EXPERIMENTAL VALIDATION OF STATISTICAL ALGORITHM FOR DIAGNOSIS OF DAMAGE FAULT

Amar Kumar[1], Amiya Nayak[2], Alka Srivastava[1], Nita Goel[1]

[1]R & D centre, Tecsis Corporation, 210 Colonnade Road, Ottawa, Canada;

[2]SITE, University of Ottawa, 800 King Edward Street, Ottawa, Canada;

ABSTRACT

A statistical algorithm was developed for the damage fault diagnosis and prognosis tool and the present work focuses on the experimental validation. The oxide scale growth experiments using laboratory samples under thermal cycling simulate the hot section turbine blade coating failures. The experimental steps, oxide thickness data measurement, collection and sampling procedures are discussed. Three data samples each from two groups under different thermal cycling conditions are considered. The data are subjected to randomness check, preprocessing, rank sum test etc. The validation is carried out with 15 possible combinations for analysis. Consistent with the mean thickness distribution for the samples in two groups, the statistical algorithm for damage and anomaly diagnosis yields expected results.

KEYWORDS: Fault diagnosis, validation, oxide thickness, statistical algorithm, rank sum test

1. INTRODUCTION

Diagonsis, prognosis and health management (DPHM) have become buzzing words among the manufacturing and service industries dealing with critical and complex structures, machineries and equipments. The avionic, nuclear and power industries are constantly in search for most effective and economic solutions in order to continue with the service of ageing infrastructures. The avionic industries, in particular, have ever increasing demands for DPHM technology for avoiding/reducing unwanted events like unplanned engine overhauling, delays and cancellation of flights, life cycle cost, environmental pollution etc. [1-3]. NASA has predicted an average number of overseas passengers to reach six millions a day and a requirement of 500 to 1500 second generation supersonic commercial flights to meet the demands [4]. The critical issues assume much greater significance for aging commercial and military aircrafts as one-half to two-third of maintenance cost goes for replacement and repair of aged parts [5]. Condition based treatment or maintenance for cause strategy helps greatly in mitigating these demands for managing modern civilian and military flights. Real- time, robust and integrated technology for structural health assessment and maintenance is the need of the day for gas turbine engines. Such technology is required for detection, classification, and prediction of developing engine faults and structural degradation in order to maintain high levels of safety and efficiency at reduced cycle costs.

A practical example is discussed here to demonstrate the application and significance of DPHM tool in industries. A complex electro-thermo-mechanical engine consists of number of parts performing various functions under different working environments. The engine health condition and its performance need to be assessed on regular basis. One important parameter for continuous and convenient condition assessment is the engine oil quality. Oil quality and properties tend to degrade with engine operations due to a host of factors like wear, erosion, corrosion, lubrication, temperature, foreign object damages. These mechanisms suggest that the oil quality change will depend on severity of the engine usage among other factors and not just on the time and cycle of operations. The oil viscosity or pH level can be a suitable and sensitive index to monitor the oil quality during the engine operation. First sign of significant changes in these indexes may be considered as diagnosis of engine fault development and the oil life. The time interval for changing the oil and/or engine overhauling may be estimated from the trend in the change of viscosity/pH with time or cycle as measured regularly and the upper bound of the tolerable values.

The authors have been involved in research and developmental activities in fault diagnosis, prognosis and health management (DPHM) for past five years in collaboration with universities and research organizations

[6,7]. The current DPHM R & D work of our group integrates three complimentry approaches, namely statistical analysis (STAN), physical damage analysis (PDAN) and data based artificial neural network (DANN). In a recent work, a technique for failure risk assessment during blade life usage based on blade tip tolerance limits was developed using statistical parameters, namely like percentile ranking and regression analysis [7].

