Original Research

# Prognosis of Failure Time in Gas Turbines regarding multi time scales

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**Abstract**

In predicting of failure time based on operating hours, after identifying the effective parameters on wear process, it's of great importance to model an associated function between parameters and their effects on acceleration the failure. Gas turbines are too complicated to simple functions, proposed by manufacturer, cover all the possible scenarios with high confidence. In this article, all the parameters affected by time and the working cycle are combined by a relation with regarding a correction function that improve the accuracy of forecast to calculate equivalent working hours. The approach presented here, all the parameters, with a defined coefficient affect the failure process and lifetime reduction of the system and the various wear fractions within the exclusive temperature range are weighed by an appropriate factor. This method helps give a more realistic estimate of the residual life with more precision. The correction function will be updated consequently base on accurate of last output in compare with actual result. Looking at the data, we can observe that 90 percent of failures happen in the area between 7800 to 8100 hours of work, which indicate accuracy with regard to these values given for the parameters. Also result demonstrates that consideration of the last corrections in lifetime prediction is more effective than consideration of all the available data.

**Keywords**

Prognosis approach; wear pattern; Gas turbine; Failure time

## INTRODUCTION

Machines and equipment that work under load wear away by different patterns and their function level often decreases over time. Observations of failure in gas turbines in a period of time indicate that their function might sometimes decline at a constant rate and at times the rate of failure may accelerate or slow down depending on the working conditions. Saravaramuttoo and Maclsaac mentioned three types of failures, namely instantaneous, delayed time-dependent and purely time-dependent, in order to explain gas turbines failure or degradation and concluded that degradation rates are rarely known and nonlinear.

Li and Nilkitsaranout [1] analyzed recognition and prediction of failure time in gas turbines by combining linear and nonlinear equations. Also, Brothertom et.al [2] considered and explained the degradation mode of gas turbines as the bathtub type. Due to such factors as change in working conditions because of the design, environmental conditions, operating conditions, state of repair and maintenance, and more, prediction of failure time in gas turbines is a very challenging task. Therefore, to find a technical method to predict the effective remaining life of motors using gas turbines is highly demanding.

Working in a competitive condition causes failure to various pieces of gas turbines. Generally speaking, one can classify prognostic approaches into model-based approaches, data-driven approaches, and hybrid approaches [3]. The first group of approaches are based on the understanding the physics of failure and degradation mechanisms in the system. So, if the system includes various parts, each of which might have several mode of failure, understanding the physical mechanisms of failure and their mutual effects will be complicated. Data-driven approaches require extensively numerous sensory data collected from the system, though they do not need to recognize the failure mechanisms and only assume a proper regression structure on the basis of the data. To form the regression formula, some assumptions are needed which can affect the prediction results. So, great skill will be required to identify the optimum structure here [4].

Many of the failure Remaining Useful life prognosis methods that apply the data of life time and failure modes by use of a statistical distribution along with a diverse set of variables, models conditions data and operational state. In this method, the system is subject to a number of failure modes, and the collected data analysis will be based on the assumption of independence between the failure modes [5]. Of course, independence of the failure modes is an unreal assumption and is not true in practical conditions [6]. Hence, clear verification and demonstration of the dependence of such modes is difficult and no strategy can simply guarantee the efficiency of the statistical model [7].

So far, many methods of failure prognosis have been used in research and industries. Reference [8] have put forward a model of Mixture Weibull Proportional Hazard Model (MWPHM) to predict failure time in a mechanical system with several modes of failure. In this study, the failure density function in the system is obtained through the relative combination of failure density functions in different states. Here, the parameters of the model were estimated by means of monitoring the life time data, collected from all failure states.

Liu et al. [9] suggested a condition monitoring model with multiple competing risks, which system failure time was given by a random process and a degradation threshold.

Ahmad Rajab et al [10] suggested a method to predict the effective remaining life time which includes two steps: machine learning and model identification that called Logical Analysis of Data (LAD). In the learning step, the multilayer LAD approach is applied in order to extract the inherent knowledge based on the monitoring data, collected from a set of similar systems exposed to competing failure states. Then, the fittest pattern was recognized to predict RUL.

