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Improved Kriging with extremum response surface method for structural dynamic reliability and sensitivity analyses

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ABSTRACT

The safety and reliability of any complex mechanical structures are critical to ensure that they can function properly. Therefore, we need to thoroughly evaluate their reliability by performing dynamic probabilistic analyses, including the reliability and sensitivity analyses, which take the variation in the input variables into consideration. The typical approach is by performing the Monte Carlo (MC) simulation, which requires thousands of runs and could be computationally intractable. An efficient and accurate surrogate model can help reduce the computational burden in these analyses. To further reduce the computational complexity, we model only the extremum values, instead of modeling all the output responses within the time domain of interest. The developed surrogate model is called the improved Kriging (IK) algorithm with extremum response surface method (ERSM), or the IK-ERSM model. Compared to the previously developed QP-ERSM, which uses the quadratic polynomial (QP) model, the improved Kriging can better model the nonlinearity within the system. To build the IK model, we employ the genetic algorithm (GA) method to find the Kriging hyperparameters $\boldsymbol{\theta}$, by solving the maximum likelihood equation (MLE). This model shows a good accuracy, with a testing error of less than 1%. The effectiveness of the developed IK-ERSM model is demonstrated to perform the reliability and sensitivity analyses of the compressor blisk radial deformation. For the direct simulation, we consider the fluid–structure coupling of the system, for a more realistic analysis. The results show that the compressor blisk has a reliability degree of 0.9984 when the allowable value of the compressor blisk radial deformation is 1.60×10^{-3} m. From the sensitivity analysis results, we identify that the angular speed has the highest impact on the output response, followed by the inlet velocity and material density. Through the validation process, we see that the developed IK-ERSM model has a better overall performance than the QP-ERSM and K-ERSM models, in terms of the fitting times and testing errors. With these results, the IK-ERSM is demonstrated to be efficient and accurate in structural dynamic probabilistic analysis. This study provide a useful insight for the dynamic probabilistic design of complex structure and enrich mechanical reliability theory.

1. Introduction

With the increasing complexity and performance of mechanical systems, the requirements pertaining to structural design and analysis have consequently become higher. A structural failure during operations could prevent the mechanism from functioning properly and could even be catastrophic, and thus must be avoided at all cost. It is therefore imperative to perform a structural reliability analysis by considering all input variables and parameters, in order to improve the performance of a mechanical system.

There have been a large body of literature on the reliability analysis of complex structures, and various methods have been proposed. Some of them will be briefly described below. An et al. verified the first-order reliability method for the structural reliability analysis of suspended cable [3]. Lee et al. studied the structural reliability analysis by employing the second-order reliability method with a non-central or generalized chi-squared distribution [25]. Leira et al. evaluated the reliability of corroding pipelines by performing a Monte Carlo (MC) simulation [26]. Henriques et al. evaluated the reliability of structural response based on perturbation techniques [18]. Depina et al. proposed an approach with meta-model line sampling for the reliability analysis of engineering structures [6]. Ezzati et al. developed a reliability analysis method on the basis of the conjugate gradient direction [9]. Zhai et al. discussed the stochastic model updating strategy with improved response surface model and advanced MC method to perform the structural reliability analysis of aeroengine stator system [42]. Al-

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laix et al. developed a novel analytical method-based response surface method (RSM) to evaluate structural reliability degree [2]. Alibrandi et al. investigated the support vector machine (SVM) model to calculate failure probability of a mechanical structure [1]. Song et al. presented multiple RSM-based artificial neural network for the probabilistic analysis of a complex structure with fluid–thermal-structure interaction [39]. Fei et al. provided an efficient SVM of regression method for distribution collaborative probabilistic design of the radial running clearance of turbine blade-tips, which offered a useful tool to perform the reliability analysis of a mechanical assembly [13]. The aforementioned efforts developed different methods for the reliability analyses of different structures. However, these works are not suitable for structural dynamic reliability analysis, since they only focused on the structural static reliability analysis, and ignored the dynamic behaviors of structures.

There have been quite a number of analytical techniques to perform dynamic structural reliability analyses developed by various researchers. Rajabalinejad et al. investigated a coupled MC simulation for the reliability analysis of an engineering structure by considering dynamic boundary [35]. Chakraborty et al. discussed time-varying reliability analysis of a laminated composite plate using RSM [4]. Zhai et al. investigated a refined RSM for the dynamic reliability of a pipe conveying fluid [41]. Radhika et al. exploited the dynamic estimation method to predict the structural dynamic reliability [34]. Gao et al. developed a dynamic reliability model of a mechanical component based on the equivalent strength degradation paths [17]. Fang et al. employed the stress-strength interference theory and probability density evolution method to estimate the structural dynamic failure probability [10]. Zhang et al. proposed the extremum response surface method (ERSM) for the dynamic reliability analysis of a flexible robot manipulator [43]. Fei et al. developed high-precision and efficient approaches including distributed collaborative ERSM and distributed collaborative time-varying least squares SVM method, for the dynamic probabilistic design of high-pressure turbine blade-tip radial running clearance [14,15]. Despite the aforementioned efforts to perform dynamic structural reliability analyses, these methods still suffer from the low computational efficiency. This issue is mainly due to the need to run thousands of dynamic deterministic analyses of structures spanning a large time domain. Moreover, the lack of accuracy is also a concern due to the limitation of quadratic polynomials, which are commonly employed in these methods, to model the highly nonlinear characteristics of the system. We therefore need to develop a computationally efficient and yet accurate dynamic probabilistic analysis method for complex structures.

