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AVAILABILITY PHASE ESTIMATION IN GAS TURBINE BASED ON PROGNOSTIC SYSTEM MODELING

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Abstract

The present paper deals mainly with the improvement of the degradation indicators of a gas turbine. Therefore, to achieve this purpose a prognostic approach is used in order to provide an adequate diagnostic function of the studied gas turbine. In this context, this paper proposes a degradation modeling of the studied gas turbine system in order to increase its safety and to ensure accurate future decision making process that allow to enhance the operating state of this industrial equipment. Indeed, the prognostic system proposed in this work takes into account the eventual vibration impacts over all phases of the life cycle process of the studied system to provide a diagnostic function with the required availability at with lowest maintenance cost.

Keywords: Availability time, fatigue prediction, faults prognosis, gas turbine, prognostic system.

1. INTRODUCTION

Nowadays, the early failure forecasting and failure detection in industrial plants equipments are attracting more attention, both in theory and application from researchers and industrial plants owner. Indeed, when a failure appears on industrial plants equipment, on-site experts try to identify the exact causes of the failure or fault damages based on the available obtained indications that may guide them to final identification. Especially, when the idea of the type of failure is known, they search for the cause in a family of probable causes and based on a elimination process, they can find the most likely cause of the considered failure. However, with the modernization of industrial equipments through the appearance of a new high range of technologies that lead to more complex systems with high costs, the aforementioned approach for finding the real cause may take more time and has become almost difficult to identify the cause of failure under such constraints, this kind of problems push the experts forward to look for new solutions. On the other side; the increasing of the number of economics challenges of all industrial companies pushed them for looking to a more reliable and optimized operation of their equipments in order to improve the productivity by ensuring its availability and its quality under the compliances of safety and environment compatibility imposed by the usual standards.

The failure prognostic prediction is the residual life which is called the Remaining Useful Life (RUL). Indeed it is a relatively new area of research to the scientific community which is attracting a more increasing attention. This approach is designed to estimate the probability that a failure can be occurred at a given future time. Using failure prognostic system, it is possible to estimate the remaining useful life (RUL) of equipment or a component of equipment within an industrial plant under a given operating conditions. Consequently, the main role of the prognostic system is to answer to the following questions: How much time is needed for the intervention to ensure the corrections or the maintenance of a considered system? And what will be the impact of this prognostic goal on the production targets?

To answer to these questions, several studies have been achieved in this area [4, 6, 10-14 and 17]. Indeed, the failure prognostic approaches can be divided into three main categories as illustrated in Figure 1. Whereas, it is obvious that the prognostic approach should be selected based on models and knowledge of a given system.

However, in several industrial applications to ensure equipment diagnostics, different methods have been proposed to find solutions dealing with fatigue problems, depending on the choice of the measurement variables and the fatigue criterion for the determination of the lifetime of these equipments. Indeed, the rule of Miner supposes that there is no influence of the timing application of the loads, that is to say no effect of vibration order. Where, fatigue cycling tests are of large amplitude of vibration, followed by small amplitude up to rupture, and the reverse for small amplitude which are followed by large amplitude of vibration, this shows that vibrations accumulation is not linear because it is non-commutative. However, in many cases, the different amplitude cycles of vibration are mixed, linear accumulation is most used in the most reliable fatigue tests. In 1924, Palmgren in [18] proposed an equation to take into account the inflection point, i.e the beginning of malfunction of the system under vibrations. In this work, the model of Miner is proposed, due to its simplicity and ease of implementation, to address the case of sequences of variable amplitude of vibration load of the studied gas turbine.

Therefore, the prognostic process is an important issue in real plants applications to predict the future state of a process after each behavior change detection in the considered process [4, 8, 13 and 15]. This paper focuses on building a prognostic system of a gas turbine which is installed at the gas compression station of Hassi R'Mel in south of Algeria, where the main aim is to ensure an adequate maintenance schedule strategy for this type of equipment.

