and variation of the gas control valve CGV, represented by the following equation:

$$HP_{speed} = [P_3, T_3, W_f, CGV] \quad (8)$$

With the pressure P_3 is determined by the following formula:

$$P_3 = P'_2 - \Delta P_{cc}$$
$$P_3 = P_2 - \Delta P_{cc} \quad (9)$$
$$P'_2 = P_1.\tau$$

where ΔP_{cc} is the pressure drop in the combustion chamber.

The temperature T_3 is determined by the following formula:

$$T_3 = T_0 + \frac{Q_{ac}.C_{p(T'_2-T_0)} + \eta_{cc}.Q_c.P_{ci}}{(Q_{ac}+Q_c).C_{p(T_0,T_3)}} \quad (10)$$

where Q_{ac} is the flow of combustible air, Q_c is the fuel flow, η_{cc} is the efficiency of the combustion chamber, $C_{p(T'_2,T_0)}$ is the average specific heat of the air between the temperatures T'_2 and T_0, P_{ci} is the lower calorific value of fuel.

For the vibration dynamics monitoring of the turbine, a model based on neural network techniques with predictive control of shaft speed is used, as shown in Figure 3, to predict the optimum performance of this machine, using the performance criteria given by:

$$j=\sum_{j=N_1}^{N_2}(y_r(t+j)-y_m(t+j))^2 + \rho\sum_{j=1}^{N_u}(u^{'}(t+j-1)-u^{'}(t+j-2))^2 \quad (11)$$

where N_1, N_2 and N_u represents the horizons on which the tracking error reference model, $u^{'}$ is the control signal of the shaft speed, y and y_m are the desired response and response of the network model.

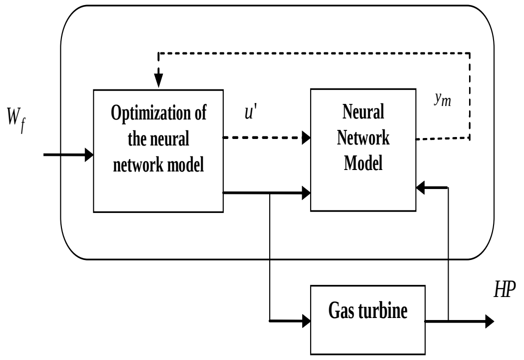

Fig. 3. Predictive model for high-speed shaft speed control based on neural networks

In the next section, the results of application of the predictive model method to controlling the parameters of a gas turbine will be presented, this method makes it possible to carry out the design of a dynamic controller with constraints on the control and the output, for the examined gas turbine.

3. APPLICATION RESULTS

In this section, the obtained experimental results will be presented, the experimental tests of the proposed approach were carried out under real conditions on the examined gas turbine. To collect and analyze the data of this machine, computer and software means were used to process the signals emitted by the different types of vibrations generated by the various components of the examined gas turbine. Where, the real-time spectrum analyzer using data collectors, on the examined gas turbine system, has a quick access to information and exchange standardized data from this gas turbine. The signals were recorded directly on a computer in the control room with a control and acquisition card, or we used this data acquisition system. The temporal signals and the test conditions are archived and attached to each point of measurements carried out, with the choice of parameters appropriate to the predictive model approach to controlling the parameters of a examined turbine.

Indeed, the model developed in this work, shown in Figure 4, treats the dynamic behavior of a rotor of the gas turbine, rotating at high speed and supported by unbalance and misalignment (vibration) defects, taking into account the effects of constraints on the examined system.

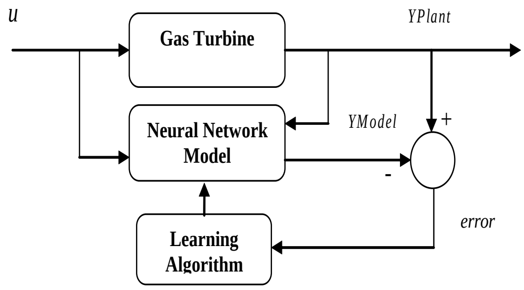

Fig. 4. Model predictive control based on neural network

And showing that the system studied has zones of instabilities vary with the frequency of rotation and the responses of the rotors to unbalances. This can create new critical frequencies on the gas turbine being examined.

