Health Risk Assessment and Prognosis of Gas Turbine Blades by Simulation and Statistical Methods

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Abstract – Algorithmic approaches for failure risk assessment, anomaly detection and life prognosis of gas turbine blade are discussed. Modeling of blade tip clearance and Monte Carlo simulation considering creep, vibration and other damaging effects lead to two probabilistic distributions with blade tip clearance data. Failure risk can be determined during blade life usage based on blade tip tolerance limits. Statistical treatments considering percentile ranking of sample mean and regression analysis of blade tip clearance data for anomaly detection and usage life analysis respectively are also discussed.

I. INTRODUCTION

With increase in demand for power and technological advancement of gas turbines, the power market all over the world has become highly competitive. Maintaining high efficiency, low life cycle cost and high reliability of the gas turbine systems are the key practical boundaries and challenges set for all future R & D activities. These are especially relevant and significant to aerospace industries as NASA has predicted an average number of overseas passengers to reach six millions a day [1] and a requirement of 500 to 1500 second generation supersonic commercial flights to meet the demand. Among other areas of modern gas turbine, hot section region and parts (like blade, vane, combustor etc.) exposed to highest temperatures during operation demand special attention with regards to three criteria as stated above. Gas turbine blades are in general exposed up to 1400°C at inlet and 40 bars pressures and undergo severe metallurgical damages, often limiting their designed lives. The blades undergo creep, microstructural instability and embrittlement, oxidation, thermal fatigue, hot corrosion, vibration, foreign object damages etc. [2, 3]. However, the process which finally controls the blade health and overall life will depend on a large number of factors. The blades are subjected to centrifugal forces due to high rotational speed, bending stresses by the moving gas stream in the presence of highly oxidizing atmosphere at high temperature and thermal stresses due to temperature gradient. Nickel base superalloys superior in high temperature strength and combined with corrosion and oxidation resistance are used as the blade material [4].

However, apart from the superior design and construction material used for gas turbine blades, blade health monitoring and maintenance are very vital for achieving high engine efficiency, safety and reliability in operation. Blade tip clearance (BTC) defining the gap between the tip of blades and the casing is a vital parameter considered by the designers and maintenance managers [3, 5-7]. In this paper, an attempt is made to use this parameter to address the following two aspects for blade health assessment and future usage predictions:

i) Blade failure risk assessment by Monte Carlo simulation of operational data,

ii) Fault diagnosis in blade by anomaly detection and prognosis in turbine blade by statistical treatments.

In this paper we also present an algorithmic approach to be followed, data to be used and different criteria to be adopted in achieving the above goals.

II. BLADE TIP CLEARANCE

Gas turbine engine efficiency has an inverse relation with tip clearance between rotor blade and casing. Pressure rise and flow range of turbo machineries are also affected by BTC [5]. A 15% increase in flow coefficient and a 23% drop in pressure can occur in a typical large compressor. A clearance between the blade tip and the casing is essential to allow blade rotation and thermal expansion. Blade tip gap allows hot and high pressure gas to escape from main flow path. Large gap leads to large leakage of gas resulting in low efficiency, while small tip clearance tends to touch the case leading to disintegration. In order to maintain a balance between the two, the BTC need to be continuously monitored. This parameter has been in use as an efficiency measuring index and blade failure criterion in gas turbine engines. The BTC is measured by a number of techniques even under fast transient conditions. Some of the traditional methods use sensors mounted on casings, eddy current, discharging probe, capacitance, inductive, microwave, infrared, etc. However, real-time non-contact measurements in conjunction with high data acquisition unit are also being employed [3, 7]. The sensors are capable of monitoring BTC during operation and in turn allow detection of any anomaly in data due to vibration, cracking, rubbing, creep and high cycle fatigue damages.

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III. FAILURE RISK ASSESSMENT

Turbine blade failure risk assessment or blade failure probability is important and provides a measure for safety and performance. Monte Carlo simulation for the turbine blade is proposed for the purpose. A model may be developed for risk analysis considering significant mechanisms that lead to failure [8]. The BTC continues to diminish with the usage life of the blade by the changes in dimensions and profile. The predominant mechanisms as illustrated in Figure 1, involved with blade lengthening and thickness reduction include creep deformation, vibration effects, loss of stiffness, and strength by cracking due to fatigue, foreign object damage, temperature rise, etc. [3-5, 9]. These mechanisms are operative in competition and sensitive to the operating condition and environment.

