Diagnostics and Damage Prediction Model for Heavy Duty Gas Turbine Combustor Hardware Failure

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Abstract: The focus of this paper is on the degradation of the combustion liner and developing the risk prediction model to predict the damage based on hours, starts and key operating parameters. The multivariate K-means clustering technique is used for classifying the data into different sets of clusters i.e. hours, starts or hours to start ratio vs. deformation. The effect of hour to start ratio on the liner deformation was studied, with the significant clusters obtained from K-means clustering. It is concluded that the hours-to-start ratio (N-ratio) can be a good indicator of component life and provides useful information while modeling the metallurgical damage for component life prediction. The damage growth model is developed using Liner Bulging data and it is shown that N-Ratio is a critical factor in damage prediction as well. The analysis is illustrated with the help of a limited set of combustor liner inspection data for actual heavy-duty gas turbine operation. Future guidelines provided in the paper are expected to spawn additional work in the area of advanced gas turbine diagnostics.

Keywords: Combustor; hot-gas-path; N-ratio; K-means clustering, damage prediction model.

1. Introduction

Gas turbine technology has steadily advanced since its inception and continues to evolve; research is active to increase efficiency and reliability of the gas turbine while reducing emission. Achievement of high thermal efficiency in gas turbine systems is strongly related to the increase in the turbine inlet temperature. However, increase in turbine inlet temperature exposes the combustor and hot-gas-path components of the turbine to severe thermo-mechanical stresses and may generate thermal damages. These components therefore have relatively short lifespan. It increases the maintenance cost of repair and replacement of these parts. In general, up to one-half to two-thirds of the maintenance costs of the unit is attributable to the repair and replacement of combustor and Hot-Gas-Path (HGP) parts [1]. Such components in a gas turbine include combustion liners, end caps, fuel nozzle assemblies, crossfire tubes, transition pieces, turbine nozzles, turbine stationary shrouds and turbine buckets. The increased maintenance costs of these parts reduce the benefits of the thermal efficiency. Therefore, it provides considerable economic incentive either to extend the total lives of these components or to increase the interval between inspections.

In recent years, several researchers have attempted the failure analysis of combustor and hot-gas-path components. Kim et al. [2] have found the locations of high stresses under the steady state operation and the base-load operation using the thermal analysis of the after section of combustor liners. The objective of their study was to find major causes of thermal damages affecting the component creep lifetime impacted by the temperature and thermal stress distribution. Moritsuka et al. [3] have described a gas turbine maintenance management program of combustor and hot-gas-path parts for management of multiple combined cycle power stations in order to obtain an optimal gas turbine performance.
maintenance schedule considering part rotation, repair and replacement, or exchange of those components.

Wood [1] reviews the sources of degradation in combustor and hot-gas-path components, technology available to quantify the damage, and available assessment procedures which can be used for component life assessment. The author has also identified some of the areas that require further attention. These can be summarized as:

- Metallurgical damage quantification techniques,
- Metallurgical damage accumulation models,
- Improved engine sensor data (as an input into the historical operational conditions for the unit) and,
- Consequence of uncertainties in data and methodologies on residual life estimation.

Any metallurgical damage accumulation model depends on the operating profile of the gas turbine. For example, the failure of the stationary, rotatory components is affected by the start/stop cycle. Such cycles can be planned start-up/shut-down cycles or due to unplanned forced outages. Figure 1 illustrates the firing temperature change occurring over a normal start up and shut down cycle. Operational events such as light off, acceleration, loading, unloading and shutdown will result in varying gas temperatures across the cycle, resulting in a corresponding metal temperature variation. Furthermore, any abnormal behaviour in turbine performance warrants immediate shutdown of the gas turbine, as defined by control system logic.