2. PRONOSTIC SYSTEM

The estimated Remaining Useful Lifetime (RUL) is very useful in practical industrial application, it indicates the estimated lifetime before the considered equipment undergoes a failure. It is mostly used to make an accurate decision of the maintenance schedule, whether to do it, or to delay it, depending on industrial plant state operation constraints, such as the production requirements. where the main aim is to avoid unnecessary maintenance expenses and sudden equipment breakdown [16, 20 and 22]. The prediction of this time can be achieved using the prognostic approaches that are based mainly on the evaluation of the studied systems operation behaviours during the previous and actual times. Indeed, an adequate forecasting of this time is considered to be an important task for ensuring the reliability system [2, 5, 20 and 22].

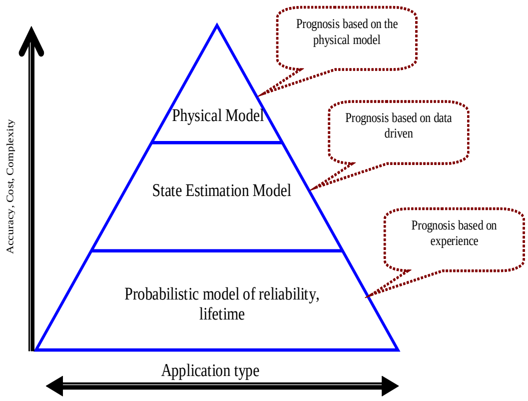

Fig. 1. Prognostic approaches [5]

In practical, the prognostics and health management (PHM) solutions are increasingly attracting more attention, both in theory and applications, where the main aim is to be implemented in important industrial plants in order to complete the maintenance activities accurately. This last task can be achieved by the estimation of the remaining useful life (RUL) of a system which is by definition the remaining time to a system to fall in failure, it is a random variable and cannot be predicted with certainty. For a rotating machine, which is the case of a gas turbine presented in this paper. It suffers from the high vibration phenomenon stress resulting from the high-cycle fatigue due to the crucial rotational motion of such systems. Indeed the estimation of the remaining useful file is based on the measurement and observation of the signals obtained by the vibration sensors during the normal operation of such machines.

In the case studied in this work over a period of observation of these constraints, which causes the creation of vibrations, the remaining useful life will be calculated using the reliability model R_Θ as a function of the failure probability P_Θ of system, as follows:

$$R_\Theta(t|X_1,...,X_n) = P_\Theta(X(t) \prec L|X_1,...,X_n) \quad (1)$$

where $(X_1,...X_n)$ are the system state, t is the observation time, Θ is the usage conditions of the rotating machine, L is the degradation threshold.

In the case of stress degradation at the same time in several observation time T_S , the reliability of the machine, is given by:

$$\begin{aligned} &R_\Theta(t|X_1,...,X_n) \\ &= P_\Theta(X(t) \prec L) \cap (T_S \succ t)|X_1,...,X_n) \end{aligned} \quad (2)$$

The degradation process depends on the number (n) of stress resulting from the high-cycle fatigue due to rotational motion. Therefore, the evaluation of the RUL requires the knowledge of the number of accidental peak vibrations occurring before the current time t_0, depending on the mode of operation of the machine. In the normal mode, there is not stress degradation; the estimated number of previous stress degradation will be calculated through the distribution of Weibull reliability, with the use of the method of maximum likelihood or the method of moments, given by:

$$(\alpha, \beta) = (\alpha_1 * \tau^n, \beta_1) \quad (3)$$

where α is the scale parameter (characteristic life), β is the shape parameter (slope) and τ is the location parameter (failure free life), used in the 3-Parameter of Weibull reliability.

In the case of degraded mode, the estimated number of previous stress degradation is detected during operation of the equipment. Indeed, it can be estimated through the cumulative sum method (CUSUM). This method allows the detection of the mode changes to $t = N.\Delta T$, the statistical variable for detection of such changes N are given by [9, 19]:

$$N = \min\left\{ \begin{array}{l} m \geq 1, \\ 1 \leq \overset{\max}{k} \leq m \sum \log \dfrac{f_r(\Delta X_i, \alpha_2 \Delta T, \beta_2)}{f_r(\Delta X_i, \alpha_1 \Delta T, \beta_1} \geq h \end{array} \right\} \tag{4}$$

where m is the expected vibration mean, k is the observed vibration mean, f_r is the failure function, h is the alarm value, (α_1, α_2, β_1, β_2) are the Weibull reliability parameters, ΔX_i is the system state variation and ΔT is the time derivative.