Creep deformation in blades results from the combined effects of both high temperature and high stress over a long time. Higher are these parameters, higher is the creep strain and lower is the BTC. Gas turbine blades are exposed up to 1400°C and are subjected to high stress resulting from centrifugal forces, hot gas pressure and torque. Nickel superalloys with high melting point, stable microstructure, high creep and oxidation resistance are the ideal choice. Creep strain (ε) data can be obtained by integrating the strain rate over the exposed time (t) and given in [10] as

$$d\varepsilon/dt \times d = C\,\sigma^{m} \times e^{-Q/kT} \qquad \ldots(1)$$

where T- temperature in K, σ - applied combined stress, d - grain size, Q - activation energy, k -Boltzmann constant, and m - exponent depending on creep mechanism. Typically, superalloys exhibit creep strain rate around 10^{-8} to 10^{-11} per second when stress on the material lie around 100 to 10 MPa and temperature remains in the range of 1275K to 1075K [4,10, 11]. Equation 1 yields an approximate increment in blade length due to creep effect of 1500 microns for operating hours of 1000 hrs. Fractional change in blade length is additive (i.e. $F_C + F_V + F_D$), where F stands for fractional contribution and C, V and D represent blade lengthening due to creep, vibration and damage factors, respectively. Cracks being the ultimate damage in structural parts introduce local flexibility in reducing stiffness and cause changes in vibration amplitude [12]. In gas turbine blades and vanes, combustion products, metallic particles and foreign object damages introduce structural problems reducing the post impact strength substantially [13]. A parametric model for simulation prediction may be established for F_{BTC} considering the damage effects by vibration and damages in addition to creep effects as in Equation 1. The model uses random data as continuously monitored from turbine blade as input parameters as shown in Figure 1 using sensors and computes the BTC. Today's aircraft turbine systems are typically equipped with a suite of sensors (temperature, pressure, rotor speed, accelerometer, BTC, etc.) [2,3,6,7]. The blade tip clearance is the difference in the original OEM designed BTC (D_{BTC}) and the fractional increment in blade length. With any given operational data set, the BTC is given empirically as $F_{BTC} = |D_{BTC} - (F_C + F_V + F_D)|$.

Assuming an interval of 5 seconds for monitoring and processing of a set of input data, around 700 iterative simulations can be completed in one hour using the model and as many BTC data points can be used to construct a probability distribution curves as shown in Figure 2. Mean and standard deviation for sample set of one hour can be used for this purpose [14-17]. The distributions are envisaged for failure probability assessment considering the randomness of input data, BTC tolerance limits as may be set by the OEM designers and blade usage life fraction.

Asymmetric lognormal distribution with positive skewness during early blade life with mean around the lower tolerance limit is expected (Figure 2a), while lognormal distribution with negative skewness may be expected after considerable life usage and blade damage with the mean lying around the upper tolerance limit (Figure 2c). A lognormal distribution appears to be logical when most of the data will be either negative or positive in relation to the two extreme BTC tolerance limits. Alternately, a normal distribution over the full blade usage life appears appropriate with mean at the peak lying around the average tolerance limits (Figure 2b). This distribution fits better during midlife of the blade where most of the simulated BTC data points are expected to fall between the upper and lower tolerance limits. The blade tip failure probability (as marked by the two shaded areas in the normal distribution curve) from the distribution curves in Figure 2b over the allowable limits can be determined.

During early life of blade higher failure risk implies that the gap size is more allowing easy escape of hot gas and thus reducing engine efficiency. Failure risks, on the other extreme, will be more as the gap size reduces with blade damage (cracking, lengthening, vibration) leading to safety and integrity problems. With continued model input data during operation and iterative simulations, the anomaly in blade performance can be determined from the changes in blade failure probability.

IV. FAILURE ANALYSIS BY STATISTICAL TREATMENTS

Real-time diagnosis and prognosis for turbine blade that will detect, classify, and predict developing faults is critical to reducing operating and maintenance costs. The objectives of failure analysis by statistical techniques as discussed in the following sections are two-folds:

i) Detection of anomaly (deviation), i.e., diagnosis (D) of fault

ii) Estimation of remaining useful life beyond anomaly detection and fault growth, i.e., prognosis (P) for life