![Figure 1: Turbine Start/Stop Cycle-Firing Temperature Change](4)

Frequent shutdowns and restarts due to planned and unplanned events produce rapid change in gas temperature and may cause temperature gradients within the combustor and hot-gas-path components. Such gradients, in turn, produce thermal stresses that, when cycled, can eventually lead to failure. Hence, any life assessment technology also needs to study the effect of such start/stop cycles on the failure pattern of the components. In this real world scenario, any system comprised of multiple components encounters different varieties of failure modes like, fatigue, creep *etc*. The amount of component or system exposure (measured in time or cycles of operation) is expected to influence the nature and extent of the damage or degradation. Analysts may characterize damage by developing a model from operational and component specific data. The developed model predicts an estimate of failure risk due to specific failure modes at either the component or system level. The popular methodology of failure risk estimation can be divided in to two basic model categories: a Weibull or Lognormal model and Damage Growth Model.
Weibull models characterize the reliability of a component or system as a function of operational exposure. Damage Growth Models characterize damage growth trends as a function of operational exposure. Weibull models predict the probability of damage events during the life estimation whereas the Damage Growth Models are usually able to produce risk and reliability results for any component or system over time, which provides an effective means for continuous assessment, based on the past and current conditions of the system.

In this paper, the major focus is on the combustion liner, which is one of the critical components of the combustor. The specific failure mode studied in this paper is bulging at the forward section of the liner. The multivariate K-means clustering technique is used for classifying the data into different sets of clusters i.e. hours, starts or hours/start vs. bulging. The effect of hour-to-start ratio on the liner bulging is studied, with the significant clusters obtained from K-means clustering. It is concluded that the hours-to-start ratio (N-ratio) can be a good indicator of component life. The analysis is illustrated with the help of a limited set of combustor liner bulging data for actual heavy-duty gas turbine operation. The input data to the Damage Growth Model consists of damage measurements as the bulging value as a function of several vital X’s like operational parameters as hours, starts, trips, N ratio etc. N ratio is described as ratio of operational Hours and Starts. The work reported in this paper is expected to help the researcher in building more accurate life prediction models by incorporating the effects of the number of starts on the component damage data obtained from the inspection.

2. Gas Turbine Combustor

Heavy-duty gas turbines are commonly used to generate electricity in simple cycle or combined cycle power plants. A typical simple cycle power plant consists of an air compressor, combustor, a turbine and a generator. A combined cycle power plant includes exhaust heat recovery steam generator and steam turbine in addition to the simple cycle power plant equipment. Parts unique to a gas turbine requiring the most careful attention in both types of power plants are those associated with the combustion process and those exposed to high temperature from the hot gas discharged from the combustion system. They are called the combustor section and rotatory parts. The focus in this paper is on failures related to the combustor portion of the gas turbine.

3. Failure Diagnostics of Combustor

Different components of gas turbine combustor have different failure modes. Some of the historically observed failure modes in a combustor are effusion plate cracks, liner cracks, liner bulging, TBC spallation and TP cracks, fuel nozzle contamination, etc. Each gas turbine may have unique operating characteristics and modes of operation affecting the life characteristics of the combustor components. Figure 2 shows a cause and effect diagram of the combustor failure. By observing the field physics of failure, there are various factors which affect the combustor failure modes which are described in Figure 2. However; it has been observed that the operating profile pertaining to start-up and shutdown plays an important role in failure diagnostics of the combustor components.

In the combustor, a proper balance of fuel and air mixture is needed to have an efficient combustion process. It would be desirable to run the process at the stoichiometric Fuel-to-Air (F/A) ratio. However, the combustion process also produces toxic by-products such as NOx and CO. As the F/A ratio increases the flame temperature increases which results in increased NOx formation. The production of NOx can be reduced by lowering the combustion temperature, which is achieved by operating at lower F/A ratios and/or
using forced cooling techniques. At low F/A ratios, the combustion process approaches the lean blowout limit where the combustion zone becomes sensitive to fluctuations and tends to become unstable.

These instabilities occasionally result in high combustion dynamics that can lead to combustor damage. Such kinds of abnormal behaviour in the gas turbine can cause it to trip to prevent further damage of the turbine. Trip of a gas turbine is a phenomenon when operational parameter goes beyond the threshold and control system shut down the gas turbine from the operating nature to stop. The unplanned shutdowns due to trips and the subsequent restarts lead to excessive temperature fluctuations and thermal stresses. Planned shutdowns of gas turbines are also becoming increasingly common as the power-plant owners try to meet the fluctuating demands of their customers. Operational trends have been introduced earlier in the paper. As a result, power plants are tending towards cyclic operation rather than the base load mode. Such planned start-ups and shutdowns again leads to fluctuating loads on the different gas turbine components causing wear and other forms of degradation.