The model identification for the variables control of turbine is complete, where the performance optimization of this model has been tested by the used neural network learning algorithm. Thus the minimum and maximum values for the fuel flow rate input are in the order of 23.0799 - 26.6069 and the minimum and maximum values of the gas generator shaft speed output are obtained in the order of 93% 100%, after learning of used neural networks, using data from the 12612 data network, shown in Figure 5.

The tests carried out are distributed over three parts, according to three phases of operation of the turbine, as shown in Figure 6; The first phase on 75% for learning, then on 15% of the second phase and finally on 10% of the third phase for the validation of the neuronal model.

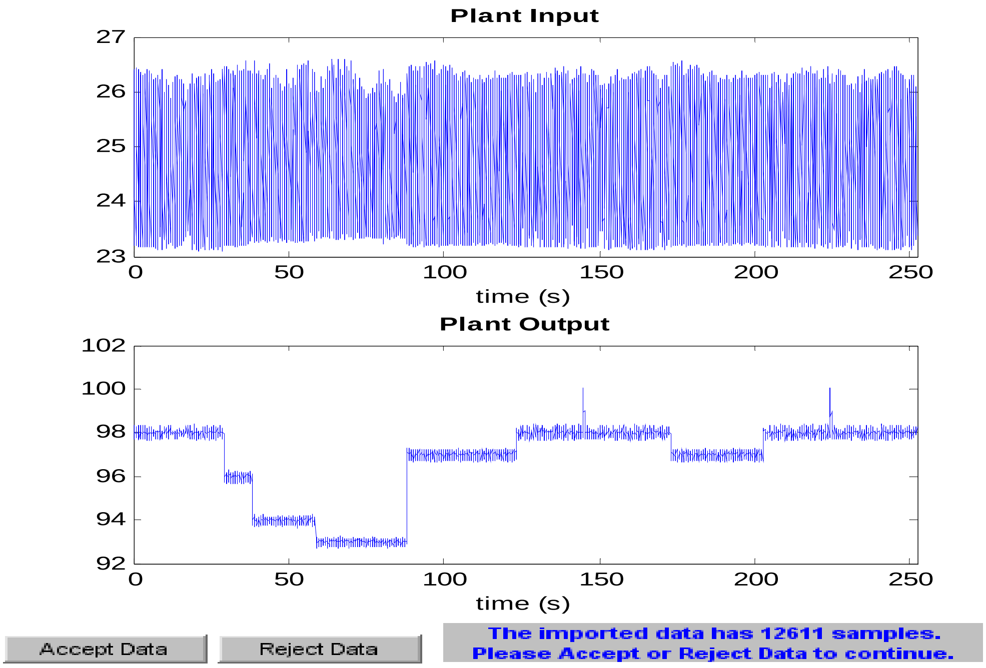

Fig. 5. High-pressure shaft rotation speed with neural networks model

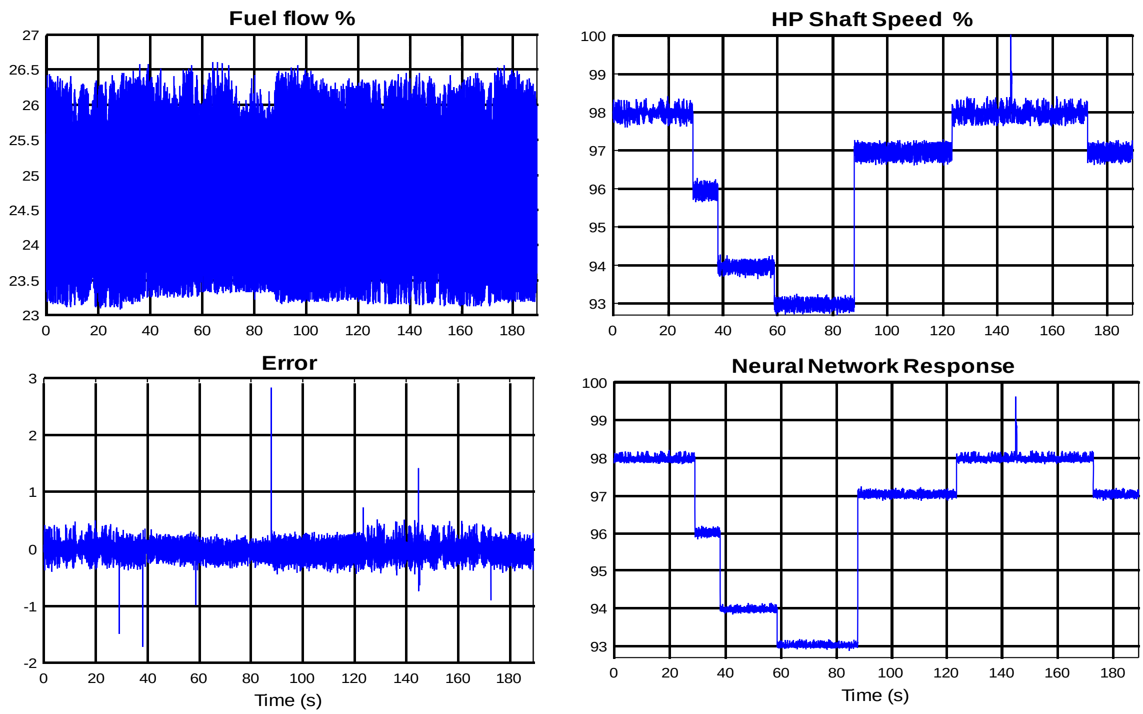

Fig. 6. Phases of neural network model learning