Most models reviewed in the above paragraphs assume that the age data for a particular failure mode are based on a specific parametrical failure distribution function. This assumption, however, requires a lot of experience and knowledge on the efficiency of any distribution in different modes. Moreover, it has been mentioned that some studies have supposed that different competing modes of failure are independent of each other. In addition, many of such models are restricted to a few failure modes. As a consequence, it is difficult for expert in industries to choose a prognostic model proper for their purpose. Therefore, the main challenge in prognosis of failure is creating a comprehensive model for estimation of age in systems that possess some dependent variables.

Along all the papers reviewed, a number of them have put forward approaches that take into dependence of variables as a condition. Noorossana and Sabri-Laghaie [11] studied the certainty level in systems with competing risks and two-time scales where the second scale follow the Poisson process. They assumed that modes of the failures were independent. Instead of obtaining a limited form for the certainty level of the system, they proposed an upper parametrical limit.

The goal of this paper is prognosis of the possible failure time in a system with multi-time scales considering the possible change of failure patterns over time. Many scales could affect failure, which are independent of each other and dependent on the first variable. The regression formula given for failure by the producers of the system is upgraded through a correctional function that follows a particular distribution. Gas turbine is considered as a case study and the data are collected in a certain period.

The present research is divided into five sections: The second section introduces gas turbines and the approach towards their failure. The third section puts forward the approach for the solution. And the fourth section goes about the use of the model and analysis of the results. Finally, the last section concludes it.

## GAS TURBINE FAILURE PROCESS

The first step to get the right results in prognosis of failure time in a system is a thorough study and recognition of all parameters affecting failure. Then, by choosing the best approach base on inputs, we can gain the most effective output. The failure process in gas turbines is too complicated to allow individual signals, used for diagnosis and prognosis, to cover all the possible scenarios.

### *I. Description of the gas turbine studied*

Gas turbines have a simple and robust design so that their repair and maintenance is done over long intervals. Their wear is a function of time and cyclical process. Such turbines normally work at high temperatures where erosion and wear happen along hot gas path under temperature. The parts of gas turbines that are under more pressures, include the casings and blades of the turbine. Pollutants and dust could also cause wear. These factors can also affect fatigue and its damages and entail the natural deterioration of gas turbines. Like any other machine, gas turbines are also subject to wear due to long period of use. Timing of inspection and repair must be based on accumulation of all kinds of wear caused by various sources, which is called the Equivalent Operating Hours (EOH)

*II. The suggested approach*

As can be seen in Figure.1, the approach to the failure time of turbine could be divided into four steps with regard to data collection: The time of system's failure, evaluation of the effect of the present failure function in failure prognosis, upgrading the coefficients of the correctional function, and estimation of the failure time. Following the failure time, data collection is carried out continuously. At this step, the amounts of all parameters affecting failure at the time of failure are gathered. Then, on the basis of accumulation of the effects of all effective parameters, ROH is calculated according to section *III* considering the effect of each parameter. In this step, the precision of the failure function is assessed through consideration of the latest temporal data of the failure time. By analyzing precision of the failure function estimated, the correctional function is upgraded, which is given in section *IV*. The last outputs of this approach are the estimation of next failure time and the certainty level. Due to inherent uncertainty in the deterioration process and the errors of prognosis approaches, consideration of certainty limits seems logical.

