Improved gas turbine supervision system based on fuzzy estimation of their reliability and availability

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Abstract. In this work, we study the optimization of reliability and availability of complex industrial processes using the techniques of fuzzy logic in order to improve their monitoring systems and exploitation. The advantage of the proposed approach in this work is to increase efficiency in industrial facilities, by recent studies with tests on the examined gas turbine. This allows analyzing the monitoring parameters of this rotating machine, to ensure a good reliable and safe operation of the studied gas turbine system.

*Keywords***:** *Availability, gas turbines, monitoring system, reliability, optimization, industrial installation.*

1. Introduction

The reliability approaches development and analysis are aimed at finding the causes which may affect system reliability, and to determine all effects generated by one of its potential failures. In many industrial applications, reliability approaches are organized in different analytical methods [1-8]. In this work, we propose the analysis of the effects and consequences given by the failure can have on the system itself and its environment. Indeed, it is to identify the impact of a rotor vibration of a gas turbine on the turbine itself and the effects felt by the operator. So it comes to the causes of an event or failure and rather to try to identify what is causing this vibration in an examined gas turbine. However, the analysis methods deployed in these processes are many and various, the role of the reliability analyst; firstly is to choose the most appropriate type of problem by the addressed methods. Then it must ensure that the exploitation of these methods result in the realization of a model of reliability and system failures that affect [1-12, 15, 18 and 19].

In this paper, a fuzzy modeling with reliability and availability optimization of a gas turbine is proposed, in order to improve their exploitation systems and to improve their monitoring system based on reliability and availability estimation using fuzzy approach.

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2. Reliability assessment methods

In practical reality, before any reliability study, it is essential to have internal and external functional analysis of the system. These two tests are complementary; they are used at different times and with different goals [10-13]:

- External functional analysis is independent of any solution and enables the setting of performance targets (material limits of the system, the functions and operations performed by the system, operating configurations) and express the expectations of users,

- Internal functional analysis focuses on the general definition of the system and determining the path of the technical functions of the different components in the system.

At each stage of simplified development cycle, we have combined the reliability analysis methods, based on the data collection, which represents a set of validated data and / or developed after a long process of expertise and treatment, on a domain of knowledge and organized to be offered to user consultations. As a result, reliability of the tests, it is intended to verify or supplement existing reliability data or develop them when they are not available, and this by conducting tests on a number of systems. They apply to study models or prototypes and the pre-production systems. And finally, the experience feedback which aims to develop a knowledge base from an analysis of the system throughout the life of the system, its commissioning until its disintegration [11-15].

Indeed, the development of a system is performed according to a sequential series of steps, all steps are conditioned by the previous ones. Reliability studies are part of this suite and reliability form the process [9, 11 and 14]. However, the reliability process has three phases: the predicted reliability, experimental reliability and operational reliability in which several methods and tools are used, the more one acts upstream (forward and experimental reliability), the more one gets sufficiently robust systems in the early stages of the specification [19].

2.1 Predictive reliability evaluation:

This phase is early in the study of reliability through qualitative and quantitative analysis, integrating different data collections. For complex systems, it is possible to model the reliability by these techniques. The predicted reliability allows making optimal design of equipments [19].

2.2 Experimental reliability evaluation

This phase occurs when product development is sufficiently advanced and the first prototypes are available, it is possible to perform robustness tests to find weaknesses and design margins. Once the product is mature (sufficient margins), a test campaign can be conducted to estimate reliability. During

production, the elimination of defaults problems (process drift and low component) is done by robustness tests [16-18].

2.3 Operational reliability evaluation:

Once the product is in operation, reliability estimation is made based on exploitation data. It is practiced from the first commissioned and is used to correct the design faults and manufacturing production [19].

