Development of a Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures

PRADEEP KUNDU*, SEEMA CHOPRA, and BHUPESH K LAD

1Industrial Engineering Research Lab, Discipline of Mechanical Engineering, IIT Indore, INDIA
2General Electric (GE) Power & Water, Bangalore, INDIA

(Received on November 03, 2014, revised on March 20 and June 16, 2015)

Abstract: Machine availability and reliability are two of the most essential concerns for a gas turbine power plant system. A good maintenance program that increases power plant availability while reducing the losses due to unplanned shutdowns should be instituted. A Risk Based Maintenance (RBM) methodology is developed in this paper. It calculates the future risk of failure of a gas turbine power plant system so that the maintenance can be planned just before occurrence of failure. To calculate the risk, first a General Log Linear Lognormal (GLL- Lognormal) model, which tells about damage growth of the machine, is developed. Bayesian approach is then used to update the model parameters (i.e., GLL-Lognormal parameters) on the basis of new inspection data (i.e., crack length) and calculate the updated risk. It is recommended that risk should be continuously updated with the age of the unit to increase the effectiveness of RBM policy. The novelty in this work is that the failure probability is directly dependent on observed crack length instead of time to failures. The whole analysis is illustrated with cap effusion plate inspection data of actual gas turbine system. It is found that the proposed risk based approach gives more accurate results than a normal fleet level model.

Keywords: Risk Based Maintenance, Gas turbine, Combustor, Lognormal Proportional Hazard Model, Bayesian Approach.

1. Introduction

Competition and aging of equipment create financial pressure on businesses to reduce operating cost and consequential cost of forced outages [1]. Proper maintenance of the machine helps in achieving this goal. Generally, there are two types of maintenances: proactive and reactive maintenance. Reactive maintenance is generally a corrective or break down type of maintenance which is performed on failure of the unit. It generally leads to excessive unplanned downtime losses. Proactive maintenance is again divided in two parts viz., preventive and predictive maintenances. Preventive maintenance is performed after a fixed interval of time. The time is either the calendar time or age of the unit. It is very conservative, typically costly, labor intensive, and often makes unneeded inspections and repairs in an effort to ensure failures do not occur. Predictive maintenance is an on-demand maintenance strategy. It is performed based on the condition of the unit. Therefore, it is often referred to as Condition Based Maintenance (CBM). CBM is also a costly technique because prediction of condition requires costly sensors and lots of historical data. The effect of the cost on different maintenance approaches is shown in Figure 1.

From Fig. 1, it can be seen that corrective maintenance approach has a relatively low maintenance cost but high operating costs associated with the high cost of unplanned shutdowns. In contrast, preventative maintenance generally has a low operating cost, but often results in high maintenance cost associated with the replacement/repair of components before they have reached the end of their useful lives [2]. Most efficient
approach is to plan proactive maintenance just before the failure of the machine. Condition Based Maintenance (CBM) can be used for the same.

![Figure 1: Cost associated with Different Maintenance Approaches [2]](image)

However, the effectiveness of the CBM depends on the accurate prediction of the future risk of failure of the unit. A Risk Based Maintenance (RBM) methodology is used in the present paper to predict future risk of the failure of the unit to assist in effective implementation of the CBM strategy in the industry. Some of the risk based maintenance approaches, available in the literature are discussed hereunder.

In general, RBM approaches are classified as qualitative and quantitative approaches. Butler [2] proposed particle filter approach to calculate the remaining useful life of a thermal processing unit and wind turbines. Sepeda [3] discussed a qualitative approach to calculate the risk and proposed a hierarchy of maintenance attention based on various equipment failure risks. Krishnasamy et al. [4] used Weibull and exponential distributions to calculate the risk of Holyrood thermal power generation. Their models depend only on one parameter i.e., time to failures. Hamlin [5] developed a Probabilistic Risk Assessment (PRA) methodology for a space shuttle. Author also studied impact of design, process, and operational changes on risk. Tan et al. [6] discussed the application of analytical hierarchy process (AHP) to select the maintenance strategy for equipment using risk base inspection. AHP generally used to integrate qualitative and quantitative information. Li et al. [7] proposed a combined regression technique, including both linear and quadratic models to calculate the remaining useful life of turbine. Cha et al. [8] proposes a competing risks model for the reliability analysis of unit subject both to degradation and catastrophic failures. Their study addressed to the analysis of real data which refer to some electronic devices. Authors also considered risk assessment based on time to failures only. Igba et al. [9] applied a qualitative reliability centered maintenance approach (RCM) on wind turbine gearbox to optimize the asset value adding contribution at minimal total cost to the operator. Khan et al. [10] also proposed risk based maintenance quantitative approach using Weibull distribution to Heating, Ventilation and Air-Conditioning (HVAC) system. However, their approach also considers only single aging parameter.