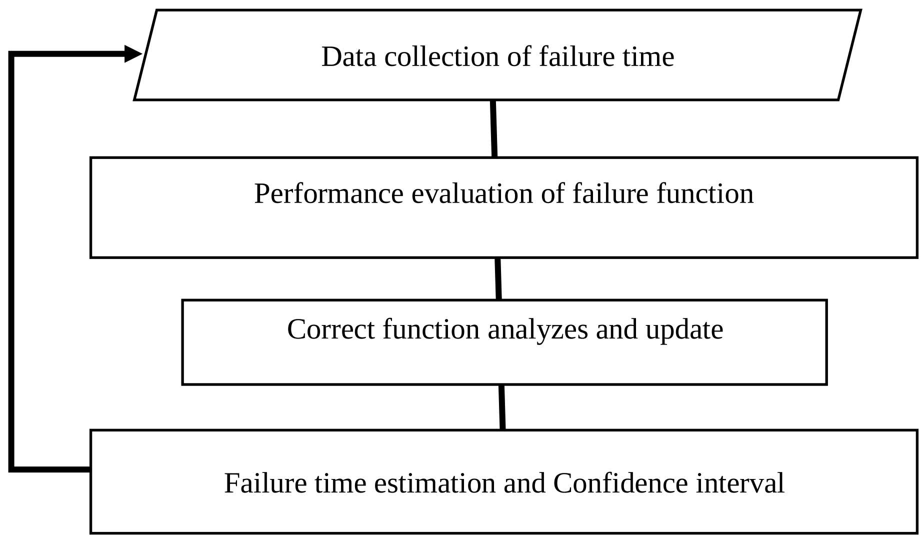


FIGURE 1
THE VARIATION OF THE RATE OF FUEL FLOW

*III. Effective Parameters on turbine failure process*

As mentioned before, the parameters effective in wear of gas turbine are functions of time and working cycles. In the relevant literature, various models have been introduced to combine the time-dependent wear fraction and the working cycle. In the present paper, the model applied is the one which the producers of the machine have suggested for LCF evaluation based on working hours. Table.1 shows all the parameters effective in the failure process. The current approach requires that all the parameters affected by time and the working cycle are combined by (1) for the calculation of equivalent working hours. Relation.1 indicates that all the parameters, with a defined coefficient affect the failure process and lifetime reduction of the system and the various wear fractions within the exclusive temperature range are weighed by an appropriate factor.

In accordance with Table.1, the start and turn-off of gas turbines, rapid temperature changes, protective measures load rejection and trip, rapid loading, and working time are

TABLE I
EFFECTIVE PARAMETERS ON FAILURE PROCESS

$$t_{equ} = \sum_{i=1}^{2} a_i n_i + \sum_{j=1}^{n} t_i + w * f * (\dots . t_{base} + b_2 t_2) \qquad (1)$$

| | |
|---|---|
| $t_{equ}$ | equivalent operating hours |
| $n_1$ | number of starts |
| $a_1$ | start factor |
| $n_2$ | number of trips |
| $a_2$ | rapid loading factor |
| $t_i$ | equivalent hours due to rapid temperature change |
| $n$ | number of rapid temperature change |
| $t_{base}$ | operating hours at up to base load |
| $t_2$ | operating hours from base load to peak load |
| $b_2$ | peak load factor |
| $f$ | fuel weighting factor |
| $w$ | weighting factor for injection of water |

among the effective parameters in speeding up the turbine failure process. Also, the dependence of creep strength on temperature and its effect on the equivalent working hour are given by weighing factors $b_1$ and $b_2$. Given the effect of temperature on reduction of lifetime, the basic load factor is assumed as $b_1 = 0$. At temperature rates higher than the basic temperature rate, the input temperature and consequently the temperature of metal parts along the gas path items increase thus causing the load factor at temperature rates higher than the basic rate ($b_2$) to be equal to 1. The tests run by the machine producers demonstrate that the number of working hours between the basic load and the peak load ($t_2$) affect the calculation of the EOH with a coefficient of $b_2 = 4$ , which shortens the inspection intervals.

The basic fuel weighing factor is the light liquid fuel for which one can assume $f = 1$. As fuel pollutants increase, f approaches 1.5 ($f = 1.5$). For heavy fuels, the fuel weighing factor varies between 1.5 and 4 as a function of concentration and the turbine input temperature (More details are provided in the repair and maintenance manual.) Weighing factors of w and f cannot be directly combined for water and polluted liquid fuels since they follow different chemical and mechanical mechanisms; so producers advise that the weight of these two are fully discussed with designers of the turbines in the factory.

Each start that involves measured and registered gas temperatures, clearly elevated to indicate ignition of the main flames, is designated as start $n_1$. Moreover, automatic registration (major inspection meter) is considered a start while the switching speed above ignition speed is exceeded (approx. 1/3 rated speed). And for starts, the associated weighing factor is $a_1 = 10$ (start factor). Measurement of working time is also carried out on the basis of this speed switching point.

Each time the associated selector switch is actuated during operation, a rapid loading $n_2$ is counted. The weighing factor $a_2 = 10$ (rapid loading factor) is attributed to the standard setting of the rapid loading sequence. As a result, a start with rapid loading is weighted 20 EOH. In the event the option of a start with reduced startup power is chosen, acceleration goes ahead at a higher temperature of the hot gas. This type of start is to be weighed as a rapid loading, in terms of its additional loading.