3. Reliability improvement

To improve the reliability of an industrial system, it is finding the best way to increase reliability. The most used methods to achieve this improvement is to reduce system complexity to a minimum and increase the reliability of components in the system. With a maintenance repair faulty components or preventive maintenance of components, that will be periodically replaced with other new even if they are not yet failed. In this case, the total reliability of the system for serial components is given by:

$$R_s(t) = \prod_{i=1}^{n} R_i(t)$$

(1)

And for components in parallel is given by:

$$R_s(t) = (1 - \prod_{i=1}^{n} (1 - R_i(t)))$$

(2)

With: $i \in \{1, n\}$ and R_i is the reliability of the component i

Improving the reliability of industrial systems is based on the development of the used reliable approach. Indeed, the reliability development of a system is carried out according to the predictive assessment and the experimental evaluation and finally the operational reliability evaluation. For the reliability estimation of a system is an important economic issue for any business in industrial installations. The measure of that greatness is necessary first steps towards control, in many companies have found that reliability is an important factor in competitiveness. Designers and users of complex systems show great interest for assessments of the reliability of the overall system, the hardware and software parts and interactions between different parts of the system. Reliability modelling covers multiple aspects: systems failure analysis, reliability prediction, reliability databases, reliability testing, operational reliability, forecasting methods of reliability and safety, the assurance of reliability and quality.

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The characterization of the reliability of a device in industrial system can be obtained in three ways which are distinguished by the type of data available, as shown in Figure 1. These data may reflect failure times from a historical failure (statistical models based on historical events), to measures of physical degradation collected over time which we know the deteriorating law (physical models of failure) or to evolution of explicit variables degradation (followed by a degradation indicator).
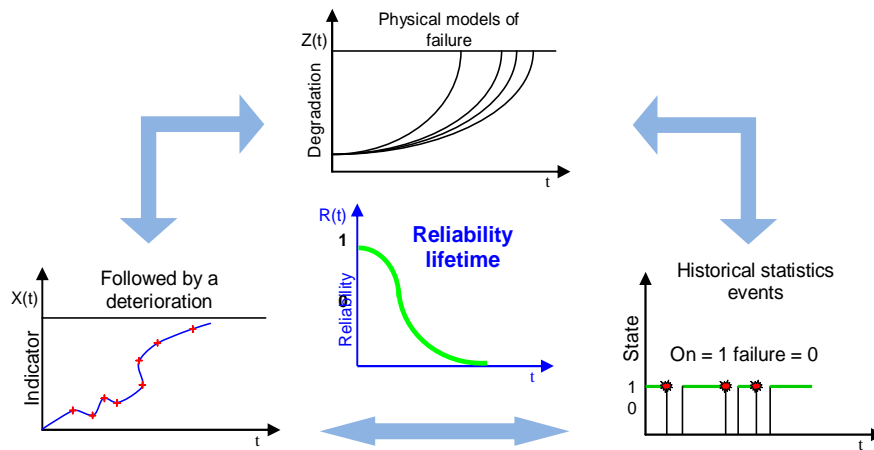
Figure 1: Reliability Estimation Approach

3.1. Validation of reliability modeling

In the reliability modeling the weight is minimized with the size in the studied system, using the impact of the cost and constraints to improve the reliability in this industrial system. In practice, there are several laws for reliability modeling; Among these laws, there is the Weibull distribution, that has many applications in various fields in many scientific and industrial work. It describes the life of materials that undergo failures. The law of reliability is given by the flowing relation [15]:

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3}$$

The probability of the density function is the derivative of the distribution function is given by:

$$f(t) = F'(t) = -R'(t)$$

$$f(t) = \left(1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}\right)' = -\left(e^{-\left(\frac{t}{\eta}\right)^{\beta}}\right)' \tag{4}$$

The derivative of the formula (2) gives us the following:

$$f(t) = -\left(-\left(\left(\frac{t}{\eta}\right)^{\beta}\right)' e^{-\left(\frac{t}{\eta}\right)^{\beta}}\right) = \left(\left(\frac{t}{\eta}\right)^{\beta}\right)' e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{5}$$

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This leads to :

$$f(t) = \beta\left(\frac{t}{\eta}\right)'\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} = \beta\frac{1}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{6}$$

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{7}$$

Finally the probability density function is given by the following relationship:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{8}$$

The failure rate is given by the formula:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1 - F(t)}$$

$$\lambda(t)\frac{f(t)}{1 - F(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \frac{1}{e^{-\left(\frac{t}{\eta}\right)^{\beta}}} \tag{9}$$

Finally we can write:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{10}$$

The instantaneous failure rate $h(t)$ is given by:

$$h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{11}$$

3.2. Reliability estimation based on fuzzy logic

Artificial intelligence can help automate some of the decisions taken manually in the industrial world and be an effective alternative to processes based on rules, for artificial intelligence would be able to take into account more factors and variables, while learning, unlike the automatic scheduling engine based on fixed algorithms. Indeed, this work is devoted to the use of a basic fuzzy expert system for reliability estimation of a gas turbine examined.

In fact, fuzzy logic trait is a technique of treatment of imprecise knowledge processing based on linguistic terms, it provides the means of converting a linguistic decisions based on human reasoning in automatic decisions, allowing the decisions in complex systems whose information is expressed in a vague and ill-defined [8-15].

In the classical theory of sets, membership of an element to a subset is defined by a standard logic value 1 if the item belongs to the subset, 0 otherwise. In fuzzy theory, a component can belong partly to a subset; its membership degree is described by a value between 0 and 1. Fuzzy logic is based on the theory of fuzzy sets in and can integrate and process the approximate nature or wave of human knowledge by using groups with ill-defined boundaries such as 'speed' or 'small' intermediate situations between right and wrong and to introduce a gradual transition from one property to another. Which allows to components belong completely or to a set or the other, or even to partially belong to each.

Definition

Given X be a countable set or not, a fuzzy subset A in X is characterized by its membership function μ_A, such as:

$$\mu_A : X \to [0,1]$$
$$x \to \mu_A(x)$$

(12)

Where $\mu_A(x)$ is the degree of membership of x in the fuzzy set A.

In this concept, the notion of linguistic variable is used to model imprecise or vague knowledge on a variable, whose precise value is unknown. A linguistic variable or fuzzy variable, is a variable whose values belong to the fuzzy sets that can represent words of natural language, thus a fuzzy variable can take simultaneously several linguistic values.

For example, the "Speed" tag can belong to the fuzzy sets, as shown in Figure 2; Slow, Medium and Fast. Linguistic variable can be represented by a triplet(x, $T(x)$, U), where x is the name of the language variable, $T(x)$ all the names of linguistic values and the reference x and U set (universe of discourse).
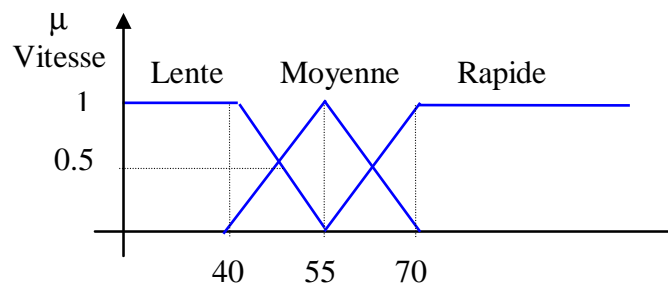
Figure 2: Fuzzy representation of variable speed

Also, for a example of size variable, the linguistic variable is represented by a triplet (V, X, T_v) where V is the variable itself, X the universe of discourse and T_v all the fuzzy characterization

of the variable. In this example, consider the variable size defined on the set of positive integers and characterized by fuzzy sets Old and Fasting, in the case of a simple linguistic variable, and Fasting but not too Fasting, Fasting and not Old and more Old or less and extremely Old, in the case of a compound or complex variable, this representation is shown in Figure 3.
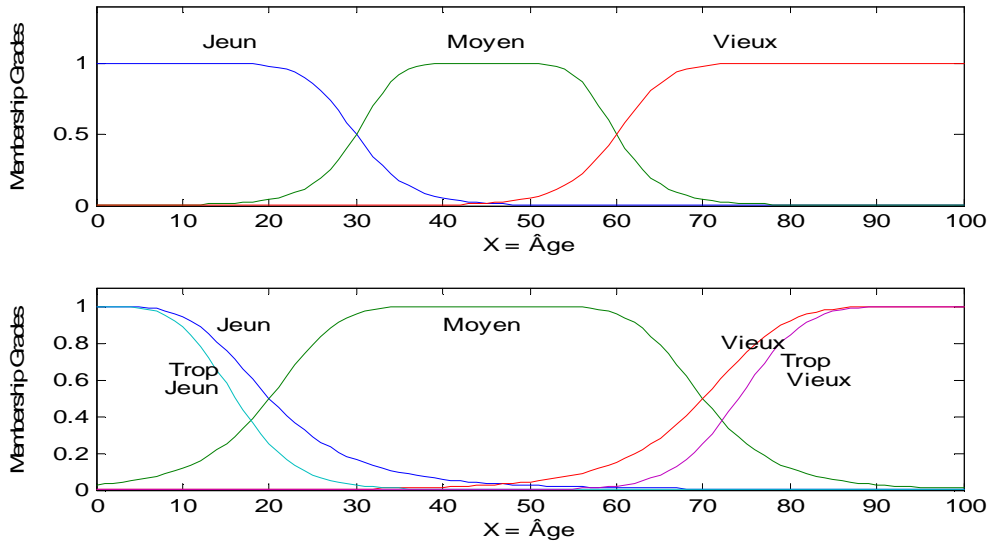

Figure 3: Fuzzy sets

The creation of a decision support system involves the definition of fuzzy variables and determining the corresponding fuzzy sets, a fuzzy set A defined on the universe of discourse X is noted:

$$A = \sum_{i=1}^{n} \frac{\mu_A(x_i)}{x_i} = \frac{\mu_A(x_1)}{x_1} + ... \frac{\mu_A(x_n)}{x_n} \quad Discreet\ case$$

$$A = \int \mu_A(x) \big| x \qquad Continuous\ case \tag{13}$$

The aggregation rules gives the opinion on the value to be assigned to the fuzzy system, the weight of each notice depends on the degree of truth of the conclusion, as shown in Figure 4.
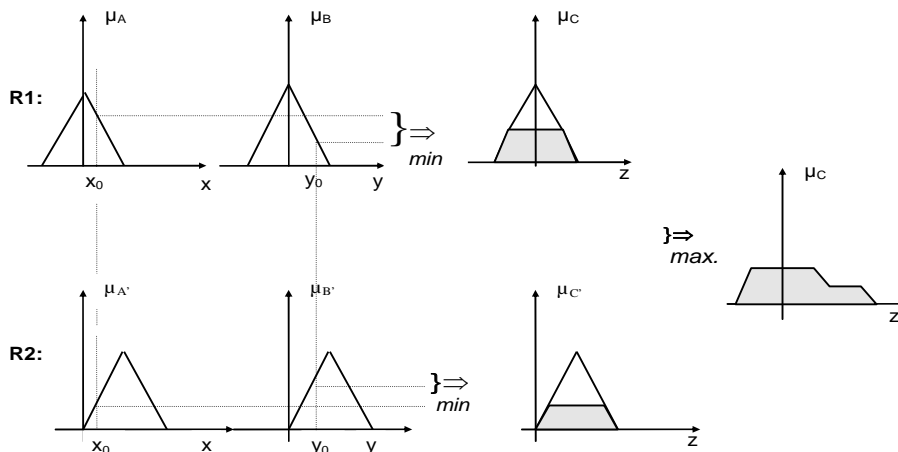
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Figure 4: Aggregation rules