Several methods are used in the industry for assessing the residual life (RL) in degraded mode, such as the heuristic methods for optimizing the cumulative sum (CUSUM).

The prognostic system based on the analysis of remaining life (RUL) requires the development of models for representing uncertainty, quantification and management failures. Although these three tasks are different, they must be performed in order to guarantee the accuracy of estimation uncertainty in the prediction of the residual life of the studied equipment, to plan adequate maintenance strategy. The mathematical formulation of the remaining life using the cumulative sum (CUSUM), is given by the following representation [9, 19]:

$$\begin{aligned} & R_\Theta(t \,|\, X(t_0) = x_0) \\ & = f_\Theta(L - x_0) = \int_0^{L-x_0} f_\Theta(x)dx \end{aligned} \tag{5}$$

Where the function f_Θ is determined as a sequence:

$$\begin{aligned} & f_\Theta(x) = g(x).P\ (no\ \ stress\ \ before\ t) \\ & + \int_{T_1}^{t} f^{c_1}(x).P(1^{st}\ \ stress\ at\ \ c_1(\ < t))dc_1 \\ & =\ \ g(x).\exp(\,-\lambda(t - T_1)) \\ & + \int_{T_1}^{t} f^{c_1}(x).P(1^{st}\ \ stress\ at\ \ c_1(\ < t))dc_1 \end{aligned} \tag{6}$$

When the damage is caused by vibration phenomena and cyclic loading is composed of c_n load levels, the function f_Θ is determined in the following way to calculate the value of the total damage.

$$\begin{aligned} & f^{c_1}(x) = (f_1 * f_2 * f_3)(x).P(2\ \ stress\ after\ \ t \,|1^{st}\, stress\ at\, c_1) \\ & + \int_{c_1}^{t} f^{c_2}(x)..P(2\ \ stress\ at\ \ c_2(\ < t\,)|1^{st}\, stress\ at\ c_1)dc_2 \\ & = (f_1 * f_2 * f_3)(x).\exp(\,-\lambda(t - c_1)) \\ & + \int_{c_1}^{t} f^{c_2}(x).\lambda x \exp(\,-\lambda(c_2 - c_1))dc_2 \end{aligned} \tag{7}$$

The function f_Θ at c_n load levels Is given in the form:

$$\begin{aligned} & f^{c_n}(x) = (f_1 * f_2 * f_3\ \cdots * f_{n+2})(x).\exp(-\lambda(t - c_n)) \\ & + \int_{c_n}^{t} f^{c_{n+1}}(x)..\lambda.\exp(-\lambda(c_{n+1} - c_n))dc_{n+1} \end{aligned} \tag{8}$$

For the development of analytical models of residual life of industrial equipment, a development of the reliability model of this equipment is needed. On the other side, when the material is subjected to deformation, its lifetime N (in cycles) is given by the curve of MANSON-COFFIN expressed by the following equation [3, 21]:

$$\varepsilon_a = \varepsilon_e + \varepsilon_p = \frac{\sigma'_f}{E}(2N_f)^b + \varepsilon'_f(2N_f)^c \tag{9}$$

Where ε_a is the total deformation, ε_e is the amount of the elastic deformation, ε_p is the plastic deformation, ε'_f is the limit ductile deformation in tiredness, σ'_f is the resistance limit in tiredness, E is the Young's modulus and b and c are the constants of the material.

For predicting the life fatigue deduced from the formula of MANSON COFFIN, which establishes that the variant strain given by vibration phenomena, is related to the number of breaking stress cycles presented in the following equation [3, 21]:

$$\frac{\Delta\varepsilon}{2} = \frac{\sigma_f}{E}(2N_f)^b + \varepsilon_f(2N_f)^C \tag{10}$$

Where E is the Young's modulus and b and c are the constants of the material are equal to -0.12 and -0.6 respectively, σ_f is the strength of materials.