Where the rapid temperature varies, $t_1$ equivalent working hours also accrue in the manner identical with rapid load changes or when the protective measures load rejection and trip take place. Equivalent operating hours caused by rapid temperature changes are shown on the working hours meter as dynamic working hours. Rapid load changes are particularly likely to happen in small, island-like electric power supply grids when large power loads (for example, electric arc furnaces) are supplied or on loss of a major power plant.

### *IV. Correctional function*

Repair and maintenance instructions for gas turbines are upgraded on the basis of data and information exchange between the producers and the factory. Following such instructions, gas turbines could operate for 8500 equivalent time units at a great certainty level, after which begins the process of damage. However, what is reminded by operational units is that the equivalent time calculated is a guiding measure which could increase or decrease as a function of working conditions and findings of inspections. This degree of diversion could be covered by the correctional function and to do this, we can rewrite (1) as (2):

$$t_{equ-new} = t_{equ} + g\left(t_{equ}\right) \qquad (2)$$

The measures affecting turbines failure are a set of consistent and inconsistent measures. As mentioned above, wear in gas turbines systems is a function of time and working cycles. Time as a basic measure gives the use of the system till failure time affects wear and working cycle variables assume their values during the process of use. In fact, such measures affect the product's failure alongside the first measure and they are dependent on the first measure, that is at the beginning (time is zero) they are equal to zero and then they gradually increase, so they are non-negative and non-diminutive. In the literature, these systems are called systems with two scales [12]. So, there is one basic rate of failure according to the temporal process and the natural deterioration. In the course of using the system some factors quicken the deterioration process with a particular coefficient. In gas turbines, the basic measure is the working time, and the variables listed in Table.1 affect the failure process of the system as additional measures.

According to [11], the measures defined above could affect the rate of risk in the system by (3):

$$r(t) = r_0(t) + \eta_1 M_1(t) + \eta_2 M_2(t) + \cdots + \eta_m M_m(t) = r_0(t) + \sum_{i=1}^{n} \eta_i M_i(t) \qquad (3)$$

Where $r_0(t)$ is the basic hazard rate and $M_1(t)$ is the effect of the first additional temporal measure on the hazard rate; so $M_m(t)$ is the effect of the mth additional temporal measure on the hazard rate. If $Z(t) = \eta_1 M_1(t) + \eta_2 M_2(t) + \cdots + \eta_m M_m(t)$ the joint distribution function is defined as:

$$f_{T,U}(\mathrm{t},\mathrm{u}) = f_{T|Z(t)}(t|u) f_{Z(t)}(u) \qquad (4)$$

The correction function given in (2) is a linear function as $g(t) = ct$ in which $t$ is an random variable in the probable distribution of $fz(t)$. So in the step following calculation of joint probability distribution, we can calculate $f_{Z(t)}(u)$. The additional temporal measures are dependent on the basic measure and independent of each other. Different values of each additional measure happen with a certain probability at any time. For different values of the additional measures at any time, different values of $Z(t)$ is found; so due to independence of the additional measures from each other, probability for each value of $Z(t)$ is the multiplication of the probabilities for the similar values belonging to the additional measures. Moreover, we might have different sets of additional measures for a constant value of $Z(t) = u$. Therefore:

$$f_{Z(t)}(u) = \sum_{j=1}^{J} p(\mathrm{z}_j(t)) \qquad (5)$$

Where for each value of $Z(t) = u$, J is equal to the number of states in which $\eta_1 M_1(t) + \eta_2 M_2(t) + \cdots + \eta_m M_m(t) = u$. The simulation approach used for estimation of the probability distribution function of $fz(t)$ is:

1- Consider every possible amount of failure time, $(t_i, \forall i = 1, \dots, N)$.
2- Partition the interval $[0\ t]$ into K equal parts.
3- Generate points on the sample path of $M(s), s \in \{0, \frac{t}{k}, \frac{2t}{k}, \frac{3t}{k}, \dots, t\}$
4- According to the generated random values, find the possible values of $\omega(t) = u$
5- Approximate $\mathcal{W}_i(\mathrm{t})$ conditional on $(t) = u$
6- Find probability distribution of $\mathcal{W}_i(\mathrm{t})$.

## APPLICATION AND ANALYSIS

Table.2 provides all the data gathered from a gas turbine. These data have been obtained from 12 times of repair on one gas turbine in the same place. The operational data in various working conditions have been seen as the basic data to evaluate the system. Each working condition consists of 12 different variables.

