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Review

Estimation of beam material random field properties via sensitivity-based model updating using experimental frequency response functions

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ABSTRACT

Structural parameter estimation is affected not only by measurement noise but also by unknown uncertainties which are present in the system. Deterministic structural model updating methods minimise the difference between experimentally measured data and computational prediction. Sensitivity-based methods are very efficient in solving structural model updating problems. Material and geometrical parameters of the structure such as Poisson's ratio, Young's modulus, mass density, modal damping, etc. are usually considered deterministic and homogeneous. In this paper, the distributed and non-homogeneous characteristics of these parameters are considered in the model updating. The parameters are taken as spatially correlated random fields and are expanded in a spectral Karhunen-Loève (KL) decomposition. Using the KL expansion, the spectral dynamic stiffness matrix of the beam is expanded as a series in terms of discretized parameters, which can be estimated using sensitivity-based model updating techniques. Numerical and experimental tests involving a beam with distributed bending rigidity and mass density are used to verify the proposed method. This extension of standard model updating procedures can enhance the dynamic description of structural dynamic models.

Contents

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1. Introduction

Quantifying uncertainty in numerically simulated results is not recent. However, during the last few years, this research area has undergone remarkable development, in special for dynamic systems. The method most used is Monte Carlo (MC) simulation [1]. Otherwise, non-sampling approaches such as the Perturbation Method may be used. It consists of expanding a random field in a truncated Taylor series around its mean [2]. The Direct Method consists in applying the moment equations to obtain the random solutions. The unknowns are the moments and their equations are derived by taking averages over the original stochastic governing equations. A powerful method in computational stochastic problems is the Stochastic Finite Element Method (SFEM) [3]. SFEM is an extension of the classical deterministic FE approach to the stochastic framework, i.e., to solve static and dynamic problems with stochastic mechanical, geometric, or loading properties [4]. Adhikari [5] presented a doubly Spectral Stochastic Finite Element Method, where the Spectral Element Method is given a stochastic treatment.

The spectral element method (SEM) [6,7] is based on the analytical solution of the displacement wave equation, written in the frequency domain. The element is tailored with the matrix ideas of FEM, but in SEM the interpolation function is the exact solution of the wave equation [8–20]. Both techniques, SFEM and doubly Spectral SFEM, are formulated in a context of random fields. A method with a wide application when considering random fields is the Karhunen-Loève (KL) expansion [3,21,2]. The KL expansion can be used to discretize the random field by representing it by scalar independent random variables and continuous deterministic functions. By truncating the expansion, the number of random variables becomes finite and numerically treatable. Many authors use the KL expansion to model Gaussian random processes, but it is possible to extend the KL expansion to non-Gaussian processes [22–25].

Model updating methods in dynamic structural analysis are basically a process of minimizing the differences between the numerical model predictions and measured responses obtained in experimental tests using a parameter estimation procedure [26,27]. The model updating procedure starts with the parameter choice (parametrisation), followed by a correction procedure based on the available measured data. The parametrisation is an important topic in model updating which requires considerable physical knowledge regarding the system. More details can be found in references [28–32]. In the field of structural dynamics, some authors traditionally use modal parameters (natural frequencies and mode shapes) for updating the model due to the facility in estimating the modal parameters using modal analysis [33,34] and also to the freedom in the choice of the updating parameters and the applicability of the method [35]. Examples of theoretical and practical applications can be found in references [36,27,37,38,32]. However, in a structural dynamic test, it is a common practice to measure the data in the form of Frequency Response Functions (FRF), which requires an additional modal parameter estimation [33,39] to extract the modal parameters. Natke [40] presented a model updating procedure using measured FRFs instead of modal parameters. After that, a growing number of researchers focused on model updating algorithms using the measured data directly [41–47]. In the practical applications of model updating, the measured data are often incomplete and include randomness. Based on the system variability, some authors proposed stochastic model updating techniques [48–51]. The main advantage of this approach is to add randomness in the model updating process. Statistical techniques combined with model updating can improve the parameter estimation. The first works that incorporated statistical methods for the treatment of measurement noise in model updating were presented by Collins et al.[52] and later by Friswell [53]. Differences between measure data and model predictions may arise due to randomness present in the system, e.g. manufacturing variability as well as to variations in the material properties of the structure components. In Friswell's paper [53], errors in the analytical model and in the measurements (e.g. caused by noise [27]) are associated to a weighting matrix and it is shown how to estimate the variance in the updated parameters. This technique is called the minimum variance estimator. Other techniques for model updating in the presence of uncertainty are the Bayesian probabilistic framework presented by Beck, Katafygiotis, and Mares [54–56], model updating based on an inverse approach, and fuzzy arithmetic [57]. Soize [58] presented a methodology for robust model updating using a non-parametric probabilistic approach. Uncertainty in structural properties, such as Poisson's ratio, Young's modulus, mass density, modal damping, etc., are considered irreducible uncertainty and require different mathematical approaches for the updating procedure. The distributions of the updated parameters are then modified in order to improve the correlation between model-predicted distributions and measured data distributions. This is a technique developed by Mottershead et al., and Mare et al. [59,56] and it is called stochastic model updating or uncertainty identification. The stochastic model updating is efficient, not only because it includes variability data due to measurement noise, for example, but also because it includes the variability already existing in the structural property [59,56,48–50]. Govers and Link [60] presented an approach for stochastic model updating with covariance matrix adjustment from uncertain experimental modal data. Further, researchers have investigated different problems using stochastic model updating [52,53,61–63]. The majority of those methods can include and estimate of the global model randomness or uncertainties that are assumed to be spatially homogeneous along the structure. By considering that structure parameter values can be spatially distributed in nature, Adhikari and Friswell [64] estimated distributed parameters modelled as realizations of a random field using modal parameters.