On the other side, the metal creep is described by LARSON MILLER with it's parameter (LMP), which is expressed as follows [1]:

$$LMP = T\frac{Log(N_C) + 20}{1000} \tag{11}$$

Where T is the temperature in [K], N_C is the time of the creep break in hours.

For the model of interaction fatigue- creep, many approaches have been developed in the recent years to predict the safe life of the materials subjected to the high temperatures, where several rules for damage accumulation have been used. In this paper, two damage accumulation models are used; the linear equation given by MINER presented in the first equation of (12) and the nonlinear equation given by CHABOCHE given by the second equation of (12), which is presented in the following formula [23]:

$$\sum \frac{n_i}{N_i} + \sum \frac{t_j}{t_{Rj}} = D$$
$$RISK = P_F * C_F \tag{12}$$

where D represent the damage, P_F is the probability of failure and P_F is the consequence of failure and C_F is the a measure of the consequence of failure.

Indeed, the phenomenon of fatigue failure of mechanical components subjected to mechanical stresses is cyclic and which is the case of gas turbine systems presented in this paper. To understand this phenomenon mechanism and its characterization, the law of cumulative linear Miner given by the equation (12) is the most used. This law allows to predict the breakage of a part under variable loading by calculating its damage. In this formulation D represents the damage variable which is equal to the ratio of the number of cycles carried out n_i to the number of cycles necessary to break the components N_i in given loads.

It is supposed that, during a cycle, the creep passes to damage D_0 to D_1 and this damage increases the strain at the end of the cycle D_1 to D_2. Equations (14) gives the creep-fatigue relation with interactive damage respectively for a cycle:

$$\frac{1}{N_C} = (1 - D_0)^{K+1} - (1 - D_1)^{K+1}$$
$$\frac{1}{N_f} = (1 - (1 - D_1)^{\beta+1})^{1-\alpha} - (1 - (1 - D_2)^{\beta+1})^{1-\alpha} \tag{14}$$

The coefficients α, β and k defines the material data obtained experimentally in the used reliability distribution, in both cases, the damage is completed when the damage accumulation reaches unity. Then the creep break becomes certain, where the prediction of the number of cycles to failure can be achieved using the flowing equation:

$$\sum D_i = 1 \tag{15}$$

The building of a prognostic system requires no formal knowledge of the degradation mechanisms, in the present case study of the studied gas turbine, the implementation of the prognostic is based on obtained data is relatively more effective for use. For the analysis and interpretation of deterioration in industrial equipment based on series of measurements and observations of anomalous phenomena, that can model the causes of deterioration based on the damage indicators measurements. this is the first step of monitoring which is the diagnostic step, as shown in Figure 2. After this stage, one has to realize the prognostic phase, which is the stage of evaluation of the RUL from the laws of degradation and degradation indicators determined in the first step of monitoring system, as shown in Figure 3.

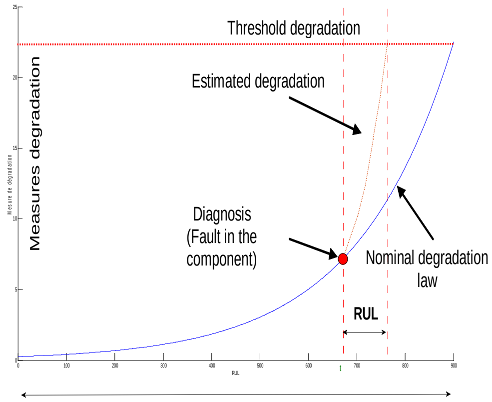

Fig. 2. Degradation measures

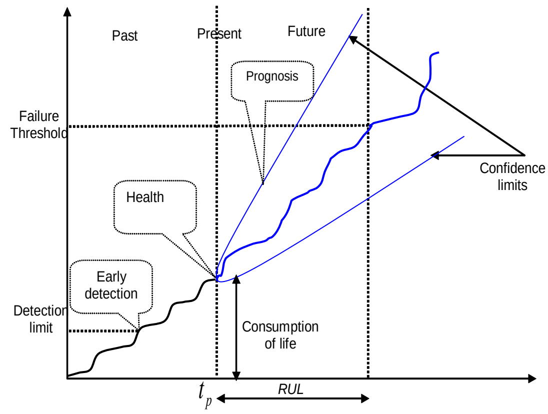

Fig. 3. Residual life estimation (RUL)