The main objective of this paper is to explore an efficient analytical technique, which is called the ERSM-based improved Kriging algorithm (IK-ERSM). This method integrates the genetic algorithm (GA) method into the Kriging algorithm, by means of the MLE optimization procedure to find the Kriging hyperparameters. The developed model is then used to perform the dynamic probabilistic analysis of complex structures within the time domain $[0, T]$. For the case study, the developed method is then applied to perform the dynamic probabilistic analyses (including reliability and sensitivity analyses) of an aeroengine compressor blisk radial deformation with fluid–structure interaction. This case study will serve as the demonstration and validation of the method.

The remaining of this paper is structured as follows. In Section 2 we provide an overview of the basic theories to develop the IK-ERSM method, starting from the basic Kriging method, the IK algorithm, ERSM and IK-ERSM methods. We also describe the dynamic probabilistic analysis procedure which employs the IK-ERSM method. We then describe the implementation of the IK-ERSM method to the dynamic probabilistic analysis for aeroengine compressor blisk radial deformation in Section 3. The analysis is performed by considering the randomness of some inputs such as the inlet velocity, inlet pressure, outlet pressure, material density, and angular speed. The validation procedure is then presented in Section 4, and we close the paper with some conclusions in Section 5.

2. Basic theories

In this section we first present an overview of the Kriging method, before going into more details in the development of the improved Kriging (IK) and IK-ERSM methods. We then briefly describe the two dynamic probabilistic analysis procedures performed on complex structures that will be demonstrated in this work, namely the dynamic reliability analysis and sensitivity analysis.

2.1. Kriging overview

The Kriging surrogate model was initially developed in the field of geostatistics by Danie G. Krige (after whom the method is named) in 1951 [23]. The term "Kriging" was coined by Matheron in 1963 [31], who was also the first to formulate Kriging mathematically. In 1973, Matheron applied the Kriging model to the mineral deposit reserves and error estimation [32]. The use of Kriging models in the design and analysis of computer experiments (DACE) was first proposed by Sacks et al. [37]; where points in the input space are analogous to the spatial (geographic) coordinates. In the recent decades, Kriging models have been commonly used in many applications, including the design optimization of structures or other engineering systems. Li et al. discussed Kriging model in the application of engineering optimization of gear train with the assistance of multi-objective genetic algorithm (MOGA) [28]. In the field of biomedical engineering, Li et al. investigated the design optimization of stent and its dilatation balloon using Kriging surrogate model [27]. Simpson et al. adopted the Kriging model for the multidisciplinary design optimization of an aerospike nozzle [38]. Zhao et al. studied the dynamic Kriging modeling method for a structural design optimization problem [44]. Liem et al. developed the mixture of experts approach with Kriging model to predict the aerodynamic performance to enable an efficient and accurate aircraft mission analysis procedure [29]. The Kriging model was used in the field of structural reliability analysis [36,21,7]. The model was shown to be very accurate and efficient in dealing with highly-nonlinear and high-dimensional problems.

In Kriging models, we assume that the deterministic response $y(\mathbf{x})$ is a realization of a stochastic process $Y(\mathbf{x})$ [37,22],

$$Y(\mathbf{x}) = \mathbf{f}^T(\mathbf{x})\boldsymbol{\beta} + z(\mathbf{x}). \quad (1)$$

The first term is a generalized linear model that determines the trend of the Kriging model. The symbols $\mathbf{f}(\mathbf{x})$ and $\boldsymbol{\beta}$ are the vectors of basis functions and undetermined coefficients, respectively. The second term, $z(\mathbf{x})$, is the stochastic component, which is treated as the realization of a stationary Gaussian random function with zero expected value, $\mathbb{E}[z(\mathbf{x})] = 0$, and covariance

$$\mathrm{Cov}\left[z(\mathbf{x}_p), Z(\mathbf{x}_q)\right] = \sigma^2 R\left(\boldsymbol{\theta}, \mathbf{x}_p, \mathbf{x}_q\right), \quad (2)$$

where $R(\cdot)$ denotes the correlation function with $R(0) = 1$, and σ^2 denotes the variance. Here, $\mathbf{x}_p$ and $\mathbf{x}_q$ $(p, q = 1, 2, \ldots, m)$ are the vectors of the p-th and q-th input samples, where m is the number of samples. The Kriging hyperparameter $\boldsymbol{\theta}$ is the correlation parameter vector for R. These correlation parameters are also called the length scales or distance weights, and they are typically found via the maximum likelihood estimation (MLE) approach. The form of $R\left(\boldsymbol{\theta}, \mathbf{x}_p, \mathbf{x}_q\right)$ is typically expressed as: