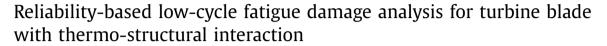


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# Aerospace Science and Technology

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### ARTICLE INFO

Article history: Received 21 April 2015 Received in revised form 16 September 2015 Accepted 14 December 2015 Available online 18 December 2015

Keywords: Reliability analysis Low-cycle fatigue life Turbine blade Thermo-structural interaction Random variable Distributed collaborative response surface method

# ABSTRACT

To improve the computational accuracy and efficiency of complex mechanical component like engine turbine structure, distributed collaborative response surface method is applied to the reliability analysis of aeroengine turbine blade low-cycle fatigue damage. The improved Manson-Coffin formulas with different confidence levels are established based on the linear variance regression analysis in the application of the fatigue data of nickel-based superalloy GH4133. The distributed response surfaces of strain range  $\Delta \varepsilon_t$  and mean stress  $\sigma_m$  are established by considering the randomness of the design sizes, working loads and material parameters. And then  $\Delta \varepsilon_t$  and  $\sigma_m$  are regarded as the basic input variables of fatigue life  $N_f$  to complete turbine blade low-cycle fatigue damage reliability analysis by the Miner cumulative damage theory. The probabilistic sensitivity analyses demonstrate that the fatigue performance parameters hold important influence on the low-cycle fatigue life of turbine blade. Through the comparison of methods, it is revealed that distributed collaborative response surface method is superior to response surface method in computational precision and efficiency, especially for low confidence level. The efforts give the conclusion that distributed collaborative response surface method is a promising approach in ameliorating the computational precision and efficiency of reliability analysis, which enriches the reliability theory and method of complex mechanical structure with multi-component and multi-failure mode.

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## 1. Introduction

Turbine blade is an important component of aeroengine and directly determines the service life and reliability of whole engine [1–3]. Fatigue is a primary failure for high-speed rotating turbine blade suffering from high temperature and mechanical loading [4]. Low-cycle fatigue is one of fatigue failure modes which seriously impact on the reliability of turbine blade [4], so that it is particularly important to accurately estimate the low-cycle fatigue damage of turbine blade.

Various methods on the prediction of fatigue life have been developed [5–14]. Manson [9] and Coffin [10] deduced the empirical formula (called as Manson–Coffin formula) on low-cycle fatigue life through numerous experiments. Because of the simple and easy operability of the linearity between fatigue life and strain amplitude by double logarithmic coordinates, the Manson–Coffin formula has been widely applied in many engineering fields. Mor-

\* Corresponding author. E-mail addresses: gaohaifeng\_3942380@126.com, ghf121117@126.com (H. Gao). based fatigue reliability analyses sprang up by considering the influence of mean stress. Fatigue life assessment has traditionally been performed using deterministic methods and models based on certain assumptions [15]. For instance, Bargmann et al. [16] described complete-probability fast integration method with the assumption that both strength coefficient  $\sigma_{\rm f}'$  and plasticity coefficient  $\varepsilon'_{f}$  were independent lognormal random variables. In accordance with the hypothesis that the fatigue life under the given cyclic strain subjected to three-parameter Weibull distribution, the parametric relationship between strain and life distribution was presented [17]. Zhao et al. proposed the strain load-strength interference model [18], where strength coefficient  $\sigma'_{\rm f}$  and plasticity coefficient  $\varepsilon'_{f}$  obey normal or three-parameter Weibull distribution. In the above approaches, it is obvious that the strength coefficient  $\sigma_{\rm f}'$  and plasticity coefficient  $\varepsilon_{\rm f}'$  obey certain distribution, and strength exponent *b* and plasticity exponent *c* are constant, which possess great calculating errors to precisely estimate fatigue life.

row [11] improved the Manson–Coffin formula by considering the influence of mean stress on fatigue life. Since the 1990s, the strain-

Reasonable reliability theory and method are the foundation of designing and controlling the fatigue life for aeroengine structure.