The diagram shown in Figure 5, summarizing the principle of fuzzy concept of use.
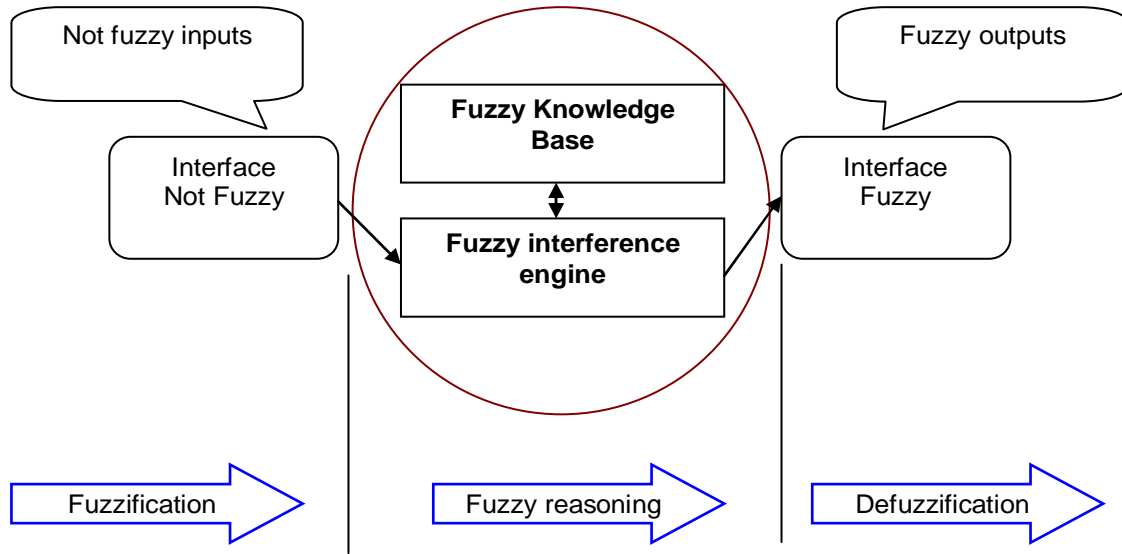

Figure 5 : Schéma de principe d'un contrôle flou

Each human expert acquired during his work expertise, that expertise or all of this knowledge is stored as facts or production rules. This set of the first step is to calculate the failure rate of each omponents selected from information and working conditions of the examined gas turbine, then based on failure rates of each component, the overall failure rate of the global turbine system is determined. The MIL-HDBK expert knowledge bases using mechanical laws and laws based on empirical knowledge of the expert are used. Figure 6 shown the architecture of the used fuzzy expert system in this work.
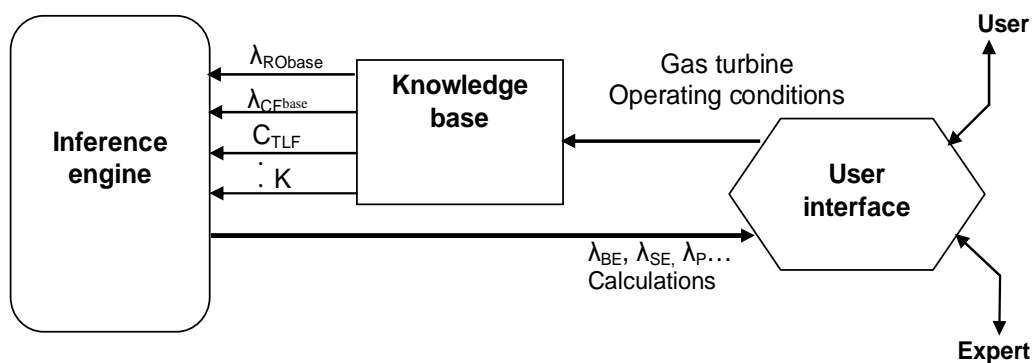

**Figure 6: Fuzzy expert system architecture**

4. Application results

To determine the failure rate chosen by a system that uses two inputs and outputs two variables, these variables are sufficient to select the architecture of fuzzy systems to model a vibration system of the examined gas turbine. The first fuzzy model that uses two inputs (Time Between Failure TBF) to generate a single output (the value of failure rate), each entry is fuzzified three fuzzy sets Gaussian. The proposed fuzzy expert system is used to determine the failure rate in the examined gas turbine.