3. APPLICATION RESULTS

In this section, a prognostic approach is proposed to model the degradation of the gas turbine system. To perform this task, a database is required to forecast and to make suitable future decisions that are managing and affecting the state of operation of this industrial equipment. Once the data of the studied gas turbine system are collected, a treatment will be carried out in order to extract the performance indicators of the gas turbine under study. The proposed prognostic system is based on the cause / effect relationships principle of the studied system which leads to system degradation and the appearance of failure, as shown in Figure 4.

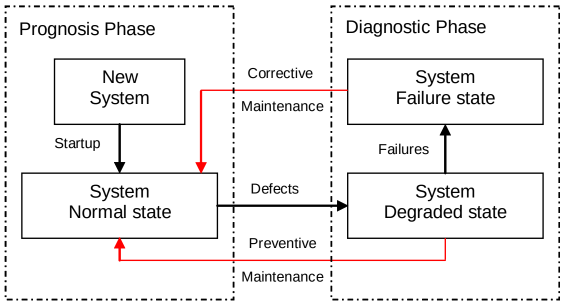

Fig. 4. Cause / effect relationships between the prognostic system and the diagnostic system

For the case presented in this paper, a prognosis approach is carried out by vibratory monitoring of a GE MS 3002 gas turbine, which is installed at Hassi R'mel gas compression station in southern of Algeria as shown in Figure 5. The main parameters that affect directly the aging of this equipment are the operating temperature and the appearance of vibration phenomena.

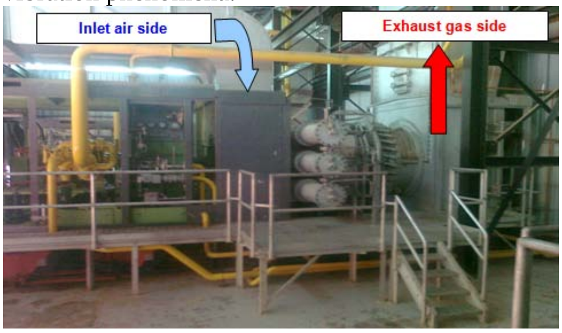

Fig. 5. GE MS 3002 gas turbine

The data are collected over 24 hours by two readings; One was collected at the evening and the second was collected at the morning on the GE 3002 turbine in operation. Each record contains six (06) variables (three input variables and the same three variables in output) ; The exhaust gas outlet temperature, the ambient intake area temperature and the bearing vibration, as shown in Figure 6. When the exhaust gas temperature reaches the range between 427 ° C and 520 ° C. These will affect the operation and the life of bearings, and are often interpreted as indicators of wear of the gas turbine blades. This inevitably will lead to vibration phenomenon in the gas turbine.