These components are subjected to worst operating situations comprising of elevated temperature, high pressure, oxidizing environment and high static and cyclic stress [5]. Thermal barrier coating (TBC) is applied on hot-section parts In order to make the blade and vane components damage tolerant, more durable, sustain higher temperature and adverse environment, as illustrated schematically in Fig. 1. Failure of the coating by deformation, cracking, foreign object damage, delamination, spallation etc. exposes the blade and shortens the operating life. The present work is confined to the study of the effectiveness of the statistical technique and the algorithm developed in diagnosing the damage initiation in coated superalloy subjected to thermal cycling. The validation of the STAN tool is tested using primary experimental data generated in the laboratory.

2. STATISTICAL ALGORITHM

Several technological breakthroughs and advancements in key areas like sensing system, signal processing, autonomic system, high computational speed, finite element and fracture mechanics analysis, nanotechnology, data mining and data fusioning are now available to make the DPHM technology matured and vastly improved. An architectural framework and design of the DPHM system considering statistical approaches has been published by the authors earlier [6-8]. In the present paper, experimental validation of statistical algorithm is discussed for the application to diagnose damage initiation and growth in coated superalloy samples subjected to thermal cycling. The authors developed a statistical algorithm using Wilcoxon rank sum model and nonlinear regression models earlier [8]. The essential steps in the algorithm for any system fault detection include, input data (historical and test) sampling, checking randomness, data preprocessing, rank sum test, selection of damage and failure criterion, regression analysis and life prognosis. The non-parametric statistical approach avoids any parametric assumption for data distribution as well as the effects of outliers. At any given instant during on-line analysis, two data sets are required to be sampled from the large population of raw data. One data set comprises of current or test data and the other is termed as historical or normal data set. The two data set samples are ranked digitally and then hypothetically tested for any significant variation in the distribution.

focussed on gas turbine components, namely turbine blades

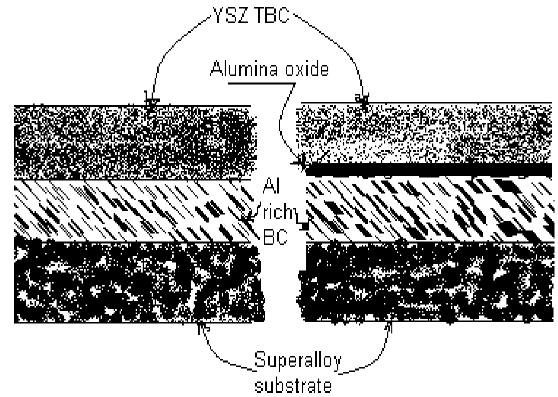


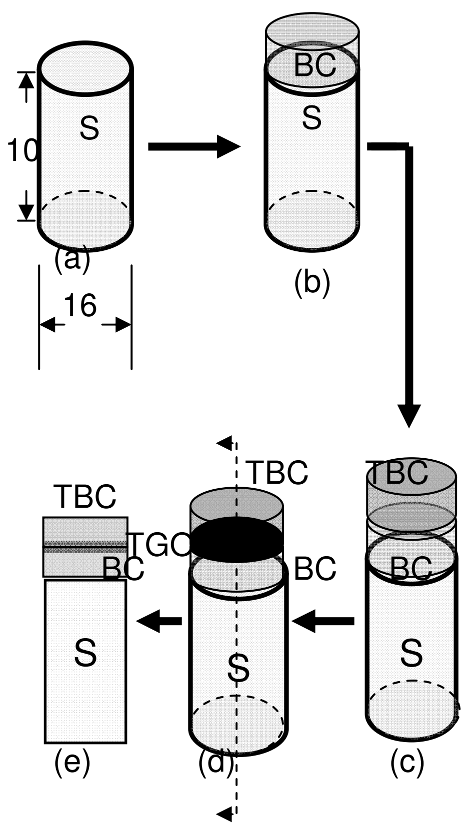
Fig. 1 Schematic representation of physical damages (aluminium and other oxides) in thermally cycled coated turbine blade material.