It is observed from the literature that most of the approaches for calculation of risk are either of qualitative nature or calculate risk based on time to failures only. Due to high complexity involved in design and operations of machine components, failures may depend on various other parameters and therefore calculating the risk based on only age parameter may not be effective. In the present paper a General Log Linear Lognormal (GLL- Lognormal) model is used to calculate the risk of failure. Furthermore, the risk of failure is updated based on new inspection data using a Bayesian algorithm. It improves the accuracy on prediction of future risk and in turn is expected to improve the
effectiveness of the CBM strategy. The paper is organized in the following manner. Next section outlines the proposed risk based maintenance approach. Section 3 presents results and discussion. Section 4 concludes the paper.

2. Proposed Risk Based Maintenance Approach

Concept of risk is important because it links the failures with engineering decision making for machinery and plant. Condition Based Maintenance (CBM) of machinery is one such decision making. Effectiveness of CBM lies in the idea to run a machine up to a point just short of failure. Risk calculation provides a basis for effective implementation of engineering decision (shutdown, repair, or replace) to increase the profit the organization. Risk Based Maintenance (RBM) framework is comprised of two main phases as shown in Fig. 2. First is the risk assessment and second is maintenance planning on the basis of the calculated risk [11]. The risk assessment phase involves (i) identification of scope/case study; (ii) Damage growth model; (iii) Risk calculation based on fleet level damage growth model; (iv) Updated risk calculation based on Bayesian approach; (v) Financial impact estimation. These are discussed briefly in following paragraphs. Use of calculated risk and financial impact for maintenance planning is discussed in results and discussion section of the paper.

2.1 Case Study: Heavy Duty Gas Turbine

The purpose of Gas Turbine is to convert chemical energy of fuel into electrical energy. Mainly, gas turbine consists of air compressor, combustor, turbine and generator. These four components also contain some subcomponents. For example, combustor consists of fuel nozzle, end covers, cap effusion plate, combustion liner and transition pieces. Different parts of combustor have different types of failure modes. Some of the historically observed failure modes in a combustor are liner cracks, liner bulging, thermal barrier coating spallation, fuel nozzle clogging, end cover braze leaking joint and effusion plate cracks [12]. In the present paper, focus is on the failure of a cap effusion plate of a gas turbine (Fig. 3). Purpose of cap effusion plate in the combustion chamber is to withstand the thermo-mechanical fatigue. It has premixed tubes acting as shrouds for the fuel nozzle (Fig. 4). Cap effusion plate failure is generally defined in terms of critical length of the crack beyond which it is not suitable to perform its function [13]. Therefore, one of the failure modes of the cap effusion plate studied in this research is the crack due to thermo-mechanical fatigue. Borescopic Inspection (BI) has been used to measure the crack length values of cap effusion plate at various exposure hours and starts. BI generally monitors the condition of internal components without removal of the casing. For example, radially aligned holes are provided in some of the designs of the combustor casing that allow the penetration of an optical borescope into the combustor flow path area [14]. Fleet of GE gas turbine has been considered for the current study. Fleet means the group of identical machines, operating under similar conditions and engaged in the same activity [15].
Figure 2: General Risk-based Maintenance Approach

Figure 3: Cap Effusion Plate Cracking [16]  Figure 4: Fuel Nozzle Assembly [17]
2.2 Damage Growth Model

For predicting the damage growth of the cap effusion plate General Log Linear Lognormal (GLL-Lognormal) model is used. A random variable is log normally distributed if the logarithm of the random variable follows the normal distribution. Because of this, there are many mathematical similarities between the lognormal distribution and a normal distribution. If crack length follows lognormal distribution then cumulative probability of failures is given in (1).

\[ F(L) = \Phi \left( \frac{\ln(L) - \mu}{\sigma} \right) \quad (1) \]

Lognormal distribution is a two parameter distribution. It is characterized by \( \mu \) and \( \sigma \), which are the mean and the standard deviation of the distribution respectively. \( \Phi \) is the standard normal cumulative density function and \( L \) is the crack length.