4. Hour-Start-Deformation Correlation Analysis

It is clear from the preceding sections that failure of combustor components are affected by the operating parameters. Any advanced gas turbine diagnostics technology must therefore consider the effect of the normal starts as well as the starts subsequent to uncontrolled trips. Such technologies are generally based on the models derived from the field inspection data. The accuracy of such models depends on the amount of data points at a given exposure of hours and starts. However, depending on the user’s requirements and current performance of the gas turbine obtained from online monitoring system, different gas turbines may undergo inspection at different exposure of hours and starts. The result is that the prognostics engineer is left with only a small number of data points against a given exposure. In order to deal with such situations, a K-means clustering approach is proposed in this paper to cluster the limited set of data points. The significant cluster obtained from K-means is then used for further study of the hour-start-deformation correlation. The approach is illustrated with the help of field inspection data for combustor liner bulging. In order to maintain the confidentiality of the data all the analysis results are presented with the help of normalized data of liner bulging.

![Figure 2: Combustor Failure Cause and Effect Diagram](image-url)
4.1 Data Collection

Combustor liner inspection data was collected for 20 gas turbine units. The failure mode focused in this study is liner bulging. It is assumed that all these units operate under the same operating and environmental conditions. Inspection data over the last 10 years was considered for the analysis. In general, the data contains bulging values at different exposures defined in terms of number of starts and hours at a given inspection date. More specifically, the data was collected for - turbine number, date of inspection, part number, interval hours the turbine has run, the corresponding number of starts and bulging depth.

4.2 Cluster Analysis

Data clustering is a common technique for statistical data analysis, which is used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics. Clustering is the classification of similar objects into different groups, or more precisely, the partitioning of a data set into subsets called as clusters, so that the data in each subset share some common trait - often proximity according to some defined distance measure.

5. K-Means Clustering

K-means clustering [5] is the most common statistical based data clustering method in use today. Clustering of a data set could be either fuzzy (having vague boundaries among the clusters) or crisp (having well-defined fixed boundaries) in nature [6]. K-means is also the simplest unsupervised learning algorithm that solves the well-known clustering problem.

K-means clustering partitions the observations in data into K mutually exclusive clusters, and returns a vector of indices indicating to which of the K clusters it has assigned each observation. These differences often mean that K-means is more suitable for clustering large amounts of data, as it does not create a tree structure to describe the groupings in data, but rather creates a single level of clusters.

Also, K-means clustering uses the actual observations of objects or individuals in data, and not just their proximities. K-means treats each observation in data as an object having a location in space. It finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume K clusters) fixed a priori. Initial cluster centres are chosen randomly; at each iteration, data are assigned to the closest cluster centre, and the new cluster centres are calculated based on the new data allocation. Figure 3 shows the flow chart of the K-mean clustering algorithm. Steps for K-means algorithm are as follows:

- Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
- Assign each object to the group that has the closest centroid.
- When all objects have been assigned, recalculate the positions of the K centroids.
- Repeat Steps 2 and 3 until the centroids no longer move.

This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

K-means require an estimate of the number of clusters, K. Many criteria have been introduced to find an optimal K. Silhouette coefficient [7] is a data separation metric that assesses the average distance from the i\textsuperscript{th} point to all other points in its cluster C\textsubscript{i}. Let’s assume this value as average ‘a’.
Then calculate the average from the \( i^{th} \) point to all other cluster points in cluster \( C_b \). Let’s assume this value as average ‘\( b' \). Then, the Silhouette coefficient is defined as:

\[
S_i = \frac{b - a}{\max(b, a)}
\]  
(1)

The silhouette value for each point is a measure of how similar that point is to points in its own cluster compared to points in other clusters, and ranges from -1 to +1.

- +1, indicating points that are very distant from neighbouring clusters,
- 0, indicating points that are not distinctly in one cluster or another,
- -1, indicating points that are probably assigned to the wrong cluster.

