

Improvement of Gas Turbine Availability Using Reliability Modeling Based on Fuzzy System

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Abstract The development of the reliability approaches mainly aims at finding the probability that the studied system or a part of it will perform the required function without interruption or failure under the actual stated conditions of defects for a determined period. In this work, the analysis of the effects and consequences resulting from the failures that can affect the industrial system itself and its environment is proposed, where an application on gas turbine system is presented. The main objective is to identify the impact of the gas turbine rotor vibration on the turbine itself and on the operator based on reliability modeling. Indeed, this approach will allow to discover accurately the causes of this kind of vibration. In this paper, a fuzzy modeling method to optimize reliability and availability of the gas turbine is proposed, with the main aim to improve the system exploitation and monitoring.

Keywords Availability · Gas turbines · Monitoring system · Reliability · Optimization · Industrial installation

Nomenclature

$R(t)$	Reliability function
$F(t)$	Failure time distribution function
$f(t)$	Probability density function

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$h(t)$	Instantaneous failure rate
β	Shape parameter in Weibull distribution
η	Scale parameter in Weibull distribution
λ	Failure rate
μ	Average
σ	Standard deviation
ANFIS	Adaptive neuro-fuzzy inference system
MTBF	Mean time between failure
MTTR	Mean time to repair
γ	Positional parameter in Weibull distribution
\hat{a} and \hat{b}	Estimated parameters in regression equations
n_i	Numbers of failure
t_i	Uptime between damage (in hours)
RMSE	Root-mean-square error
CV	Coefficient of variation
MTTF	Mean time to failure
x	Variable
E	Variables set
μ_A	Fuzzy membership function
A	Fuzzy set
α	Degree of appurtenance in fuzzy set

1 Introduction

In the recent years, the insurance of continuous operation mode of industrial systems is one of the main strategic issues which is facing the industry attention, from the design of a machine to its operation in the industrial plant, this is why maintenance is considered to be an essential element in the industry. This work proposes the modeling of the reliability of gas turbines using the Weibull distribution to improve their availability based on fuzzy reliability modeling, which allows to give a status of the operation certainty level for this industrial equipment. Indeed, the reliability modeling is attracting much attention and interest in various industrial sectors, where the main goal is to maintain the continuous operation of the industrial system without unplanned interruption. Many reliability modeling methods have been presented in the literatures that can be classified into two major categories: the deterministic and the stochastic methods (Guemana et al. 2015; Djeddi et al. 2016; Mensah and Dueñas-Osorio 2014; Pham et al. 2006; Lee et al. 2014; Zhang and Xie 2011; Verma and Kumar 2014).

Indeed, among the most techniques that are used in industrial systems modeling are the approaches that are based on artificial intelligence, benefiting from the development of new fast microprocessors that can fulfill the requirement of low

cost. This work proposes the integration of a new method based on the adaptive network with fuzzy inference system in the class of the deterministic methods. The advantage of this method allows to search for the minimum of a function based on the knowledge of a research direction which is often given by the gradient of this function (Mohammadi and Montazeri-Gh 2015; Chang and Lee 2015; Wong et al. 2013; Nikpey et al. 2013).

This work aims at developing a global methodology based on a fuzzy expert approach which makes the evaluation and the estimation of the gas turbine system reliability possible. This methodology proposes a decision support tool in the operational phase; it allows to develop the modeling and the simulation of the functional and dysfunctional behaviors of the systems in order to evaluate the reliability of the studied gas turbine, where the main objective is the supervision of their availability.

2 Reliability Modeling

In industrial practice, the reliability is defined as the probability that a system fulfilled its function during a given period and under given operating conditions based on data collections, analysis, and many other means based of the feedbacks in a variety of sectors. The expression of the law of reliability, using Weibull distribution, is expressed as follows (Sabouhi et al. 2016; Djeddi et al. 2015a; Hsu et al. 2014):

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^\beta}, \quad (1)$$

where β is the shape parameter and η is a scale parameter.