The probability of failure changes with exposure as well as other factors like, environmental and operational condition factors. The General Log Linear Lognormal (GLL-Lognormal) model was developed to estimate the effect of different factors influencing the time to failures of a system. According to GLL model, the probability of failure is affected not only by the operational exposure, but also by the covariates under which it operates. The mathematical formulation of GLL-Lognormal is given in (2).

\[ F(L) = \Phi \left( \frac{\ln(L) - (a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n)}{\sigma} \right) \quad (2) \]

where, \( \mu = (a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n) \), \( a_0 \) is intercept and \( a_1, a_2 \) are the coefficients for critical \( X \)'s respectively which are correlated to failure.

As seen from (1) and (2) the GLL-Lognormal has all of the properties of a standard lognormal, except the lognormal mean is a linear function of critical \( X \)'s which are correlated to failure. For the current model critical \( X \)'s is \( \ln(\text{hours}) \). The usual form of the GLL-Lognormal used in current damage accumulation model is:

\[ F(L < L_{\text{critical}}) = \Phi \left( \frac{\ln(L_{\text{critical}}) - (a_0 + a_1 \ln(\text{hours}))}{\sigma} \right) \quad (3) \]

where, \( L_{\text{critical}} \) is critical length above which the component is replaced.

2.3 Risk Calculation Using Fleet Level Damage Growth Model

The risk of failure is defined as the conditional probability of a part failing at some additional operating time \( \Delta t \), given that it has survived up to time \( t \). So, risk is calculated as:

\[ \text{Risk} = P \left( \left( t + \Delta t \right| t \right) * 100 = \frac{P(t+\Delta t) - P(t)}{1-P(t)} * 100 \quad (4) \]

where, \( P(t+\Delta t) \) and \( P(t) \) are the probabilities of a crack exceeding a given limit at time \( (t+\Delta t) \) and \( t \) respectively.

\[ P(t) = F \left( L > L_{\text{critical}} \right| \text{hour} \right) = 1 - \Phi \left( \frac{\ln(L_{\text{critical}}) - (a_0 + a_1 \ln(\text{hours}))}{\sigma} \right) \quad (5) \]

Risk brings together contributory elements of the business and multiple engineering disciplines [1]. So from business point of view financial impact is calculated using (6).

\[ \text{Financial impact ($)} = \text{Risk} * \text{Failure Consequences ($)} \quad (6) \]

where, failure consequences are the downtime cost associated with the failure. Financial impact is used to calculate the updated inspection/maintenance schedule to accommodate customer demand of extending the inspection schedule of the gas turbine by certain hours. On the basis of financial impact decision has to be made whether to go for maintenance or not or by how many hours machine can run safely to accommodate customer demand.
2.4 Updated Risk Calculation Using Bayesian Approach

In product reliability and availability studies, Bayesian methods offer an intelligent way of incorporating the field experience and data, resulting in an overall more precise failure probability estimation.

Risk calculation using GLL-Lognormal Model is not accurate because it does not consider field data (i.e., crack length). It considers only operational exposures. Purpose of using Bayesian here is to use inspection data (observed crack length) to calculate the unit specific risk. The process of Bayesian update can be repeated continuously with each inspection. Any Bayesian update method for a damage accumulation model requires a few common elements given below:

a) An underlying damage accumulation model characterized by some parameters that have some statistical uncertainty associated with them (i.e., GLL-Lognormal here)
b) Some prior information about the uncertainty around these parameters (Ex: $\sigma$, $\mu$ are normally distributed with known mean and variance).
c) Some field data that will be used to modify the original $\sigma$ and $\mu$ (for example crack length in this paper)

Using the Bayesian method, we calculate “Bayesian update factors” for the distribution location and scale parameters. These factors adjust the location and scale parameters to reflect inspection data (i.e., they simply “push” or “pull” distribution) and on the basis of these updated parameters future risk is calculated. Bayesian approach is derived from Bayes theorem and is shown in (7).

$$P(Hypothesis/\text{Data}) = \frac{P(\text{Data}/\text{Hypothesis}) \times P(\text{Hypothesis})}{P(\text{Data})}$$ (7)

where, $P(\text{Hypothesis})$ is the prior probability of hypothesis (before taking into account new inspection data), $P(\text{Hypothesis}/\text{Data})$ is the conditional probability of hypothesis given new inspection data and $P(\text{Data}/\text{Hypothesis})$ is the conditional probability of data given hypothesis.