Once the fault is diagnosed, exponential smoothing and nonlinear auto regression methods are considered for prognosis of the state of health and remaining life. In lifing analysis, long term prediction to allow additional time for undertaking necessary measures for health management has great advantage. Lifing analysis depends on the maximum size of the tolerable damage size i.e. the thickness of the thermally grown layer formed between the thermal barrier oxide and the bond coat as illustrated in Fig. 1. The critical size of the TGO layer is a function of several operating conditions like stress, temperature cycle, microstructure and chemistry. However, a generally agreed upon damage size is around 8 microns. A different criterion of defining failure is also followed i.e. failure is accepted when coating falls off from 25 to 30 percent of total coated blade surface. The other experimental approach being considered in our project is to sense and monitor temperature and use as fault diagnosing parameter, other than the thermally grown oxide layer thickness. More the spallation of coating from surface, more will be the rise in temperature of the substrate alloy over the given time period. In different words, the temperature accumulation in the turbine blade will tend to rise with thermal exposure time for the same number of thermal cycles.

3. EXPERIMENTAL STEPS

The experimental program attempts to simulate the initiation and growth of physical damage by the formation of various oxides in gas turbine blades exposed to elevated temperatures [9 -11]. The essential steps followed consist of sample preparation, plasma spray TBC coating, thermal cycling, sectioning, mounting, metallography, carbon coating, scanning electron microscopy (SEM), measurement etc. The details of each step are beyond the scope of this paper and are given elsewhere [9]. Fig. 2 illustrates schematically the sequential steps followed in the simulated experimental program;

(a) base alloy sample preparation with dimensions of 8 mm. in height and 16 mm. in round cross-section.
(b) superalloy base coating with bond coat (around 50 to 60 microns in thickness) by plasma spray technique for stronger adherence of the thermal barrier coating (TBC). For clarity, the interfaces in between the different layers are clearly shown in Fig. 2(b, c).
(c) Yttrium stabilized zirconia (YSZ) was then coated as TBC over bond coat by air plasma spray method. The TBC thickness was later measured to be around 100-150 microns.
(d) The samples were then kept inside the programmable resistance heating furnace and subjected to thermal cycling. One cycle required 65 to 70 minutes to complete on an average. After the completion of some specified number of cycles, two samples were taken out for further examinations. The rest of the samples were continued with thermal exposure until the completion of predetermined and successive number of cycles. As shown in Fig. 2(d), as a result of thermal cycling, oxide layer (mainly aluminium oxide formed at the interface between the TBC and bond coat (marked with black thin layer) [9-11].



S – Superalloy; BC – Bond coat;
TBC – Thermal barrier coating;
TGO – Thermally grown oxide

Fig. 2 Sample configuration used and the major sequential steps followed in the experiments

(e) Thermally grown oxide (TGO) damage is a thermodynamic and diffusion controlled phenomenon and is a function of both time and temperature, both of them were varied in order to allow appreciable growth leading to TGO growth and failure. The TGO layer continued to grow with more number of thermal cycles. For quantitative assessment of TGO growth, the samples were sectioned at the middle as shown in Fig. 2(d). The cross-sectional view with all the layers is displayed in Fig. 2(e). The thickness of TGO was measured directly on the SEM micrographs taken from the cross-sectional plane.

4. RESULTS

The metallographically prepared and microscopically examined samples displayed different layers and TGO as typically shown in SEM micrographs (Figs. 3 and 4). Fig. 3 corresponds to Fig. 2(c) without the