The mean square error MSE is calculated, as shown in Figure 7, to measure the amplitude of the error and validate the proposed modeling approach using the following formula:

$$MSE = \frac{\sum_{i=1}^{n} (x_i - u_i)^2}{n} \tag{12}$$

where x_i is the desired output value, u_i is the predicted output of the neural network and n is the number of the output data.

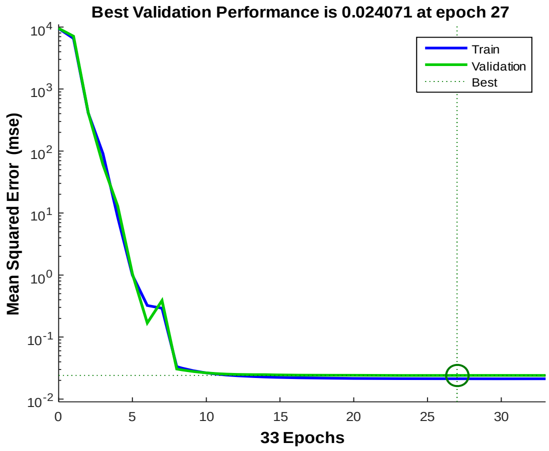

Fig. 7. Mean Square Error RMS

Another test for the robustness of the proposed approach is obtained by determining the statistical coefficient, shown in Figure 8, to see the variation of the variance in the desired outputs, this statistical coefficient is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - u_i)^2}{\sum_{i=1}^{n} u_i^2} \tag{13}$$

The *MSE* value is negatively oriented these values show better network performance, unlike statistics *MSE*, R^2 is positively oriented, the R^2 value should converge close to 1 for the best fit of model.

After the neural networks learning, the actual speed of the high pressure shaft compared by the neural network model is shown in Figures 9 and 10.

