Mechanical Systems and Signal Processing 60-61 (2015) 928–944

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

A Monte Carlo simulation based inverse propagation method for stochastic model updating

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ARTICLE INFO

Article history:
Received 23 June 2014
Received in revised form
28 November 2014
Accepted 6 January 2015
Available online 2 February 2015

Keywords:
Model updating
Uncertainty
Analysis of variance
Response surface model
Monte Carlo simulation

ABSTRACT

This paper presents an efficient stochastic model updating method based on statistical theory. Significant parameters have been selected implementing the *F*-test evaluation and design of experiments, and then the incomplete fourth-order polynomial response surface model (RSM) has been developed. Exploiting of the RSM combined with Monte Carlo simulation (MCS), reduces the calculation amount and the rapid random sampling becomes possible. The inverse uncertainty propagation is given by the equally weighted sum of mean and covariance matrix objective functions. The mean and covariance of parameters are estimated synchronously by minimizing the weighted objective function through hybrid of particle-swarm and Nelder–Mead simplex optimization method, thus the better correlation between simulation and test is achieved. Numerical examples of a three degree-of-freedom mass-spring system under different conditions and GARTEUR assembly structure validated the feasibility and effectiveness of the proposed method.

1. Introduction

During the past decades, the finite element method became the main method to predict dynamical performances of structures. However, simplification and approximation of models introduce uncertainty of some parameters such as geometric or contact connection parameters, as well as boundary conditions and load parameters [1,2], resulting in corresponding error between the results of test and simulation. To ensure precision of the finite element model (FEM), deterministic test data were traditionally used in model updating [3]. However, in the tests, the manufacturing error, assembling tolerance, noise interference and other factors also bring uncertainties. Mares et al. [4] point out that different test results can be got even from a nominally identical structure. Uncertain factors are ubiquitous and inevitable in practice. Since FEM and experimental tests are both uncertainty sources, uncertainties propagate between the input parameters and output response characteristics (such as modal frequency, etc.). Thus, deterministic analysis procedure is not suitable to accurately describe the structural system and its uncertainties [4,5], and stochastic model updating method needs to be taken into account.

In the past, model updating as a dynamic inverse problem has been constantly developed and several approaches to stochastic model updating have been extensively studied. Nowadays the main methods for stochastic model updating are the Monte Carlo method and the perturbation method. Monte Carlo simulation (MCS) is a probability analysis method widely used to describe the uncertainty problem. Although the results achieved by applying MCS are reliable, the technique

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http://dx.doi.org/10.1016/j.ymssp.2015.01.011
0888-3270/

requires a great number of samples and results in low calculation efficiency, especially in updating the models with complex structures. Schuëller et al. [6] investigated the effect of uncertainty parameters on structural performance by combining MCS with FEM. Mares and Mottershead et al. [4,7] proposed a Monte Carlo inverse propagation procedure by using the gradient and regression method. Fang et al. [8] presented a stochastic model updating process. A series of deterministic model updating processes divide the stochastic, and the inverse problem is solved within a deterministic framework by using second-order response surface model and multiobjective optimization. Rui et al. [9] used Hermite polynomial chaos expansion stochastic response surface method together with MCS for stochastic model updating based on the gradient method.

The perturbation method relies on Taylor series expansion. The method takes into account the calculation efficiency and retains the first or second order Taylor expansion that contains first-order and second-order sensitivity matrix. However, this method is depends on the initial value and distribution range of parameters [10]. Hua et al. [11] proposed a perturbation method to update uncertainty parameters of the model requiring the calculation of the second-order sensitivities. Hence, Haddad Khodaparast et al. [12] presented an efficient perturbation method using first-order sensitivities neglecting the updating parameters and the measured response correlations. Govers et al. [13] defined an objective function to identify parameters covariances; the updating process was divided into two independent steps by which parameter means and covariance matrices were adjusted in sequence based on the gradient iteration method. Thus, in stochastic model updating, both the precision and calculation efficiency should be considered.

This paper proposes an efficient method for stochastic model updating based on statistical theory. The incomplete fourth-order polynomial response surface model is constructed by using F-test evaluation and design of experiments (DOE). To reduce the calculation amount, the technique that integrates RSM and MCS is applied. The minimization of the weighted objective function leads to improve the correlation between simulation and test performing the inverse uncertainty propagation based on efficient MCS and hybrid of particle-swarm (PSO) and Nelder–Mead simplex (N–M simplex) optimization method. The paper is divided into five parts: Section 2 describes theoretical methods for stochastic model while Section 3 illustrates the processes for updating the structural system with uncertainties and the stochastic model. In Section 4 the paper deals with the feasibility of the proposed stochastic model updating by introducing a three degree-of-freedom numerical example under different working conditions. To conclude, Section 5 shows the systematic elaboration of the practical application of the proposed method, and the verification of the updating results using the coincidence ratio criterion, by employing the GARTEUR assembly structure as an example.

2. Theoretical base for stochastic model updating

2.1. Parameters significance evaluation

The great number of parameters involved in the FEM of complex structures critically increased the amount of calculation in model updating. Thus, selection of parameters that have significant influence on the response is the precondition for model updating. Performing an analysis of variance (ANOVA) [14,15] helps in analyzing the effect of factors on a response. ANOVA decomposes the variability in the response variable amongst the different parameters, helping the significance evaluation of parameters in a global design space.

This paper implements ANOVA by design of experiments. Optimal Latin Hypercube design and FEM calculation generates samples of input parameters and output response. In practice, the significance of input parameter to output response is defined by an F-test statistic. Assume that ANOVA for parameter A is conducted, then F-test evaluation of A is as follows:

$$F_A = \frac{S_A/f_A}{S_e/f_e} \sim F(f_A, f_e) \tag{1}$$

where S_A and S_e are the sums of square of deviations of parameter A and error e, respectively. f_A and f_e are the degrees-of-freedom of parameter A and error e, respectively. F_A is the value of parameter A following the F-distribution, as Fig. 1 shows. If the significance level θ is set as $\theta=0.05$, then

$$P\{F_A \geq F_{1-\theta}(f_A, f_e)\} = \theta \tag{2}$$

A result of $F_A \geq F_{1-\theta}(f_A, f_e)$, (i.e. $P \leq 0.05$, where P-value is the probability of obtaining F-test statistic) indicates that the parameter have a significant influence on the response and parameter A is a significant variable that should be considered in stochastic model updating. In case of $F_A < F_{1-\theta}(f_A, f_e)$, the parameter A is insignificant.

2.2. Response surface model

The response surface method combines the probability theory with statistics, and expresses the implicit relationship between input parameters and output response of the FEM fitting the approximate function with the sample points of DOE [16]. As the distribution of sample points in parameter interval has certain influence on the precision of response surface model (RSM), based on the Latin Hypercube design a principle is introduced [17]. The principle helps optimizing the order of each level in different columns of the matrix in DOE, and makes the sample points evenly distributed, condition referred to as the Optimal Latin Hypercube design. In this paper, DOE sampling number is 1000; this size has been used to create RSM.