In this case, if $\beta < 1$ the failure rate λ decreases with time; if $\beta > 1$ the failure rate λ is increasing; and if $\beta = 1$ the system does not appear likely, the failure rate is constant and the reliability law is an exponential law (Guemana et al. 2015; Djeddi et al. 2016; Mensah and Dueñas-Osorio 2014; Hafaifa et al. 2016; Álvarez Tejedor et al. 2013; Lee et al. 2015; Wang 2006). A more general expression of Weibull distribution is obtained by taking $\eta = e^{(\frac{\mu}{\sigma})}$ and $\sigma = \frac{1}{\beta}$. In this case, Eq. 1 becomes

$$F(t) = 1 - e^{\left[-e^{\left(\frac{\ln t - \mu}{\sigma}\right)}\right]}. \quad (2)$$

The probability density function is the derivative of the distribution function which is given by (Akwasi 2014; Pham 2006; Lee et al. 2014)

$$\begin{aligned} f(t) &= F'(t) = -R'(t) \\ f(t) &= \left(1 - e^{-\left(\frac{t}{\eta}\right)^\beta}\right)' = \left(e^{-\left(\frac{t}{\eta}\right)^\beta}\right)'. \end{aligned} \quad (3)$$

The derivative of the formula (3) gives us the following:

$$\begin{aligned} f(t) &= \left(- \left(\left(\frac{t}{\eta} \right)^\beta \right)' e^{-\left(\frac{t}{\eta}\right)^\beta} \right) = \left(\left(\left(\frac{t}{\eta} \right)^\beta \right)' e^{-\left(\frac{t}{\eta}\right)^\beta} \right) \\ \Rightarrow f(t) &= \beta \left(\frac{t}{\eta} \right)' \left(\frac{t}{\eta} \right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^\beta} = \beta \frac{1}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^\beta}. \end{aligned} \quad (4)$$

The failure rate is given by the following formula (Mensah and Dueñas-Osorio 2014; Pham 2006; Lee et al. 2014):

$$\begin{aligned} \lambda(t) &= \frac{f(t)}{R(t)} = \frac{f(t)}{1 - F(t)} \\ \lambda(t) &= \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1}. \end{aligned} \quad (5)$$

And the instantaneous failure rate is given by (Mensah and Dueñas-Osorio 2014; Pham 2006; Lee et al. 2014; Guemana et al. 2015; Djeddi et al. 2016)

$$h(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1}. \quad (6)$$

In the rest of this work, the Weibull distribution is used to estimate its parameters using adaptive neuro-fuzzy inference system (ANFIS) model to determine the failure rate function reliability and other indicators as the mean time between failure MTBF and the mean time to repair MTTR (Mohammadi and Montazeri-Gh 2015; Chang and Lee 2015; Wong et al. 2013; Nikpey et al. 2013). For the estimation of the parameters of the Weibull distribution β, η, γ , the method of least square is used in the reliability modeling of the examined gas turbine.

2.1 Gas Turbine Reliability Modeling

As a part of the implementation of the proposed approach in this work, it is proposed to give the method of calculating the parameters of the Weibull law for the examined gas turbine, based on the history of interventions carried out in Table 1 (Djeddi et al. 2015b). In this work an analysis of the behavior of a gas turbine is introduced; this rotating machine operates in a more complex system for transporting natural gas, using compressions operation. This analysis is based on the occurrence of faults and their distribution over time. Given the complexity of mathematical functions, the use of an estimation method of least squares is recommended (Benyounes et al. 2016, 2017; Hadroug et al. 2016a; Zhang et al. 2016; Taplak and Parlak 2012; Wei et al. 2016; Fei et al. 2014). This method of least

squares estimation is used to estimate the parameters. The following equations of regression are therefore derived as follows:

$$\begin{aligned} \hat{a} &= \frac{\sum_{i=1}^N y_i}{N} - \frac{\hat{b}(\sum_{i=1}^N x_i)}{N} = \bar{y} - \hat{b}\bar{x} \\ \hat{b} &= \frac{\sum_{i=1}^N x_i y_i - \frac{\sum_{i=1}^N y_i \sum_{i=1}^N x_i}{N}}{\sum_{i=1}^N x_i^2 - \frac{(\sum_{i=1}^N x_i)^2}{N}}. \end{aligned} \tag{7}$$

In this case, the equations of y_i and x_i are

$$\begin{cases} y_i = \ln\{-\ln[1 - F(t_i)]\} \\ x_i = \ln(t_i) \end{cases} \tag{8}$$

The values of $F(T_i)$ are estimated from the median ranks, where y_i and x_i are obtained first, and then $\hat{\beta}$ and $\hat{\eta}$ can be easily obtained from the above equations.