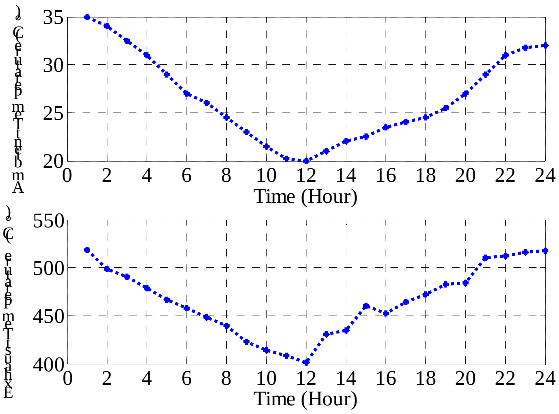

Fig. 6: Data collected on gas turbine parameters GE MS3002

The general revision intervention of the studied gas turbine which is installed at the gas compression station, which was performed in 2015, was estimated by 350 Euro /hour. This revision process has required two months to be achieved which means an amount of 504 thousands of Euro was paid for this maintenance intervention. Therefore, due to this huge problem and its technical and economical consequences, the proposed approach is proposed to identify the problem more quickly, where the main goal is the minimization of the maintenance costs and the increase of the system reliability. According to the probability of the degradation resulting from the proposed approach, the maintenance service will have an alarm in advance for a sufficient time before the failure or the breakdown of the gas turbine system will occur.

Indeed, the diagnosis determines the prognostic success by its ability to provide reliable and accurate estimation of the current health of the studied gas turbine system. Nevertheless, these machines are subject to a very important problem, mainly the vibration phenomenon which is evaluated by the prognostic system and which can give information of degradation scenarios. In the studied case, the vibration phenomenon can also be defined by a progressive loss of performance of the equipment function, for example a shaft misalignment of a gas turbine, as shown in Figure 7.

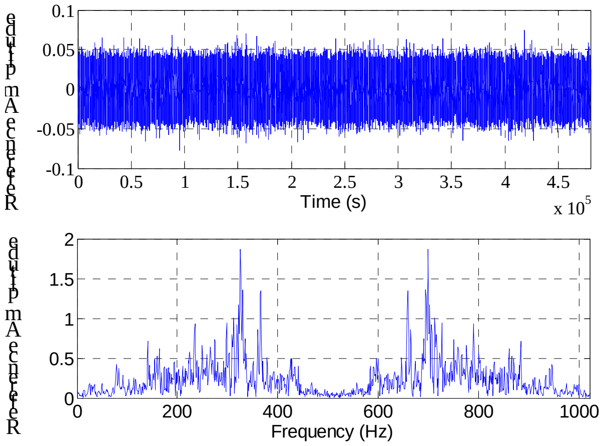

Fig. 7. Vibration signal of a angular misalignment axial

In the same time, the major problems encountered in gas turbines are the wear of these fins especially the fixed fins and the blades of the 1st and 2nd rows, shown in Figure 8. This wear is caused by:

- The erosion phenomenon caused by poor filtration of the air,
- The temperature rise up to the major thresholds (1200 ° C),
- The vibration phenomenon (misalignment of shaft relative to the other, poor balance of rotor blades, starting refrigeration of the machine).

Fig. 8. Wear of the fins of a gas turbine

Figure 9 shows the relative sensitivity factor of the stresses applied on the blade of the studied gas turbine. Figure 10 shows the stress cycle on the rotor blade (stress in Pa as a function of time). Figure 11 and Figure 12 present the MINER model and CHABOCHE model responses.

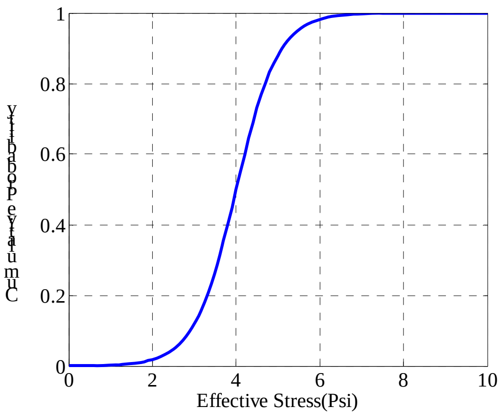

Fig. 9. Sensitivity factors of the stresses applied on the blade of the examined gas turbine