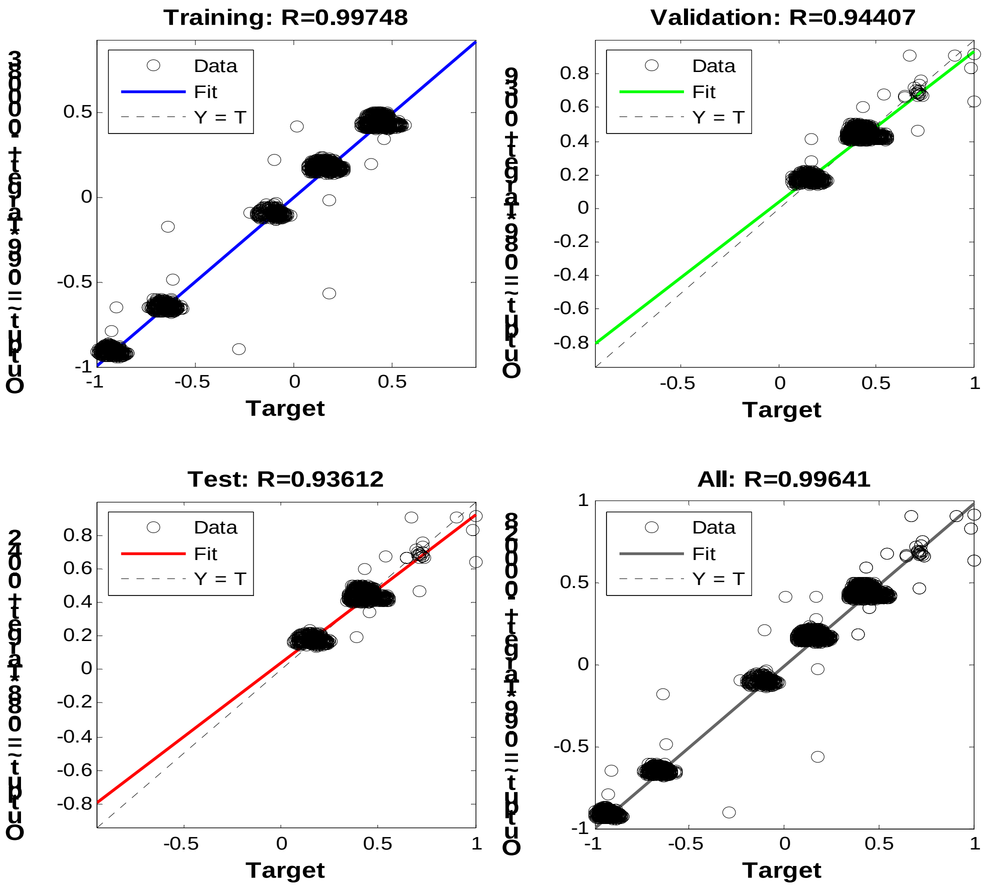

Fig. 8. Correlation of neural network model

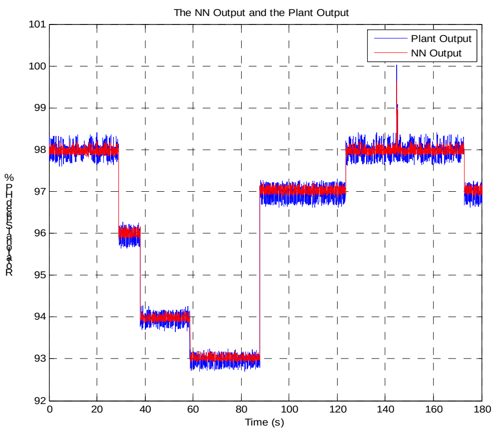

Fig. 9. High-pressure shaft rotation speed compared with there neural networks model

The actual variation of the high-pressure shaft speed with the neural network model is presented below in Figure 12.