The fuel flow that acts as the control parameter of the engine is a major contributor to the behavior of a simulated dynamic engine. For this study, the fuel flow schedule is depicted in Fig.2, where it is clear that it nonlinearly varies with regard to time.

TABLE 2
GATHERED DATA FROM A GAS TURBINE

| Description | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | G9 | G10 | G11 | G12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Start counter | 28 | 27 | 34 | 15 | 20 | 45 | 39 | 20 | 19 | 30 | 27 | 25 |
| Emergency start counter | 11 | 11 | 15 | 2 | 11 | 18 | 15 | 9 | 10 | 11 | 12 | 7 |
| Fast loading counter | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 |
| Aborted starts counter | 3 | 9 | 3 | 1 | 1 | 21 | 6 | 5 | 5 | 8 | 12 | 1 |
| Trip events counter | 42 | 31 | 8 | 3 | 16 | 35 | 22 | 4 | 6 | 15 | 32 | 4 |
| Load rejection counter | 3 | 4 | 3 | 1 | 6 | 2 | 3 | 1 | 0 | 1 | 7 | 10 |
| High loads trips counter | 8 | 2 | 2 | 1 | 3 | 2 | 3 | 0 | 1 | 0 | 6 | 3 |
| High load rejection counter | 2 | 3 | 1 | 1 | 4 | 1 | 2 | 0 | 0 | 0 | 6 | 4 |
| Peak loads hours counter | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0.1 | 0.1 | 0 | 0 |
| Fast temperature change EQ hours | 50.8 | 95.1 | 117 | 119.4 | 86.1 | 96.5 | 55.4 | 53.4 | 183.9 | 187.2 | 111.6 | 123.3 |
| Base load hours counter | 8042.2 | ٨٠٦٥ | 7395 | 8028.5 | 8002.1 | 7655.3 | 7870.6 | 7211 | 7989.4 | 7487 | 6577.2 | 6791.9 |

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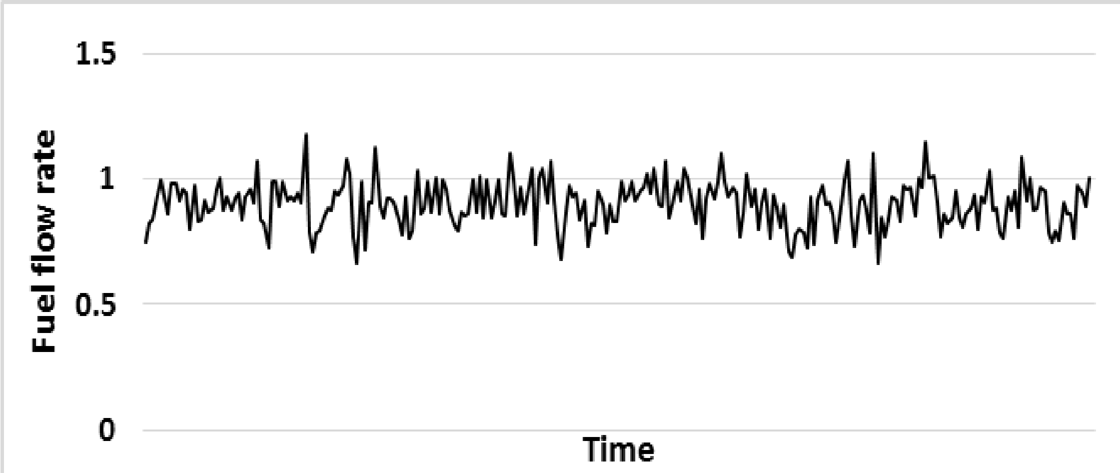


FIGURE 2
THE VARIATION OF THE RATE OF FUEL FLOW

The failure time prediction is a complex nonlinear. The goal is to predict the time of equipment failure on the basis of the available age and data of monitoring the condition. There is a very complex relationship between the input, the age and the data of the condition monitoring, and the output, the

passed life percentage, and this relationship is non-linear; hence, in a multi-time scale system, MATLAB could be a powerful tool to deal with the probability function and the problem of failure time prediction in the approach proposed, because of the capability it possesses in modeling a complex non-linear relationship.

In the present study, MATLAB has been used, along with the simulation approach given in secton.2, in order to predict the correction function of failure time in a system. Figure.3 illustrates the simulated relationship between basic working hours of the system and the EOH based on the data from Table.2 and Figure.2.