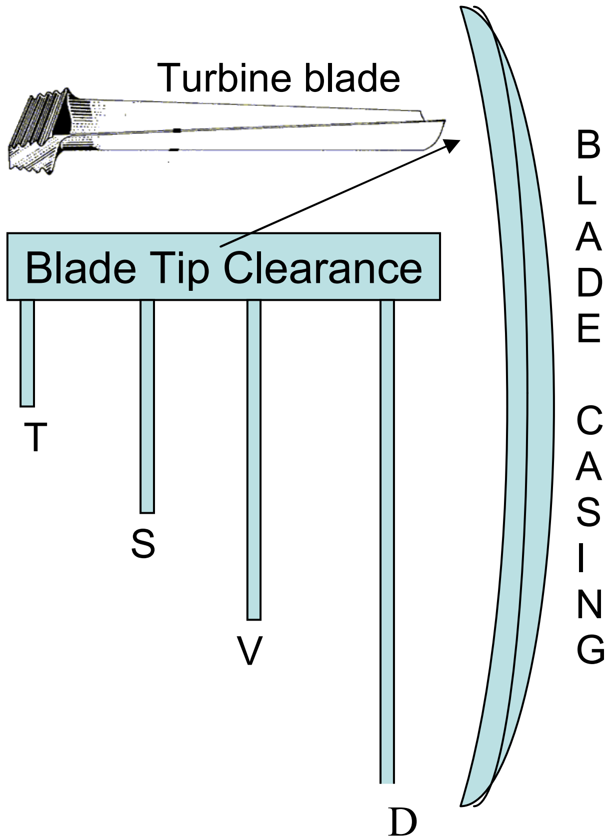

Figure 1: Competing sources leading to the changes in blade tip clearance; T- temperature, S- cumulative stress, V- vibrational effects, and D - other damaging effects like foreign objects

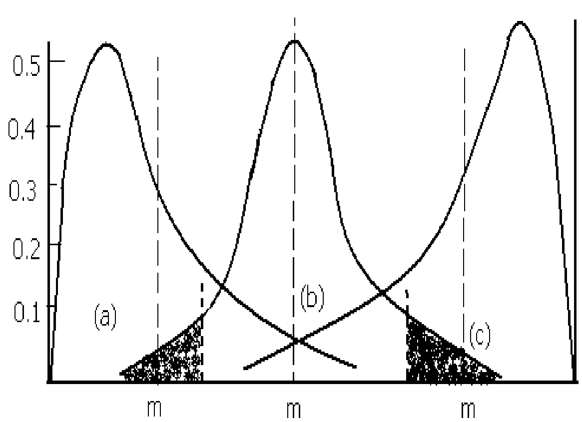

Figure 2: Probability distribution using random BTC data (mean, m) at different life usage (a) lognormal distribution during early blade life, (b) normal distribution around midlife, and (c) lognormal distribution during later part of life.

An anomaly represents, in general, any significant deviation in operational data or behavior from the expected performance of the system. The essence of the task is to analyze the failure by identifying any anomaly in the BTC data as early as possible. The system sensor signals are sampled at regular intervals, analyzed and then fed to the actuators to intelligently control the system.

The statistical analysis of input BTC data comprises of the following two statistical parameters [15, 16]:

a. Percentile ranking of mean of sample data,
b. Multivariate regression analysis.

The anomaly detection is primarily designed to be based on percentile ranking of sample mean. A significant variation in these statistical parameters over the operational cycle and time will indicate the onset of fault/damage development in TBC blade. On the other hand, the prognosis of safe and useful life left in TBC blade is designed to be based on the regression approach [15, 16]. Extrapolation of the regressed line to the limit of maximum allowable growth or accumulation of fault/damage will be the basis for the prognostic exercise.

The monitored BTC data is expected to be of random nature as illustrated in Figure 3. In view of the fluctuating nature of data, defining the normal data boundary line (upper and lower) is one of the most difficult and ambiguous tasks in the whole process. Setting the boundary limits not only depends on a number of variables (sensor type and accuracy, operating conditions, safety regulation etc.), but often changes from time to time (depending on system health condition, mission, availability of engine, external factors, etc.). Any significant variation of mean can be considered as a measure of anomaly. The standard deviation data can be used for the purpose of data filtering by considering certain probability (say 95 percent) of data to lie within the upper and lower bounds. Group of input data will be collected as the sample and stored for analysis. The sample size should be large in the early life (say 50) of the TBC blade, and it may be reduced (say 20) with increased frequency of analysis with ageing of blades and vanes. However, engine designer's, operator's and/or user's experience provides vital clue on this aspect. Mean and standard deviation are the calculated measures for each of the data samples [15, 16].

(a) Anomaly detection by percentile ranking

The percentile rank of a score is the percentage of scores in its frequency distribution which are lower. The mathematical formula is [15, 16]

$$[Cf_i + 0.5(f_i)] * 100 / N \qquad \dots (2)$$

where Cf_l is the cumulative frequency for all mean data lower than the data of interest, f_i is the frequency of the data of interest, and N is the number of data in the sample.