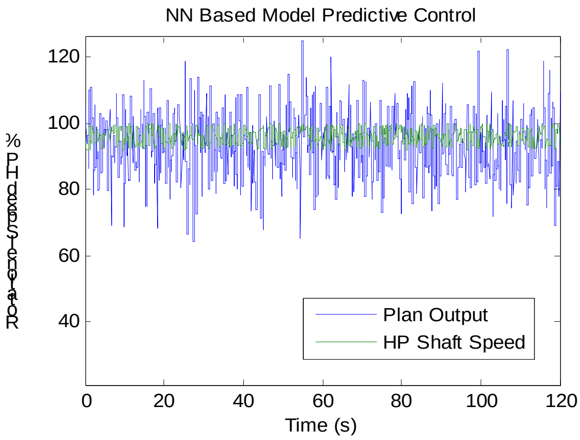

Fig. 10. High-pressure shaft rotation speed with neural networks model

The obtained results of the predictive control by model based on the neural network allows to visualize the measured vibratory signals which leads to a greater imbalance on the rotor vibration of the gas turbine under examination. The obtained results by modeling using supervised learning techniques of neural networks show that the architecture of the network is better because the values of the quadratic error are the smallest and have been obtained at small calculation time only, which explains why the desired outputs are very close to the actual outputs.

4. CONCLUSION

The developed model in this work simulates the dynamic behavior of the gas turbine rotor, rotating at high speed, intended to drive a centrifugal compressor used in natural gas transportation. A monitoring technique based on neural networks was proposed, to give a response solicited from the input variable (vibration defects) to characterize the output variables, representing the operating status of this system. This technique presents a very fine analysis of the vibration defects and makes it possible to diagnose faults of different natures in several configurations, in real-time operating mode.

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Dr **Ben Rahmoune Mohamed** was born in Messaad, Djelfa Algeria on 1988. He received her PhD degree from the Faculty of Science and Technology, University of Djelfa, Algeria in Electrical Engineering Specialization on Maintenance in Industrial Instrumentation in 2017. After having completed his Master project, he realised her Ph.D. doctorate degrees in the Applied Automation and Industrial Diagnostics Laboratory, Faculty of Science and Technology, University of Djelfa 17000 DZ, Algeria. He was author and co-author of many scientific papers. His research interest includes fault diagnosis of a gas turbine based on artificial neural networks to improve their reliability and vibrations detection.

Professor Ahmed HAFAIFA is the founder of the Applied Automation and Industrial Diagnostic Laboratory at the University of Djelfa, Algeria. He is the supervisor of many PhD Students in Algeria and he is the coordinator of several industrial research projects within the applied automatic and reliability of industrial systems. His research area of interests includes the modelling and control in industrial systems, the diagnosis and new reliability engineering, fault detection and isolation in industrials process, intelligent system based on fuzzy logic and neural networks. He is acting as an expert in several national and internationals commissions and collaboration research activities. He has supervised several Master students and published many national/international conferences and journals papers.

Professor **Abdellah Kouzou** is the founder of the Power Electronics and Power Quality research group at the Applied Automation and Industrial Diagnostic Laboratory at the University of Djelfa, Algeria. He is the supervisor of many PhD Students, he is a member of many editorial boards for several scientific journals. He is a member of the scientific and steering committees in several national and international conferences. He was an examiner in several national and international PhD dissertations. He is an experts in several national and international scientific activities and project evaluations.

Prof. **XiaoQi Chen** is Professor of Mechatronics Engineering at the University of Canterbury. After obtaining his B.Eng. in Mechanical Engineering from South China University of Technology in 1984, he received China-UK Technical Co-Operation Award for his MSc study in Materials Technology, Brunel University (1985 – 1986), and PhD study in Electrical Engineering and Electronics, University of Liverpool (1986 – 1989). He was Senior Research Assistant at Durham University (1989-1990) and Research Fellow at Brunel University (1990-1992), and Senior Scientist in Singapore Institute of Manufacturing Technology (1992-2006). His research interests include advanced materials processing, autonomous system, assistive robotics, and manufacturing automation. He is an elected Fellow of Institution of Professional Engineers New Zealand (IPENZ); elected Fellow of Society of Manufacturing Engineers (SME).