The following approach can be used as general guidelines to determine the number of clusters:

- To get an idea of how well separated the resulting clusters are, you can make a silhouette plot as demonstrated in Figure 4.
- Values greater than 0.6 silhouette value, indicates that the cluster is somewhat separated from neighbouring clusters.
- Points towards -1, indicate they are probably assigned to the wrong cluster, then number of clusters will need to be reinitialized.

6. **Combustor Liner Bulging Clustering Using K-Means Clustering Technique**

Clustering helped in identifying the significant cluster that contains most of the data points having some similarity. Figure 4 and 5 shows the results obtained from K-means clustering analysis of combustor liner bulging data.

Figure 4 clusters the data based on hour-bulging value. It seems that cluster 2 is significant, which is the cluster having higher intervals hours. It means that most of the available bulging data correspond to high interval hours. While Figure 5 clusters the data based on hour/start-bulging. It seems that cluster 1 is significant as well. It means that most of the available bulging data corresponds to lower hours-to-start ratio. Thus data of cluster 2 obtained from hour-bulging (deformation) clustering and cluster 1 obtained from hour/start-bulging will be used for further analysis.
6.1 Effect of Hour to Start Ratio (N-Ratio) on Bulging

The effect of hour-to-start ratio (N-ratio) on bulging for data of cluster 2 can be seen from Figure 6. It is observed that at lower N-ratio the variation in bulging value is large compared to higher N-ratio where variation in bulging value is comparatively less. Also, average bulging value at lower N-ratio is higher than that at higher N-ratio. Similar curve can also be obtained for data of cluster 1 in Figure 5.

A regression model is then fitted to the data of cluster 2 for both the low and high N-ratio zone. The transfer function is obtained for the limited set of normalized data points in high N-ratio zone presented in the reference [8].

\[
\text{Bulging} = -10.509 + 0.314 \times \text{Hours} + 0.03 \times \text{Hours} \times \text{Starts} - 0.00245 \times \text{Hours}^2 - 0.0034 \times \text{Starts}^2
\]

\[ R^2 \] and adjusted \[ R^2 \] values for the model was 0.5418 and 0.5246 respectively. This transfer function is applicable to the data points used in analysis, however similar methodology can be obtained to develop models for any other kind of data. Better fit can be obtained with more data points in the given region. Such a regression model is also developed for the same cluster data in low N-ratio zone which indicated that neither hours nor starts are significant for bulging in low N-ratio zone. The regression model for low N-Ratio zone is not shown here in this paper.
The results in [8] was not helpful in predicting the life of the component, but it was of high significance to the prognostics engineer. For example, high variation in bulging at lower N-ratio may be due to dominating effects of other undetermined variables. Therefore, damage accumulation model based only on hours and starts is not an efficient approach for life prediction at lower N-ratio. Instead, a prognostics engineer may be
interested to capture other explanatory variables responsible for large variation in bulging which may lead to more advanced life prediction models like proportional hazard model, shock models, etc. However, at higher N ratio, the interval hours and the starts may give a better explanation of the metallurgical damage accumulation process. In other words, the effects of other variables on damage process are relatively less in this zone. So the next topic will cover the details of Damage growth model consists of damage measurements as crack lengths, Wear Depth etc, as a function of several vital X’s like operational parameters as hours, starts, trips, etc.

7. Risk Prediction Model

In general, any damage model can be developed in two broad distributions, Weibull and Log normal distributions [9]. When damage data are observed, damage growth models may be established using either of the two types of distribution models. This section of the paper presents the generic risk analysis algorithm and damage prediction formulation based on the two most commonly-used types of distribution models. Various X’s may be considered in the modeling, resulting in different model structures (e.g., Weibull-Log-linear model, or Lognormal-Log-linear model). However, the distribution of damage data as well as the corresponding risk analysis algorithms will not vary as the model structure changes. For any failure mode, the risk of failure is defined as the conditional probability of a part failing at some additional operating time ∆t, given that it has survived up to time t. The conditional probability is calculated as:

\[ F(t + \Delta t|t) = 1 - R(t + \Delta t|t) = 1 - \frac{R(t + \Delta t)}{R(t)} = 1 - \frac{1-F(t + \Delta t)}{1-F(t)} \]

where \( F(t + \Delta t) \) and \( F(t) \) are the probabilities of part failure at time \( t + \Delta t \) and \( t \) respectively.