Using the values of Table 2, \hat{b} and \hat{a} can be calculated using the following equations:

$$\hat{b} = \frac{\sum_{i=1}^7 (\ln T_i) y_i - \frac{(\sum_{i=1}^7 \ln T_i)(\sum_{i=1}^7 y_i)}{7}}{\sum_{i=1}^7 \ln T_i^2 - \frac{(\sum_{i=1}^7 \ln T_i)^2}{7}}. \tag{9}$$

We get

$$\begin{aligned} \hat{a} &= \bar{y} - \hat{b}\bar{x} = \frac{\sum_{i=1}^N y_i}{7} - \frac{\hat{b}(\sum_{i=1}^N \ln t_i)}{7} = -9.4236 \\ \hat{b} &= \frac{20.1573 - \frac{55.626 \times 2.1042}{7}}{444.8509 - \frac{(55.626)^2}{7}} = 1.2237. \end{aligned} \tag{10}$$

Table 1 Gas turbine history reliability data

Order	Uptime t_i between damage (in h)	Nbr of failure	m. ranks (Actual data)	Accumulated		
				$\sum n_i$	F_i	F_{ii} in %
01	0–836	12	0.297105	12	0.292	29.2
02	836–1672	6	0.449466	18	0.439	43.9
03	1672–2508	11	0.728796	29	0.707	70.7
04	2508–3344	4	0.830370	33	0.804	80.4
05	3344–4180	3	0.906551	36	0.878	87.8
06	4180–5016	2	0.957338	38	0.926	92.6
07	5016–5856	2	0.982732	40	0.975	97.5

Table 2 Least-squares analysis

N	T_i	$\ln(T_i)$	$F(T_i)$	y_i	$(\ln(T_i))^2$	y_i^2	$(\ln(T_i))y_i$
01	836	6.7286	0.2926	-1.0608	45.2740	1.1253	-7.1377
02	1672	7.4217	0.4390	-0.5481	55.0816	0.3004	-4.0678
03	2508	7.8272	0.7073	0.2058	61.2650	0.0424	1.6108
04	3344	8.1149	0.8048	0.4908	65.8516	0.2409	3.9828
05	4180	8.3381	0.8780	0.7437	69.5239	0.5531	6.2010
06	5016	8.5203	0.9268	0.9610	72.5955	0.9235	8.1880
07	5856	8.6752	0.9756	1.3118	75.2590	1.7208	11.3801
Σ	23,412	55.626	0.8532	2.1042	444.8509	4.9064	20.1573

Table 3 Different calculation parameters

Parameter	Symbol and relationship	Calculated results
Shape parameter	$\hat{\beta} = \hat{b}$	1.2237
Scale parameter	$\hat{\eta} = e^{-\frac{\hat{a}}{\hat{b}}}$	2.2104e + 003 h
Positional parameter	γ	0.0000
The average time between failures	$MTBF = \int_0^{\infty} t.F(t) = \gamma + \eta * A$	1958.8564 h
Root-mean-square error	$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{F}(t_i) - F(t_i))^2}{n}}$	0.0089
Coefficient of variation	$CV(RMSE) = \frac{RMSE}{\bar{y}}$	0.0124
Mean time failure	TMP	146.4 h
Average reliability	MTBF/(TMP + MTBF)	93.05%

And finally, the shape parameter and scale parameter are given as follows:

$$\begin{cases} \hat{\beta} = \hat{b} = 1.2237 \\ \hat{\eta} = e^{-\frac{\hat{a}}{\hat{b}}} = e^{\frac{9.4236}{1.2237}} = 2.2104e + 003 \text{ hr} \end{cases} \tag{11}$$

In the next step, we calculate a set of parameters and variables that have been simplified in Table 3, to estimate the average reliability and calculate the average uptime.

The root-mean-square error and the coefficient of variation provide insight on adjusting data.