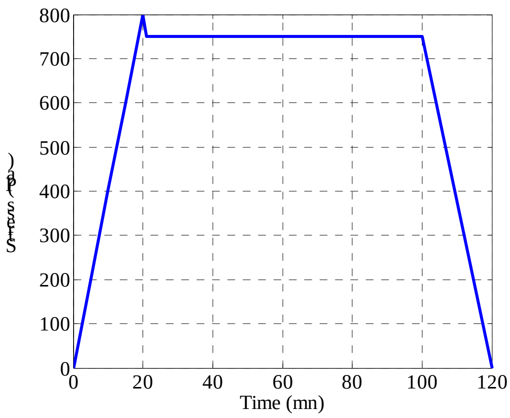

Fig. 10. Stress cycle on the rotor blade

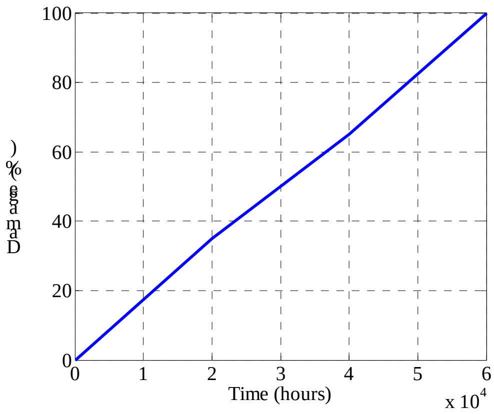

Fig. 11. MINER model

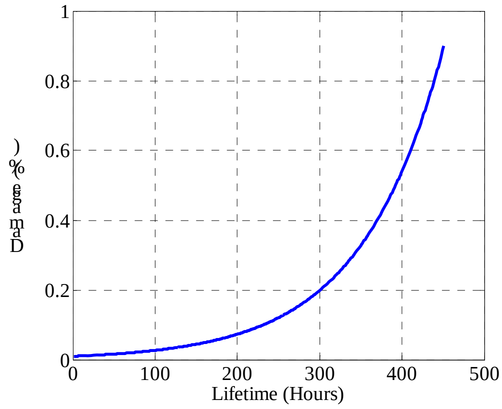

Fig. 12. CHABOCHE model

The determined usual period through the model of damage tolerance in the studied system, by using the adequate safety factor to the studied turbine at a length of 1 micron crack damage life is 70000 cycles. The results presented in Figure 13 show that the studied gas turbine is in crack limit with slow growth. Note that the temperature variation, shown in Figure 14, along the height of the blade leads to varying degrees of degradation and the Figure 15 shows the rotor vibration of the studied gas turbine.