Failure Risk: If continuous measurements of damage (e.g., crack lengths, wear depth, etc.) are available, the Weibull distribution can be used to model the distribution of damage as a function of various vital X’s (e.g., hours, starts, trips, N ratio etc.), expressed as:

\[ F(t) = 1 - \exp \left( \left( \frac{t}{\eta} \right)^\beta \right) = 1 - \exp \left( -\left( l\eta f(x) \right)^\beta \right) \]

where, \( \eta \) and \( \beta \) represent the scale and shape parameters. Also, \( f(x) \) represents the scale parameter as a function of vital X’s.

Damage Prediction: Considering a heavy duty gas turbine inspected at operational time \( T \sim \{\text{Hours, Starts, Trips}\} \), a total of \( n \) damage quantities have been observed. The predicted damage quantities can be obtained as [10]:

\[ l = f(x) \left( -\ln(1 - L_d) \right)^\frac{1}{\beta} \]

where \( L_d \) is the actual damage rank, which can be calculated using Bernard’s equation [11]

\[ L_d = \frac{r+0.3}{n+0.4} \]

where, \( r \) is the order of the unique sorted damage data, and \( n \) is the number of observed damage for that unit.

7.1 Damage Prediction Model for the Liner Bulging

As considered earlier, that Hours, Starts, and trips are normal operating parameter which are available for the modeling, other parameters like N Ratio (Hours/Starts) or Trips Ratio (Trips/Starts) can also be generated using these available parameters.
Initially, the analyst verifies that the damage measurement follows a Weibull distribution. As explained earlier, that scale parameter can be defined in terms of vital X and coefficients.

\[
\log(L) = \alpha_0 + \alpha_1 \times X_1 + \alpha_2 \times X_2 + \epsilon 
\]  

where, \(L\) is the damage variable, \(\alpha_0\) is a constant, \(\alpha_1\) and \(\alpha_2\) are coefficients for the predictors \(X_1\) and \(X_2\) (vital Xs), and \(\epsilon\) is an estimation of the error. This is a general equation taking two Vital Xs in account; it is possible to add more such terms like \(\alpha_3 \times X_3\), \(\alpha_4 \times X_4\), etc.

With the regression equation acquired from the analysis, the analyst examines the coefficients of the Xs within the equation. The coefficients and their respective signs have a physical meaning, and the analyst should verify that the meaning encoded in the coefficients and their respective signs match the real world scenario being modeled.

The analyst can compare the different models based on their log-likelihood values and Anderson-Darling statistics. Once a set of models satisfies the coefficient sign criterion and the p-value criterion, the analyst should select a model with a high log-likelihood value and low Anderson-Darling statistics. A high log-likelihood value signifies that the model parameters fit the data well, and a low value of Anderson-Darling statistics means that the residuals from the regression equation follow a normal distribution.

![Figure 7: Actual vs. Predicted Damage for Cluster 2](image)

As the model is developed and damage is predicted using Vital X in analysis for cluster 2, Model verification is shown in Figure 7 providing the fit for the model. Graph shown below is between Actual Damage and Predicted Damage. As shown, the model is able to predict the variance present in the actual damage data, though there are some outliers in the data which are beyond the confidence bound of the data. One can define the confidence bound based on the availability of data. For the present analysis, \(\pm 1 \sigma\) (standard deviation) is considered the confidence interval for the prediction.

8. **Conclusion**

In this paper, an attempt is made to study the effect of starts on the metallurgical damage of the combustor component, based on the real time inspection data of the gas turbine. It is concluded that the ratio of hours to start (N-ratio) can be a good indicator of the component life and may provide useful inputs for the development of gas turbine prognostic technology. The use of K-means clustering is demonstrated to deal with the issue of a limited set of field data availability at a given exposure level. Significant clusters obtained from the K-means clustering method is then analyzed to obtain a metallurgical damage accumulation model. A risk prediction model is developed...
considering N Ratio as the Vital X and a model is able to predict the variance present in the data though there is an opportunity to further refine the model considering other Vital X’s which will be able to define the variability in the data more accurately. It is expected that the work reported in this paper will help in development of more sophisticated life prediction models for the gas turbine components.

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References


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