3 Fuzzy Logic Model for Reliability Modeling

To determine the selected failure rate in a system which uses two input and two output variables, as shown in Fig. 1, in the present case of the studied gas turbine, these variables are sufficient to change the architecture of the neuro-fuzzy systems for the modeling, and the system of two equations that represent input–output relations is expressed as follows:

$$\begin{aligned}\lambda &= \text{Fuzzy_1}(\eta, \text{TBF}) \\ \text{MTBF} &= \text{Fuzzy_2}(\eta),\end{aligned}\tag{12}$$

where λ is the failure rate and MTBF is the mean time between failure.

The variables measured in the process, from derivatives of the plant control system or the actual instrumentation coupled to the system, are compared to their counterparts based on a computer model. The differences between the reference model and the signals obtained from the simulation model are used as input in the fuzzy system. Let the set E is given by the membership function identically equal to 1 and the empty set is given by the membership function identically zero (Hadroug et al. 2016b; Mohammadi and Montazeri-Gh 2015; Chang and Lee 2015; Wong et al. 2013). The nucleus of a blurred portion A is the set of elements that belong entirely to A , that is to say, the degree of belonging to A is 1:

$$n(A) = \{x \in E | \mu_A(x) = 1\},\tag{13}$$

where x is the fuzzy variable, μ_A is the membership function, and A is a fuzzy subset.

Supporting a blurred portion of A is the set of elements belonging very slightly even at A , that is to say, that the degree of membership in A is different to 0, given by

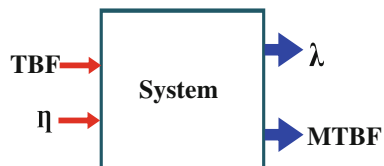
$$\text{Supp}(A) = \{x \in E | \mu_A(x) > 0\}.\tag{14}$$

The height of a fuzzy subset A of E is defined by

$$h(A) = \sup\{\mu_A(x) | x \in E\}.\tag{15}$$

A fuzzy subset A of E can also be characterized by all of its α – cuts to performing different arithmetic operations, where a part of A is the net subset

Fig. 1 General scheme of model-based system



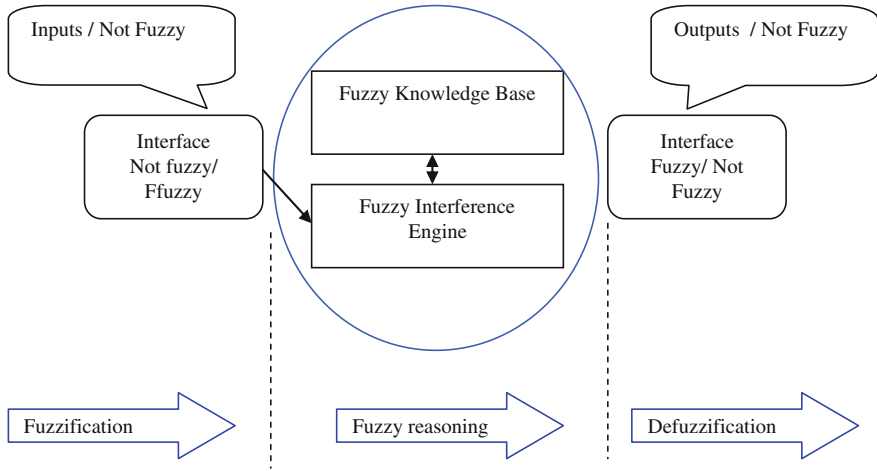


Fig. 2 Principle diagram of fuzzy concept

(classical) elements having a degree of greater than or equal membership of α given by (Chang and Lee 2015; Wong et al. 2013):

$$\alpha\text{-cuts}(A) = \{x \in E | \mu_A(x) \geq \alpha\}. \quad (16)$$

There are several features to meet these criteria given by formula (16); in this work, to estimate the reliability of the examined gas turbine, the configuration shown in Fig. 2 was chose to adopt the function of reliability of the gas turbine, summarizing the principle of using fuzzy concept (Benyounes et al. 2016; Mohammadi and Montazeri-Gh 2015)

$$No(\mu_A(x)) = 1 - \mu_A(x). \quad (17)$$

The used fuzzy system which used the inputs η , TBF to generate the failure rate, this fuzzy model consists of three parts; the first part for fuzzification, the second for calculating degree of truth for each rule, and the third part is for a normalization operation. The exit surface for the first neuro-fuzzy model is shown in Fig. 3, the flexibility of this area shows the best approximation and data modeling used for output of the failure rate λ .