http://dx.doi.org/10.1016/j.ast.2015.12.017 1270-9638/© 2015 Elsevier Masson SAS. All rights reserved. Reliability analysis methods mainly contain the first-order secondmoment (FOSM) [19-21], second-order second-moment (SOSM) [22-24], response surface method (RSM) [25-28] and Monte Carlo method (MCM) [29-31]. However, the FOSM method is only applied to the low nonlinear limit state equation and possesses low analytical precision for high nonlinear reliability problems. The SOSM is likely to improve calculation accuracy by quadric surface. However, because of the requirement of solving the second-order partial derivative of eigenfunction with respect to random variables, the SOSM holds more complex calculations and lower efficiency. The RSM holds the potential in dealing with reliability problems with a limited number of random variables. Nevertheless, the conventional RSM requires large computational efforts and shows loss of accuracy in the cases of problems exhibiting acute nonlinearity, so that some abnormal values ( $N_{\rm f} < 0$ ) may be generated during the probabilistic simulation with the fitted response surface. In the light of probability theory, the MCM was proposed for the applications in many fields due to high precision for complex failure mode. However, the MCM holds low computation efficiency and the simulation credibility depends on the size of samples.

The reliability analysis of complex structure just like aeroengine components, always involves multiple disciplines and multiple failure modes. The low efficiency of traditional reliability methods seriously restricts the development of new equipment. Based on the above backgrounds, the authors [32] propose distributed collaborative response surface method (DCRSM), a novel reliability analysis method, to improve the computational efficiency of complex structure reliability analysis. This paper applies the DCRSM to the reliability analysis of turbine blade low-cycle fatigue damage. Additionally, this paper extracts and establishes the stochastic expressions of the fatigue parameters (strength coefficient  $\sigma_{\epsilon}$ , plasticity coefficient  $\varepsilon'_{f}$ , strength exponent *b* and plasticity exponent *c*) with the linear variance regression analysis. Regarding of the influence of mean stress on fatigue life, the cyclic strain-life probability models under different confidence levels are studied based on the Manson-Coffin formula. The Miner cumulative damage theory is conceived as the criteria for failure mechanism, and then the reliability analysis of turbine blade low-cycle fatigue damage is executed based on the randomness and correlation of basic variables. Finally, the validity and feasibility of the DCRSM are validated by the comparison of methods.

### 2. Distributed collaborative response surface method

For a complex mechanical structure involving multiple failure modes, the procedures of reliability analysis based on the DCRSM are summarized as follows: ① Establish the finite element model (FEM) of complex structure according to probabilistic design features and requirement. 2 Construct independent response surface model (called as distributed response surface model, DRSM) for each failure mode by simulating the FEM. 3 Implement the DRSMs to retrieve the statistic characteristics of the output responses (called as distributed output responses) of all the DRSMs in view of failure dependency, which emphasizes on that the same samples are extracted for the same random variable considered. ④ Regard the distributed output responses as the input variables of the global output response, and establish collaborative response surface model (CRSM) in the light of the specified structure failure criterion. (5) Analyze the CRSM to acquire the global output response and solve the reliability of complex machinery.

For a complex structure with *m* failure modes, design variable vector is  $\mathbf{X} = [x_1, x_2, \dots, x_n]^T (x_l - N(\mu_l, \sigma_l^2))$ , and the global output response is *y*. According to the basic principle of the DCRSM, the global output response *y* can be regarded as the coupling

of the distributed responses  $\{y_k\}_{k=1}^m$ , which can be expressed by Eq. (1):

$$\begin{cases} y_1 = g_1(x_1, x_2, \dots, x_{n_1}) = a_{01} + \boldsymbol{B}_1 \boldsymbol{X}_1 + \boldsymbol{X}_1^{\mathsf{T}} \boldsymbol{C}_1 \boldsymbol{X}_1; \\ y_2 = g_2(x_1, x_2, \dots, x_{n_2}) = a_{02} + \boldsymbol{B}_2 \boldsymbol{X}_2 + \boldsymbol{X}_2^{\mathsf{T}} \boldsymbol{C}_2 \boldsymbol{X}_2; \\ \dots \\ y_m = g_m(x_1, x_2, \dots, x_{n_m}) = a_{0m} + \boldsymbol{B}_m \boldsymbol{X}_m + \boldsymbol{X}_m^{\mathsf{T}} \boldsymbol{C}_m \boldsymbol{X}_m. \end{cases}$$
(1)