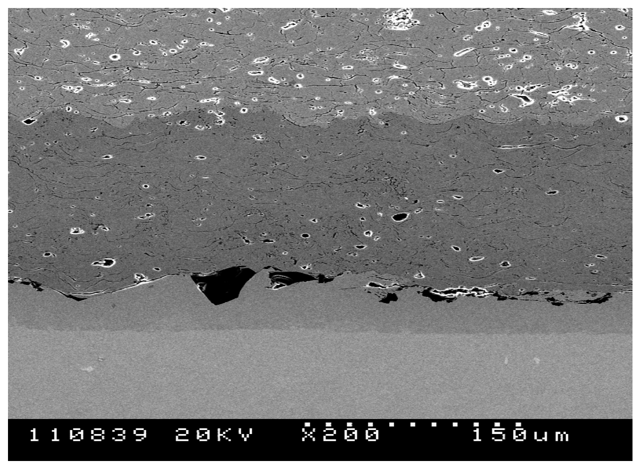


Fig. 3 SEM micrograph displaying superalloy substrate, intermediate bond coat and thermal barrier coating layers without TGO prior to thermal cycling

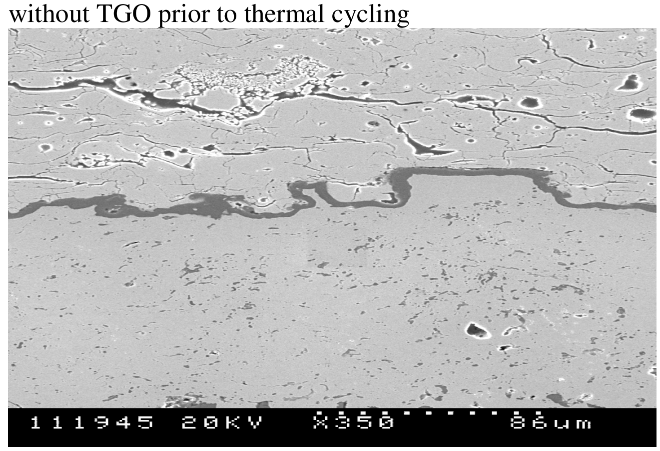


Fig. 4 SEM micrographs showing wide distribution in the thickness and the morphology of oxide layer formed at the interface. This is considered as the critical physical damage to be sensed for fault diagnosis and life prediction for coated gas turbine blade.

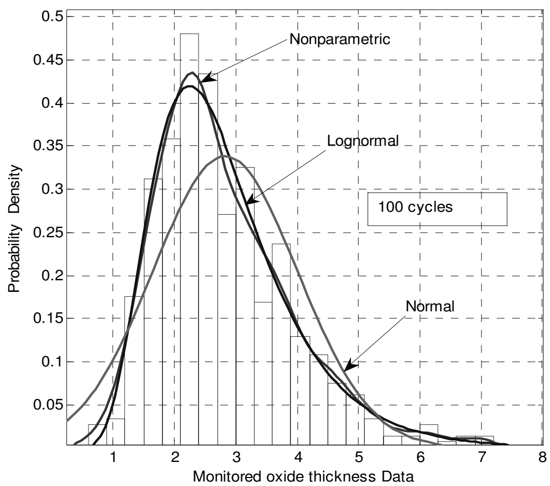


Fig. 5 Experimental oxide damage data distribution after 100 thermal cycles and typical distribution fittings

initiation of any TGO, while Fig. 4 corresponds to Figs. 2(d and e) after the formation and growth of TGO. Ideally, the damage data needs to be monitored employing ultrasonic thickness gauge and collected continuously in order to carry out the fault diagnosis and long term behavior prediction at regular intervals. In the present work, the data was collected intermittently and off-line in view of the experimental limitations. However, it may be assumed here as continuous collection of data at a regular interval while the oxide growth remain nearly constant (say after 100 cycles) with acceptable scatter. As the data gets stored and sampled intermittently, the statistical algorithm developed should diagnose the significant changes in the data distribution to identify the damage. Fig. 5 displays typical statistical parametric fittings of data assuming three different distributions, namely two parametric (lognormal and normal) and one non-parametric. The nonparametric fitting has certain advantages over other fittings and constitutes the basis of our algorithm [12, 13]. The Wilcoxon rank sum analysis assumes nonparametric approach and is used here for the purpose of diagnosing difference between two sample distributions.

5. VALIDATION AND DISCUSSION

The validation of the statistical algorithm developed for the damage diagnosis is tested with the experimentally measured oxide thickness data as described in the preceding two sections. The algorithm is developed for continuous stream of data collected over operating time. However, the present application of designed algorithm involves data of TGO thickness that were collected after certain number of thermal cycles ensuring changes in the oxide thickness statistically. At least, three random data samples of size 25 each were considered from each of two different thermally cycled specimens (N_1 = 10 and N_2 = 50). The test validation was carried out among samples under same thermal cycle (N_1 or N_2) and also among samples collected from differently cycled samples. Normal approximation is assumed for large sample size of 25 [12]. The randomness of data samples was ensured by counting the number of unbroken sequence on either side of median value and determining the probability as detailed earlier [8]. The probability values varied from 15 to 50 percent [10]. In these cases, the data samples tested to be random considering 95 percent significance level. However, one case out of six data samples studied failed and resampling was necessary for the sample failed the randomness check. As described earlier, in data preprocessing, the weighing factor was calculated for each data set to exclude outliers and the data samples were preprocessed. Only two cases out of 15 validation analysis required preprocessing of data for more than two times in order to satisfy the criterion of median values. The difference in the two successively preprocessed median values is set to be within one percent of the previous median value. Next, Wilcoxon rank sum test analysis was carried out manually for the data sets and samples. The null hypothesis (N.H) in the present analysis is assumed as the two samples are drawn from same population without any acceptable changes or difference; while the alternative hypothesis is assumed to be nondirectional i.e. one sample is statistically different from the other. The level of significance for test validation is kept at 95 percent i.e. at 5 percent error level. A synopsis of fifteen validation analysis considering three samples (ABC and XYZ) drawn from two groups are presented in table 1 below.

Rejection of null hypothesis implies that the two samples under analysis come from different source and population. In other words, the oxide damage thickness samples (XYZ) are statistically different and the data provides positive indications for damage diagnosis. The mean value for each of the sampled data group considered in the analysis is included in the first column of table 1 for confirmation of results. The mean oxide thickness for group

Table 1: Synopsis of rank sum analysis and validation

Samples source, mean and number of analysis	Rank sum at lower end	Probability range in %	Test status
A(1.30) X(1.66) B(1.38) Y(1.47) C(1.42) Z(1.55) (3) + (3) combinations	Range: 550–650 Normal approximated value - 637.5	15-40	N.H of no difference accepted
A(1.30) X(1.66) B(1.38) Y(1.47) C(1.42) Z(1.55) (9 combinations)	Range: 350–450 Normal approximated value - 637.5	<0.01	N.H of same population rejected

XYZ is consistently higher than that for ABC samples. The rank sum analysis based on nonparametric approach used in the present work is found to be consistent with the experimental observations. Further work will be carried out for prognostic analysis with the oxide scale growth data. The future work in this direction will concentrate mainly on three aspects, namely i) validation of statistical algorithm for prognosis part; ii) sampling from continuous stream of time series data and iii) real time diagnostic and prognostic applications.

6. SUMMARY

The present work focuses on the experimental validation of statistical algorithm developed for the damage diagnosis and prognosis for economic and efficient management of critical structures and components like aeroengine. The test validation is confined to the damage diagnosis part only. The validation uses oxide thickness damage data from the simulated experiments in the laboratory. Under increased number of thermal cycles between room temperature and 1080°C, the oxide layers at the interface between bond coat and thermal barrier coating continued to grow. Six data samples of size 25 collected from two different thermal exposure conditions were used for preprocessing and rank sum testing. 15 test validations using the algorithm shows consistent results at 95 percent confidence level as observed by the actual sample mean of oxide scale thickness.

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