4 Application Results

To facilitate the task of calculating the failure rate in the studied gas turbine, the modeling structure based on the fuzzy logic shown in Fig. 2 is used. This has led to the development of an expert system capable of calculating the parameters of

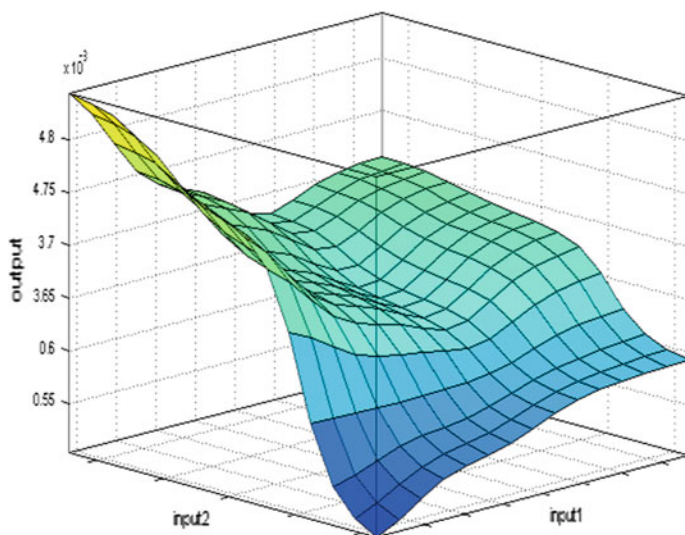
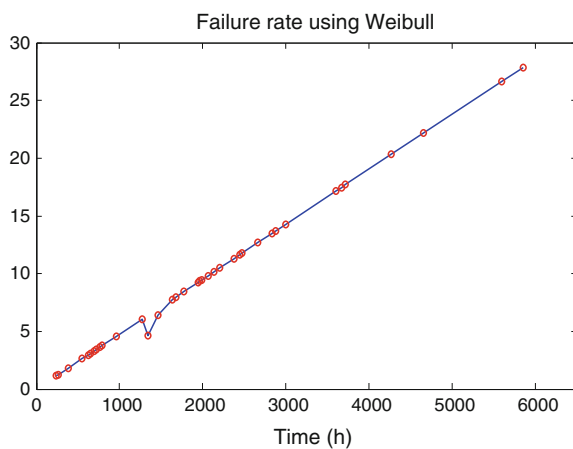


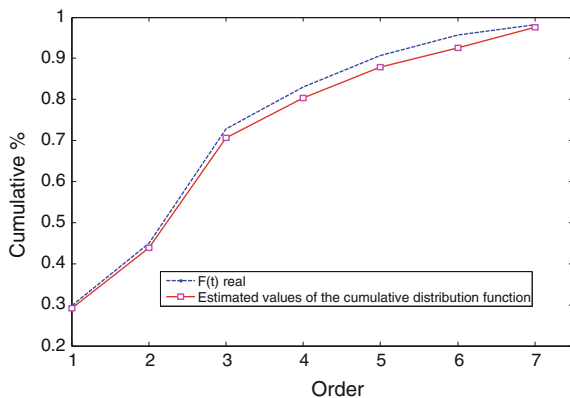
Fig. 3 Fuzzy model surface of the output system

Fig. 4 Failure rate using the Weibull function



reliability analysis of the examined gas turbine. The failure rate provides the average number of failures per unit of use; otherwise, this rate gives the number of breakdowns per time (hour) which was an average. It is represented by a separate section, as shown in Fig. 4, and shows that the studied organ fails, which is confirmed by the shape parameter ($\beta = 1.2236$), which requires the maintenance service to provide a preventive plan to improve production at the raw grinding plant, currently operating in difficulty. It has been noted that the curves of $R(t)$ real and

Fig. 5 Cumulative failure of the examined gas turbine using Weibull distribution



estimated are very close to one another and they give a good correlation with the curves determined by the modeling code.