At the end and from the operating data, the expert system can provide several results such as the parameters of the laws of failure rate distribution, predictive reliability, Mean Time Between Failure MTBF time and the instantaneous failure rate for each component as well as the rotor of the gas turbine examined. Figure 7 shown the failure rate using the Weibull distribution function, and Figure 8 shows the reliability function using the same distribution on the examined gas turbine
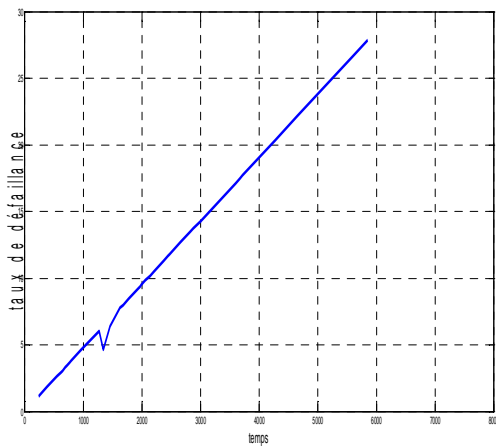
Figure 7: Failure rate using function using Weibull
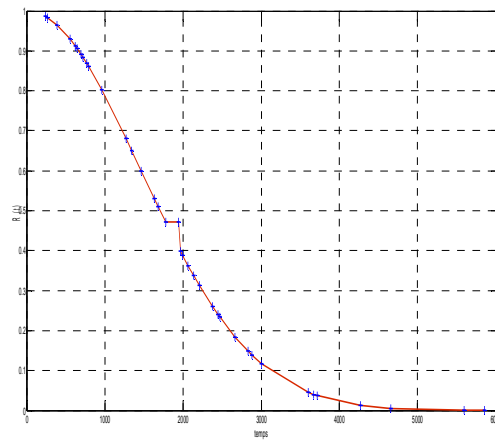
Figure 8. Reliability function

In Figure 9, the failure rate is obtained using the Weibull distribution function and in Figure 10, the probability density function is presented, which is confirmed the continued operating services of the gas turbine studies and provide a prevention plan to improve production installation
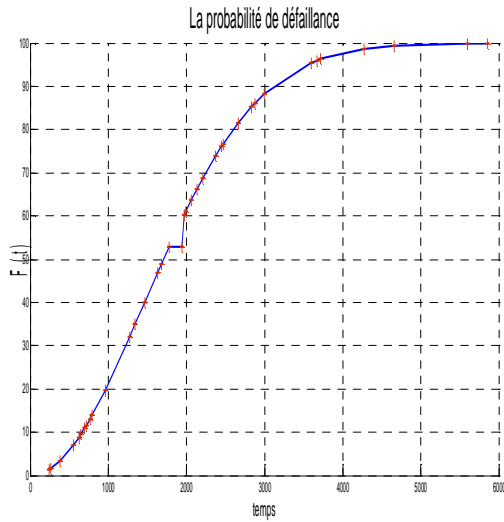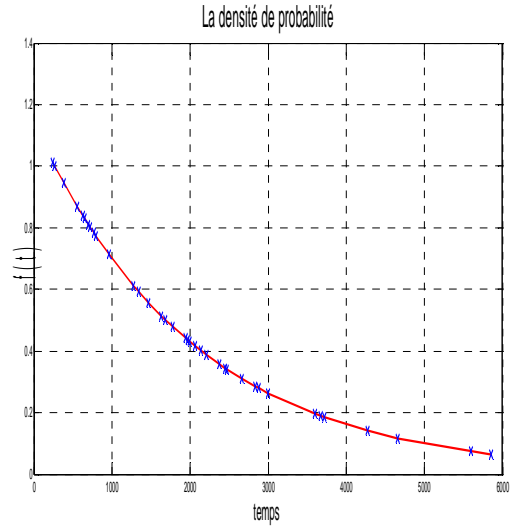
Figure 9. Failure rate function

Figure 10. Density function

5. Conclusion

The evaluation of the reliability assessment in industrial structures is essential to design more efficient systems. Unlike electronic systems, there are no unique or standardized methods to assess the predictive reliability of mechanical systems. The choice of method to be applied is based on the objectives and the tools available. In this work we have done modeling and assessment of the predicted reliability of an industrial system based on a fuzzy expert system. We took as applying a gas turbine; it is justified by the very extensive use of this type of equipment in the oil industry. A functional analysis of these components was performed to identify their failure modes, possible causes and their effects on systems to study. This approach developed using the fuzzy inference system applied to a gas turbine deducted the reliability model to estimate the time of operation of the discussed gas turbine. This is in order to reduce response costs and maximize the lifetime of the selected equipment to offer the best performance of this equipment.

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