Thus, the observations of new inspection data update information on event of interest. In the current model hypothesis is model parameters (i.e., $\mu$ and $\sigma$) and the inspection data is the crack length. So, the Bayes theorem can be rewritten for the present case to update the risk as shown in (8).

$$P(\mu, \sigma/\text{crack length}) = \frac{F(\text{Crack Length}/\mu, \sigma) \times P(\mu, \sigma)}{P(\text{crack length})}$$ (8)

where, left hand side of equation presents the posterior distribution of model parameters.

It applies to predict the updated risk. In the right hand side of equation, in numerator, first factor presents the conditional probability of observed data with assumed model (lifetime distribution) given parameters and second factor presents the prior distribution of model parameters. Denominator of equation is called normalizing constant which assures that posterior distribution is valid probability distribution and integrates to 1. Normalizing constant causes computational difficulties, so Bayes formula is expressed as:

$$P(\mu, \sigma/\text{crack length}) \propto P(\text{crack length}/\mu, \sigma) \times P(\mu, \sigma)$$ (9)

It can be written as:

$$\text{Posterior} \propto \text{likelihood} \times \text{prior}$$ (10)

where, likelihood for a lognormal distribution is given in (11).
Likelihood = \( P(l_i/\mu \text{ and } \sigma) = \prod_{i=1}^{n} \left[ \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{\ln(l_i)-\mu}{\sigma} \right)^2 \right) \right] \)  

(11)

2.4.1 Main Steps for Bayesian Update Algorithm

Consider a density function with parameters \( \theta \), written as \( f(\theta) \). The observed data is in vector data. The fundamental rule for Bayesian inference is:

\[
f(\theta/\text{DATA}) = \frac{L(\text{DATA}/\theta) \cdot f(\theta)}{\int L(\text{DATA}/\theta) \cdot f(\theta)d\theta} = \frac{R(\theta) \cdot f(\theta)}{\int R(\theta) \cdot f(\theta)d\theta}
\]

(12)

where \( R(\theta) = \frac{L(\theta)}{L(\hat{\theta})} \) is relative likelihood and \( f(\theta) \) is prior density function.

a) From damage accumulation model \( i.e. \), Log normal distribution (with a known \( \sigma \) and \( \mu \) that is not known precisely), \( \sigma \) and \( \mu \) has a prior distribution with some mean and variance.

b) Generate the \( i^{th} \) sample, \( \theta_i \), \( i=1 \ldots N \), from prior \( f(\theta) \). The prior can be sampled from the covariance matrix used in the damage accumulation model.

c) Now calculate likelihood function with prior distribution values and sampled distribution values, and then pass the relative likelihood ratio through a statistical filter (\( i.e. \), retain the \( i^{th} \) sample value, \( \theta_i \), with probability \( R(\theta_i) \)). Do this by generating \( U_i \), a random quantity from a uniform \((0, 1)\) and retain \( \theta \) if \( U_i < R(\theta_i) \).

d) It can be shown that the retained sample values, say \( \theta_1, \ldots, \theta_N^{*} \) \( (N^{*} < N) \), are a random sample from posterior pdf \( f(\theta/\text{DATA}) \).

e) The average of the updated distribution of \( \sigma \) and \( \mu \) is the new best estimate of \( \sigma \) and \( \mu \), \( i.e. \), this is the new value of scale parameters that will be used for risk calculations.

It can be concluded that Bayesian is very useful because it can build a model combining physics based models, expert opinion and data. Also, it is useful when sufficient data is not available. But to use Bayesian approach, we need to understand prior distributions and model evaluation. The overview of whole Bayesian update algorithm is shown in Fig. 5.

![Figure 5: Overview of Bayesian Algorithm](image-url)
3. Results and Discussion

The risk estimation model is constructed based on the fleet of a gas turbine. Data are in the form of exposure hours and corresponding crack length. JMP Pro 11 software is used to construct GLL-Lognormal. The coefficient obtained for the model are $a_0 = -3.1$ and $a_1 = 0.30$ and from these coefficient the risk estimation model is created which is shown in (13).

$$P(t) = \left(1 - \Phi \left(\frac{\ln(2.5) - (-3.1 + 0.30 \times \ln(\text{hours}))}{1.13}\right)\right) \times 100$$  \hspace{1cm} (13)

Let critical crack length as 2.5 inch and consequence of failure be $150$ Million. Now, from new inspection data set, risk can be calculated in two ways: using normal fleet level model (GLL-Lognormal) and Bayesian update. A program has been written in Matlab version 2011 to solve Bayesian approach. The results from both models are shown in table 1. Risk and financial impact are calculated. If we assume that the cost of planned shutdown is $1.5$ million and cost of unplanned shutdown is $150$ million, then from (6) it can be easily infer that the threshold level of risk becomes 1%. It means, whenever risk exceeds 1% then extending inspection hour or planned PM schedule is not desirable. In other words, based on the critical limit of risk as 1%, extra time, a machine can be run safely, can be calculated. In the present work, the same is obtained as 7725 hours and 7994 hours using simple GLL-Lognormal and Bayesian update respectively. Thus, the gas turbine can be made available based on the demand of the customer, for production for 269 more hours based on the updated risk calculation.