In this work, the first step is to calculate the gas turbine failure rate using the Weibull distribution from the information and operating data of this system. The goal was to see if this model can represent accurately the data of time between failures of this studied gas turbine, as shown in Fig. 5, where the curve of the probability of the Weibull distribution function is shown in Fig. 6.

The points of coordinates $(t, F(t))$ are placed on the Weibull paper and it is found that the cloud of the points is rectilinear, and we can estimate that the reliability follows a Weibull law of parameter $\gamma = 0$. To determine the parameters β and η , the cloud traces the adjustment line, and then to trace the line $D_1 // D_2$ and passes through the origin of the frame (X, Y) . This second line makes it possible to record on the Weibull functional paper the two other parameters, as shown in Fig. 6.

Then, to determine the failure rate chosen by a system that uses two input and two output variables, these variables are sufficient to select the architecture of fuzzy systems to model a vibration system of the studied gas turbine. For 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 into three fuzzy Gaussian sets. 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, and the instantaneous failure rate for each component as well as the rotor of the studied gas turbine. Figure 7 shows the failure rate using the Weibull distribution function compared by the reliability function using the proposed fuzzy model on the examined gas turbine.

It is noted that the curves of the estimated reliability $R(t)$ by Weibull distribution with the modeled reliability $R(t)$ using fuzzy logic are very close to one another and give a good correlation with the curves determined by the modeling code.

