Available online at www.sciencedirect.com
ScienceDirect
Comput. Methods Appl. Mech. Engrg. 279 (2014) 301–324
Computer methods in applied mechanics and engineering
www.elsevier.com/locate/cma

Model-reduction techniques for Bayesian finite element model updating using dynamic response data

H.A. Jensen[a,*], E. Millas[a], D. Kusanovic[a], C. Papadimitriou[b]

[a] *Department of Civil Engineering, Santa Maria University, Valparaiso, Chile*
[b] *Department of Mechanical Engineering, University of Thessaly, GR-38334 Volos, Greece*

Received 30 January 2014; received in revised form 27 May 2014; accepted 23 June 2014
Available online 26 June 2014

Abstract

This work presents a strategy for integrating a class of model reduction techniques into a finite element model updating formulation. In particular a Bayesian model updating approach based on a stochastic simulation method is considered in the present formulation. Stochastic simulation techniques require a large number of finite element model re-analyses to be performed over the space of model parameters during the updating process. Substructure coupling techniques for dynamic analysis are proposed to reduce the computational cost involved in the dynamic re-analyses. The effectiveness of the proposed strategy is demonstrated with identification and model updating applications for finite element building models using simulated seismic response data.

Keywords: Bayesian updating; Dynamic response; Finite elements; Model reduction techniques; Stochastic simulation

1. Introduction

Model updating using measured system response has a wide range of applications in areas such as structural response prediction, structural control, structural health monitoring, and reliability and risk assessment. [1–7]. For a proper assessment of the updated model all uncertainties involved in the problem should be considered. In fact, there always exist modeling errors and uncertainties associated with the process of constructing a mathematical model of the structure and its future excitation. Thus, the ability to quantify the uncertainties accurately and appropriately is essential for a robust prediction of future responses and reliability of structures [8,9]. In this context a fully probabilistic Bayesian model updating approach provides a robust and rigorous framework for model updating due to its ability to characterize modeling uncertainties associated with the underlying structural system [10,11]. Bayesian probabilistic tools for identifying uncertainty models as well as performing robust prediction analysis are usually based on asymptotic approximations [9,12–14] or stochastic simulation algorithms [15–20]. Asymptotic approximation methods in the Bayesian framework involve solving an optimization problem for finding the most probable model,

* Corresponding author. Tel.: +56 32 2654383; fax: +56 32 2654115.
E-mail address: hector.jensen@usm.cl (H.A. Jensen).

http://dx.doi.org/10.1016/j.cma.2014.06.032
0045-7825/

as well as estimating the Hessian of the logarithm of the posterior probability density function. On the other hand stochastic simulation algorithms involve generating samples for tracing and then populating the important uncertainty region in the parameter space. The application of asymptotic approximation methods faces several difficulties when the chosen class of models is unidentifiable based on the available data [9,21]. Since stochastic simulation algorithms are more general than asymptotic approximation approaches a stochastic simulation algorithm is considered in the present study. In particular the transitional Markov chain Monte Carlo method is implemented here because of its generality and versatility [17]. Such algorithm requires in general a large number of re-analysis to be performed over the space of model parameters. Thus, the computational demands depend on the number of re-analysis and the time required for performing each re-analysis. It is noted that alternative Bayesian model updating techniques can also be used for the identification process. For example the Hybrid Monte Carlo method, which is quite efficient for solving high-dimensional Bayesian model updating problems [17], or the population-based Markov chain Monte Carlo method [20] are certainly alternative choices. The implementation and comparison of different identification tools in the context of model reduction techniques will be the focus of a future work.

The present work proposes to use an efficient model reduction technique to alleviate the computational burden involved in the implementation of the transitional Markov chain Monte Carlo method in the framework of finite element model updating using dynamic response data. Specifically, a class of model reduction techniques known as substructure coupling for dynamic analysis is considered in the present implementation [22]. Such technique can be used to carry out system analysis in a significantly reduced space of generalized coordinates. The methodology is quite useful to efficiently handle the computational effort in system re-analyses that arise from finite element model variations caused by perturbations in the value of the uncertain parameters [23]. Such variations require that the assembly process of the finite element model be repeated in each re-analysis. Clearly, the objective of methods involving dynamic re-analyses of finite element models with varying properties is to control the number of re-analysis of the system.

In this regard, the main objective of this work is to present a strategy for integrating a class of model reduction techniques into a finite element model updating formulation in order to reduce the computational cost involved in the dynamic re-analyses of large scale linear models, including localized nonlinearities. The model reduction technique involves dividing the structural system into a number of linear and nonlinear substructures obtaining reduced-order models of the linear substructures, and then assembling a reduced-order model for the entire structure. It is demonstrated that substantial computational savings are achieved under certain parametrization schemes arising often in finite element model updating formulations.

The organization of this contribution is as follows. Essential aspects of Bayesian finite element model updating using dynamic data are presented in Sections 2 and 3. The mathematical background of the substructure coupling technique for dynamic analysis is outlined in Section 4. The integration of the model reduction technique with the Bayesian model updating approach is discussed in Section 5. The effectiveness of the proposed scheme, in terms of computational efficiency and accuracy is demonstrated in Section 6 with damage identification and model updating applications for finite element building models using simulated seismic response data. The contribution closes with some conclusions and final remarks.

2. Finite element model updating using dynamic response data

2.1. Bayesian formulation

Consider a finite element model class M of a structural system parameterized by a set of model parameters $\boldsymbol{\theta} \in \Theta \subset R^{n_p}$. The plausibility of each model within a class M based on data D is quantified by the updated joint probability density function $p(\boldsymbol{\theta}|M, D)$ (posterior probability density function). By Bayes' Theorem the posterior probability density function of $\boldsymbol{\theta}$ is given by

$$p(\boldsymbol{\theta}|M, D) = \frac{p(D|M, \boldsymbol{\theta})\ p(\boldsymbol{\theta}|M)}{p(D|M)} \tag{1}$$

where $p(D|M)$ is the normalizing constant which makes the probability volume under the posterior probability density function equal to unity, $p(D|M, \boldsymbol{\theta})$ is the likelihood function based on the predictive probability density function for the response given by model class M, and $p(\boldsymbol{\theta}|M)$ is the prior probability density function selected for