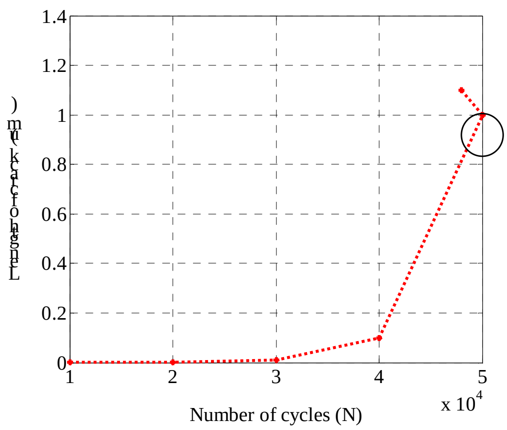

Fig. 13. Length of the evolution of the damage during operation

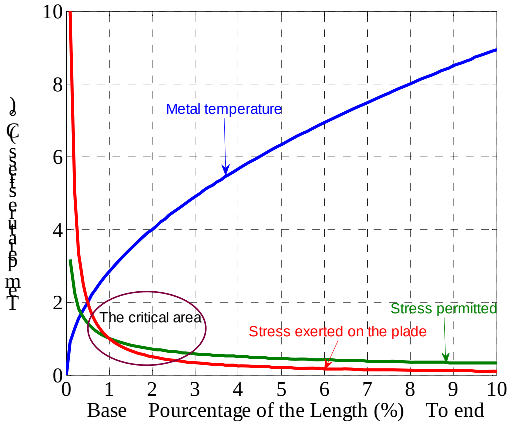

Fig. 14. Strain and temperature distribution within a turbine blade

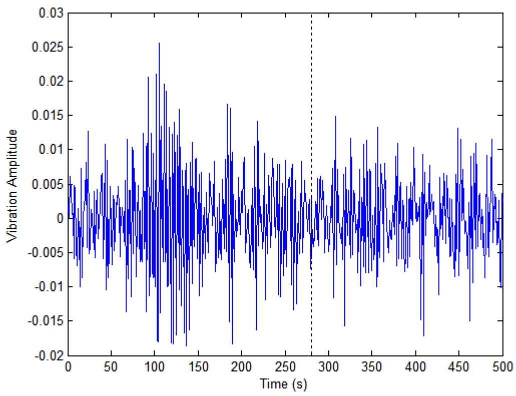

Fig. 15. Rotor vibration

The vibration amplitudes using prognostic system prediction are tested, as shown in Figures 16 and 17 these amplitudes are considered validation tests and performance robustness of prediction method.

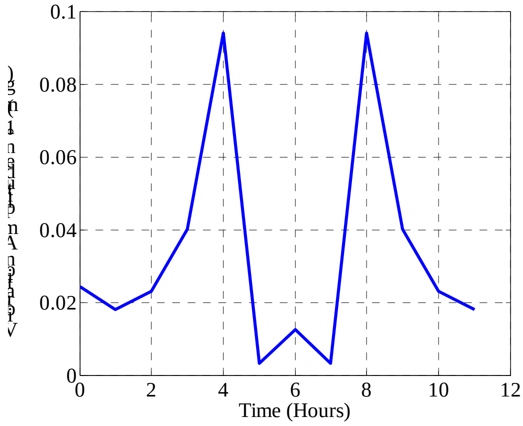

Fig. 16. Vibration amplitude / Test 1

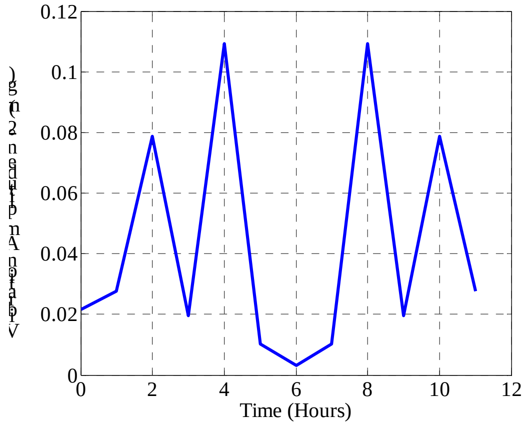

Fig. 17. Vibration amplitude / Test 2

The proposed prognostic approach has been tested and validated with prediction errors converging to zero more quickly when the horizon of observation data is small, of course, the horizon more data, the more accurate the prognostic is poor. This proposed prognostic approach has allowed to build the components degradation model of the studied gas turbine, as well as the prediction of the vibration future state of the gas turbine components along an estimated time horizon. It can be said that the prognostic, is an approach which has the ability to provide reliable estimation of future health status of the studied gas turbine, this task can be performed based on the diagnosis of the current status, the history of failures and the achieved maintenance operations. Where the main aim is to ensure the best estimation of the remaining useful life of the studied system.

4. CONCLUSION

The work presented in this paper has dealt with the calculation of the availability of gas turbine components and the evaluation of the thermo mechanical stress cycle under the thermal evolution. This task has been achieved by building a failure prediction model based on a prognostic approach. The presented study has allowed to understand the effect of different stresses applied to the different components of the studied gas turbine such as the blades and their interaction for the evolution of creep and fatigue damage inside the studied gas turbine. Furthermore, the major merit of the presented study, that it can be used to ensure an optimized design of a reliable maintenance making-decision process, especially for industrial oil and gas installations that are characterized by a complicated production requirements and constraints. Indeed, this work can find it applicability in industrial applications where it is difficult to have enough knowledge about the complex degradation phenomena, or enough past experience which allows to use significant statistical approaches due to the intrinsic deterioration constraints of the studied system.

Finally, it can be deduced that the use of a prognostic system can be a promising solution for achieving the prediction of the expected failures along an estimated time, for ensuring the an optimised making decisions process and for planning an accurate and adequate maintenance schedule under production requirements.

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