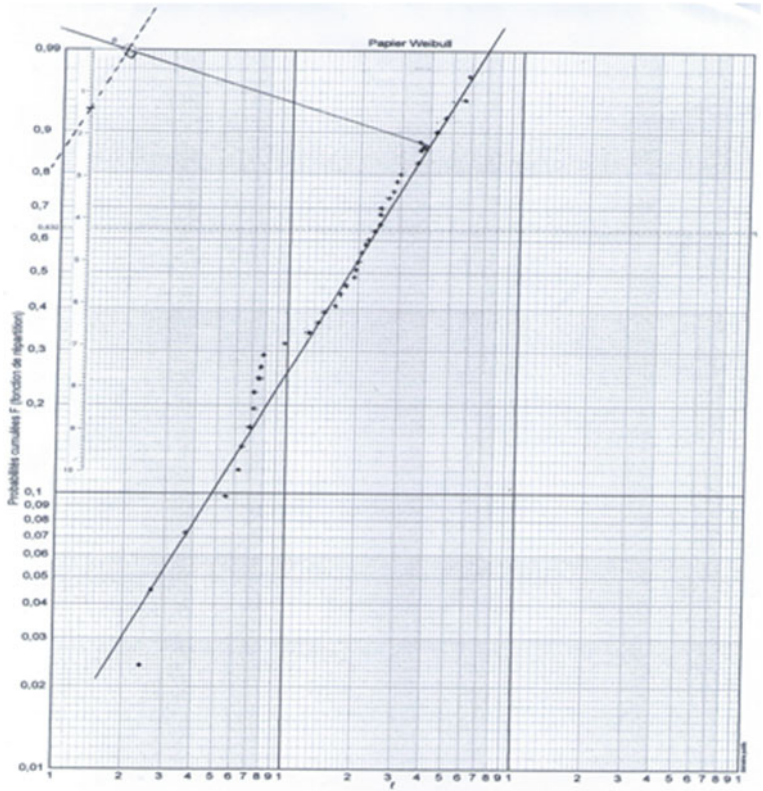


Fig. 6 Plot of Weibull distribution using Weibull Paper

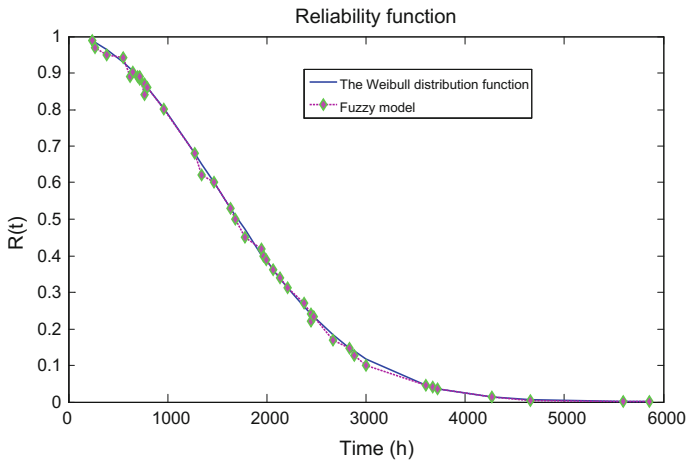


Fig. 7 Reliability function

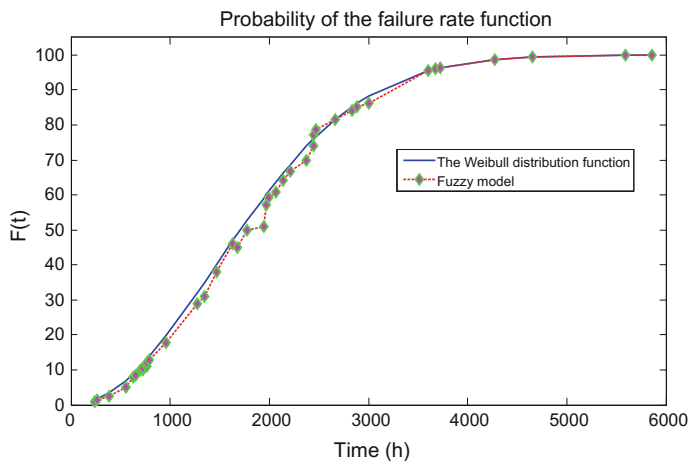


Fig. 8 Failure rate function

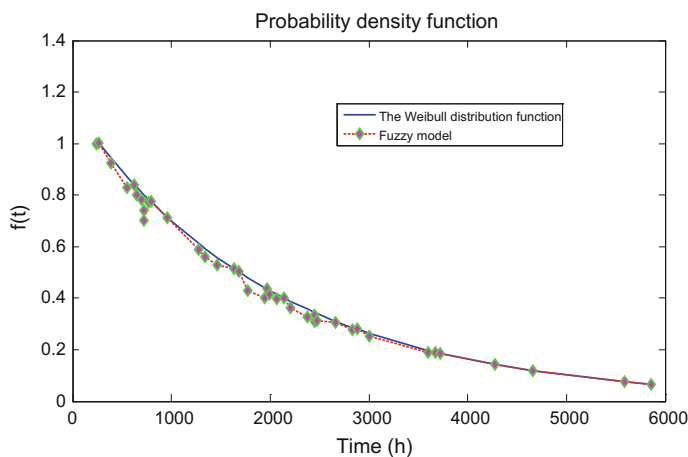


Fig. 9 Density function

In Fig. 8, the failure rate is obtained using the Weibull distribution function compared to the obtained failure rate using the proposed fuzzy model on the examined gas turbine; this result clearly shows that the fuzzy model is very close to the Weibull distribution and they give a good correlation.

In Fig. 9, the probability density function is presented, which confirmed the continued operating services of the studied gas turbine and provide a prevention plan to improve production installation. Also, this result shows that we are in front of an organ in phase of fatigue aging modeled by the Weibull model of parameters $(1.2237, 2.2104e + 003 \text{ h})$. This result requires the operator to follow up by

conditional maintenance and visits in order to detect the fatigue index of this bearing and predict its failure.

5 Conclusion

The evaluation of the reliability in industrial structures is essential for designing more efficient systems. Unlike electronic systems, there are no unique or standardized methods to assess the predictive reliability of mechanical systems. The choice of the method to be applied is based on the objectives and the available tools. In this work the modeling and the assessment of the predicted reliability of an industrial system are performed and realized based on a fuzzy expert system. For the validation of the proposed approach, an application of a gas turbine system is taken; it is justified by the very extensive use of this type of equipment in the oil industry. A functional analysis of this equipment was performed to identify its failure modes, possible causes, and their effects on studied system. This developed approach using the fuzzy inference system is applied to the present system of a gas turbine; it allows to deduce the reliability model of the studied system which is used for the estimation of the operation time, where the main aim is to reduce response costs, to maximize the lifetime, and to offer the best performance of the studied equipment.

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