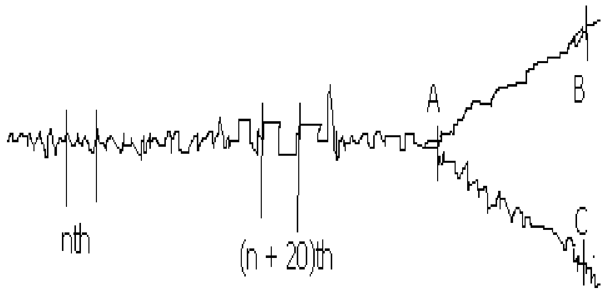

Figure 3: Illustration of random BCT data, data sampling and deviation

The percentile ranking of means between successive samples as well as over extended sample means will be compared, say between n^{th} and $(n+20)^{th}$ as illustrated in Figure 3. A significant difference criterion between the two rankings will suggest if and when any anomaly is noticed. Point 'A' in Figure 3 indicates the onset of anomaly. In the early life of usage, without the presence of any damages and changes, no variation in mean ranking will be expected. However, with ageing the development of physical changes will lead to variation in mean data. The progressive change may happen at an extremely slow rate and in certain cases may be even at negligible rate. In such situation, extended sample difference over 20 or so will give an indication of the changes. The significant difference in mean ranking over four seems to be a reasonable criterion for anomaly detection. A suspicious situation may be defined with the difference lying between 2 to 4.

(b) Prognosis for remaining life

For turbine blade as an extension of fault detection, leftover life analysis can be made based on 'Blade tip clearance' (BTC) data following the anomaly detection. The part AC in Figure 3 indicates the expected reducing profile of the BTC signal with the thermal cycles or time of operation. An increasing trend as 'AB' in Figure 3 will be followed by other parameters like temperature and vibration. A regression analysis with the filtered and sampled BTC data points will result in predicting the end of life. Either a linear regression (Equation 1) or polynomial regression model of different orders (Equation 4) need to be tried depending on the nature of data and coefficient of correlation (R^2). Higher R^2 value determines the preferred regression model owing to better data fitting [15-17].

$$y = mx + b \qquad \ldots(3)$$

where m is the slope of the line and b is y at x equals to zero

$$y = a_1x^n + a_2x^{n-1} + a_3\,x^{n-2} + \ldots\ldots.. + b \qquad \ldots(4)$$

where a_1, a_2, a_3 are the fitting coefficients and n is the order of polynomial. While x represents the operating time or number of load/thermal cycles, and y is related to the minimum tolerable blade tip clearance data as per OEM for life prognosis analysis. From a large number of input data are available, the fitting constants can be determined and verified.

As illustrated in Figure 4, with the usage of operational life, the BTC is consumed with blade damage and so the remaining life will gradually reduce. The upper limit of the BTC tolerance can be used as the critical BTC for prognosis analysis by extrapolation of data. Regression analysis with the data points set (a-b, c-d…) will predict the end of life much larger than the actual ones when regression analysis is done with early life data (lines 1 and 2 for instance). The life prognosis gets more and more refined and closer to actual failure life with the continued usage of life. However, in order to avoid any catastrophic event, some degree of safety measures based on the experience need to be attached with the BTC tolerance.

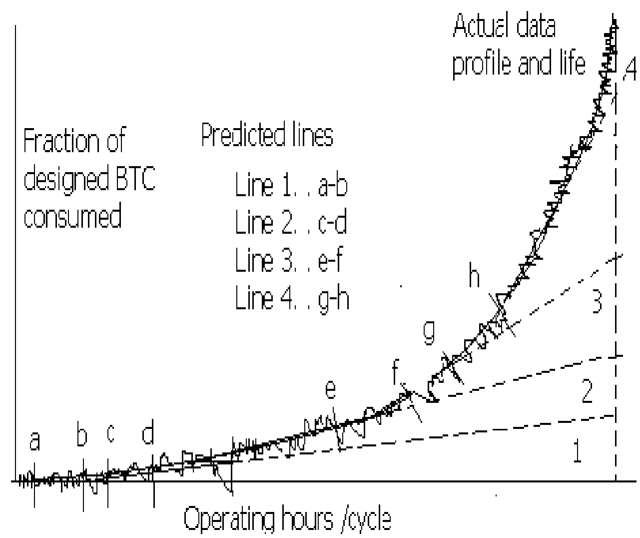

Figure 4: Consumed life fractions as a function of changes in the predicted life with new data points using linear regression analysis

The general methodologies and analyses (modeling and simulation, statistical treatments) discussed is this article for turbine blade failure risk assessment and prognosis need to validated using field blade tip clearance and other operational data. The work will be extended in future in this direction.

V. SUMMARY

Engine efficiency and integrity are the two major concerns with turbine blade performance. An algorithmic approach for modeling and simulations for blade tip clearance is discussed. Two probabilistic distributions (lognormal and normal) of blade tip clearance data with life usage are proposed for statistical failure risk assessment. As an alternative approach, operational blade tip clearance data can be monitored using sensors, processed and statistically treated to determine percentile ranking of mean for anomaly detection. The BTC data can be further treated with regression analysis for turbine blade life prognosis.

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