<table>
<thead>
<tr>
<th>Normal fleet level model (GLL-Lognormal)</th>
<th>Bayesian Update</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hours</td>
<td>Hours</td>
</tr>
<tr>
<td>Current Interval (6500)</td>
<td>Current Interval (6500)</td>
</tr>
<tr>
<td>Future Interval (7500)</td>
<td>Future Interval (7500)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>-0.466</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1.13</td>
</tr>
<tr>
<td>$F(l &gt; L_{\text{critical}})$</td>
<td>11.059%</td>
</tr>
<tr>
<td>$P(t+dt</td>
<td>t)$ Risk</td>
</tr>
<tr>
<td>Financial Impact</td>
<td>1.24 Million $</td>
</tr>
</tbody>
</table>

Risk value from both the approaches at various intervals of time is also calculated (table 2). It can be seen at time interval of 7900 hours the risk calculated using the conventional approach is 1.134% whereas the risk calculated from the Bayesian approach is 0.952%. It means by conventional approach turbine is above the critical limit (i.e., 1%) whereas from Bayesian approach it is away from the critical limit. Therefore, according to conventional approach turbine has to be stopped before 7900 hours but from the Bayesian approach it can run beyond 7900 hours also.
Table 2: Comparative Risk Analysis Table at Various Interval of Time

<table>
<thead>
<tr>
<th>Time (Hours)</th>
<th>% Risk (GLL-Lognormal)</th>
<th>% Risk (Bayesian)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6700</td>
<td>0.171597</td>
<td>0.145435</td>
</tr>
<tr>
<td>6900</td>
<td>0.339758</td>
<td>0.287491</td>
</tr>
<tr>
<td>7100</td>
<td>0.504639</td>
<td>0.426337</td>
</tr>
<tr>
<td>7300</td>
<td>0.666386</td>
<td>0.562128</td>
</tr>
<tr>
<td>7500</td>
<td>0.825131</td>
<td>0.695009</td>
</tr>
<tr>
<td>7700</td>
<td>0.981002</td>
<td>0.825115</td>
</tr>
<tr>
<td>7900</td>
<td>1.134115</td>
<td>0.952569</td>
</tr>
<tr>
<td>8100</td>
<td>1.28458</td>
<td>1.077488</td>
</tr>
</tbody>
</table>

Thus, for the current problem, the Bayesian approach may give extra run hours, when requested. Owing to the strict data control policy of GE, the exact results are replaced with the current table. The results in current table are scaled version of actual results.

4. Conclusion

The paper presents an approach to optimize the Risk based maintenance using Bayesian algorithm on GE gas turbine. This approach not only increases the availability but also reduces maintenance cost. It is also found that forecast of risk using Bayesian is better than normal fleet level model because it considers field experience and data. Finally, it is concluded that proposed Risk Based Maintenance (RBM) approach using Bayesian update can be used to increase the availability and optimize the high value critical assets (i.e., Gas Turbine) while reducing overall maintenance costs.

Acknowledgement: The authors would like to extend their heartfelt thanks to Manish Rawat, John Korsedal, Binod Pandey, Yogesh Agarwal and Rachana Panuganti, GE Power & Water Bangalore-India for their constructive comments and suggestions.

References


Pradeep Kundu is a research scholar in Discipline of Mechanical Engineering at the Indian Institute of Technology Indore, India. He received his Bachelor of Technology in Mechanical Engineering from BRCM College of Engineering and Technology Bhiwani, India. His research interests include prognosis, reliability engineering.

Seema Chopra is currently working as a technical leader at General Electric Power & Water Bangalore, India. She received her Ph.D. (Controls) from, Indian Institute of Technology Roorkee, Her current areas of research include Prognostic and Diagnostic, Condition based Maintenance.

Bhupesh K. Lad is an Assistant Professor in Discipline of Mechanical Engineering at the Indian Institute of Technology Indore, India. He received his Ph.D. from Indian Institute of Technology Delhi, India. His research interests include Reliability Engineering, Prognosis and Manufacturing Operations Planning.