Here  $\mathbf{X}_1 = [x_1, x_2, \dots, x_{n_1}]^T$ ,  $\mathbf{X}_2 = [x_1, x_2, \dots, x_{n_2}]^T$ ,  $\mathbf{X}_m = [x_1, x_2, \dots, x_{n_m}]^T$ , and  $n_1, n_2, \dots, n_m = 1, 2, \dots, n$ ;  $y_k$  is the response of the *k*th failure mode, which is called as distributed response surface function (DRSF).

Based on failure dependency, all the distributed output responses are retrieved and considered as the input variables of the global output response y. With the relationship between the structure response y and distributed responses  $\{y_k\}_{k=1}^m$ , the CRSM is established and denoted by

$$y = \overline{g}(y_1, y_2, \cdots, y_m), \tag{2}$$

where  $\overline{g}(\cdot)$  is the specified mathematical relationship between the global output response *y* and the distributed responses  $\{y_k\}_{k=1}^m$ . Eq. (2) is distributed collaborative response surface function.

From the above analysis, DCRSM decomposes an intricate and difficult issue into several simple and solvable problems for the limited computer resource by constructing different response surfaces, and then the intricate and difficult issue is solved by the collaborative analysis of several simple response surfaces. The process of decomposition and synergy brings a great convenience in improving the computational efficiency and accuracy of complex machinery reliability design, mainly includes: 1) The nonlinearity between design variables and global output response is reduced to improve calculation accuracy through the establishment of the DRSMs. <sup>(2)</sup> The time of fitting response surface model is saved by simultaneously implementing parallel computation for the DRSMs on different computers and considering some random variables rather than all the design variables, which are promising to improve the computational efficiency. 3 Besides guadratic function with cross terms, the DRSM can be established into more reasonable response surface model, such as support vector machine model, artificial neural network model, Kriging model, etc. Therefore, the DCRSM provides an enlightened insight for the reliability analysis and optimization design of complex mechanical structure.

### 3. Low-cycle fatigue life prediction theories

The Manson–Coffin [9,10] formula shown in Eq. (3) was used to predict turbine blade low-cycle fatigue life:

$$\frac{\Delta\varepsilon_{\rm t}}{2} = \frac{\Delta\varepsilon_{\rm e}}{2} + \frac{\Delta\varepsilon_{\rm p}}{2} = \frac{\sigma_{\rm f}'}{E} (2N_{\rm f})^b + \varepsilon_{\rm f}' (2N_{\rm f})^c. \tag{3}$$

Here  $\sigma'_f$  is the fatigue strength coefficient;  $\varepsilon'_f$  the fatigue plasticity coefficient; *b* the fatigue strength exponent; *c* the fatigue plasticity exponent,  $N_f$  the structural low-cycle fatigue life and  $\Delta \varepsilon_t$  the strain range.

By taking the effect of mean stress  $\sigma_m$  on the fatigue life into consideration [33], Eq. (3) can be rewritten as following:

$$\frac{\Delta\varepsilon_{\rm t}}{2} = \frac{\sigma_{\rm f}' - \sigma_{\rm m}}{E} (2N_{\rm f})^b + \varepsilon_{\rm f}' (2N_{\rm f})^c,\tag{4}$$

where  $\sigma_{\rm m}$  is mean stress considered, and the other parameters are the same as Eq. (3).

Although there are several criterions to calculate the low-cycle fatigue life under multiple levels of cyclic load, the Linear Damage Accumulation (LDA) law is one of the most popular criterions, which is expressed by Download English Version:

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