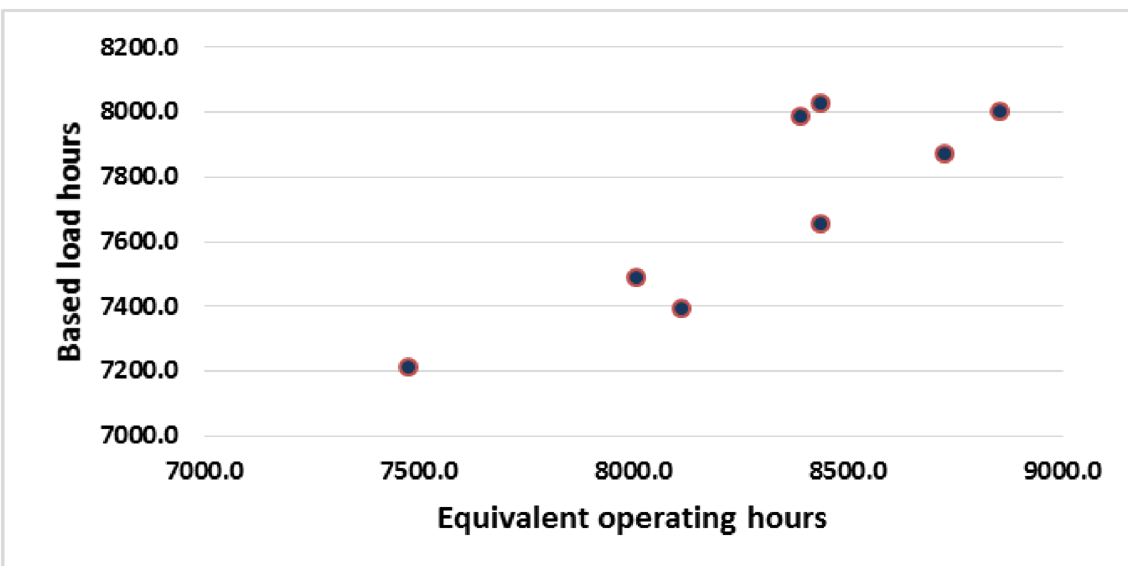


FIGURE 3
THE RELATIONSHIP BETWEEN WORKING HOURS OF THE SYSTEM AND EOH

Looking at the data, we can observe that 90 percent of failures happen in the area between 7800 to 8100 hours of work, which indicate accuracy with regard to these values given for the parameters.

The average prediction error, $\bar{e}$ is considered as prediction precision index and calculated as below:

$$\bar{e} = \frac{1}{n}\sum_{k=1}^{n}|p_k - \hat{p}_k|.100\% \qquad (6)$$

Where n is the number of inspection times in order to test the system, $p_k$ is the passed life percentage of the system at the time of inspection, and $\hat{p}_k$ is the predicted remaining life percentage at $K_{th}$ inspection time. The results is as shown in table 3.

$\bar{e}_{L2}$ is the average of prediction error for the two last times of inspection, which demonstrates that consideration of the last corrections in lifetime prediction is more effective than consideration of all the available data.

TABLE 3

THE RUL PREDICTION RESULTS FOR DIFFERENT TEST HISTORIES USING PROPOSED METHOD

| Period No. | Average prediction error ($\bar{e}$) | |
|---|---|---|
| | $\bar{e}_{all}$(%) | $\bar{e}_{L2}$(%) |
| 1 | 12.5 | 12.5 |
| 2 | 15.6 | 15.6 |
| 3 | 10.4 | 10.7 |
| 4 | 11.7 | 9.3 |
| 5 | 8.1 | 8.0 |
| 6 | 11.2 | 7.4 |
| 7 | 10.5 | 7.1 |
| 8 | 9.1 | 6.9 |

## Conclusion

The first step to get the right results in prognosis of failure time in a system is a thorough study and recognition of all parameters affecting failure. Then, by choosing the best approach base on inputs, we can gain the most effective output. The failure process in gas turbines is too complicated to allow individual signals, used for diagnosis and prognosis, to cover all the situations. The objective of this research is to forecast the failure time of the gas using a linear regression model with regarding a correction function that consider second variables dependent on the time scale as first variable. The results show that considering multi time scales significantly improve forecast accuracy.

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