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Effect of measurement noise and excitation on Generalized Response Surface Model Updating

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ABSTRACT

This paper investigates the robustness of a parameter estimation procedure for nonlinear Finite Element (FE) model updating. Through this procedure, polynomial Response Surface (RS) models are constructed to approximate the response of a nonlinear FE model at every time step of the analysis. Subsequently, the optimization problem of model updating is solved iteratively in time which results in histograms of the updating parameters. With the assumption of White Gaussian measurement noise, it is shown that this parameter estimation technique has low sensitivity to the standard deviation of the measurement noise. In order to validate this, a parametric sensitivity study is performed through numerical simulations of nonlinear systems with single and multiple degrees of freedom. The results show the least sensitivity to measurement noise level, selected time window for model updating, and location of the true model parameters in RS regression domain, when vibration frequency of the system is outside the frequency bandwidth of the load. Further application of this method is also presented through a case study of a steel frame with bilinear material model under seismic loading. The results indicate the robustness of this parameter estimation technique for different cases of input excitation, measurement noise level, and true model parameters.

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1. Introduction

Structural Health Monitoring (SHM) procedures have been primarily developed to assist with lifetime maintenance of constructed structures through assessment of their condition. With the recent advancement in sensing technology, this goal can be served through instrumentation of the structures and monitoring their global behavior. The main components of vibration-based SHM in interpretation of the monitoring data fall into three categories: identification of dynamic characteristics of the monitored structures [1,2]; detection, localization, and quantification of the damage in the system [3–6]; and updating the Finite Element (FE) simulations of the structures based on their measured responses [7–10]. Among these, FE calibration methods attracted significant attention in the recent decades, mainly because having a FE model calibrated with reference to the actual structure, enables a variety of applications such as futuristic reliability study, assessment of retrofit alternatives, and designing structural control strategies. Moreover, parameter estimation through model calibration serves as the basis for many model-based damage detection algorithms which aim to assess the structural damage in a more objective way than non-parametric damage detection procedures [11–14].

FE model updating is an inverse parameter estimation problem where unknown parameters of an a priori structural FE model are estimated based on measurement data. This parameter estimation problem is solved as a constrained optimization problem with the objective of minimizing an error function representing the discrepancy between certain measured response features and their analytical counterparts. Selection of the reference response features for this optimization problem depends on the behavior of the structure and the future application of the calibrated model. When the FE model is used to study the behavior of the structure in low levels of vibration – in which most of the structures behave linearly – experimentally identified modal quantities (e.g. natural frequencies, and mode shapes) are commonly used for estimation of the model parameters. However, when a system behaves nonlinearly, such features fail to estimate model parameters, and other metrics are required for FE model calibration. While the linear model updating techniques and their applications on full scale structures are well-documented in the literature [15–17], the parameter estimation of nonlinear systems is still under ongoing research due to the individualistic nature of various types of local

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and global nonlinearities which exist in the structural dynamics [18]. Silva et al. [19] presented a comparison of the performance of four time – and frequency-domain measures for use in nonlinear model updating through a numerical two degree of freedom (DOF) system having a spring with cubic stiffness. The parameter estimation based on noise-free simulated data showed that while most of the metrics were effective in cases with local and weak nonlinearities, time-domain measures (proper orthogonal decomposition (POD) and restoring force surface (RFS)) yielded more promising results. However, application of POD and RFS were reported to suffer from sensitivity to the sampling frequency and number of data samples used, and requiring complete knowledge of the system through measuring all model DOFs, respectively. Therefore, developing a generalized time-domain strategy for nonlinear model calibration is of significant value.

Intensive computations and convergence problems are common challenges in many of the proposed model updating techniques, where sensitivity of the structural responses to the model parameters are calculated iteratively by means of the local gradients. As an effort toward decreasing such computational load, application of Response Surface (RS) methodology [20] was introduced in the process of FE model updating. The RS models – commonly used in the form of polynomial functions – approximate the relation between pre-selected inputs and output of the FE model. Then, the optimization problem of model updating is solved using these RS models as surrogates of the full FE model.

Previous studies of this method in updating the uncertain parameters of linear FE models has proved: efficiency of this method over traditional sensitivity-based model updating approaches [21,22]; low computational effort associated with such technique integrated with evolutionary optimization methods [23,24]; reduced computational cost in stochastic model updating [25,26] ; successful application on full scale bridge FE model calibration [27,28]; and success in detection and localization of the structural damage [29]. However, the literature related to application of RS-based model updating for nonlinear systems is scarce. Schultze et al. [30] used RS models in parameter selection and calibration of an FE model of a sandwiched layer of hyper-elastic foam and steel assembled on a drop table based on peak acceleration response and its time of arrival in a series of drop tests. Zhang and Guo [31] proposed a model updating procedure based on principal component decomposition and RS method to update a frame model with thin wall components showing strain-rate-dependence nonlinearity under impact test.

As an effort toward developing a generalized procedure for nonlinear model updating that addresses the above-mentioned issues regarding the nonlinear model updating metrics and computational load, an RS-based time-domain model updating procedure was previously proposed by the authors [32]. This method – called *Generalized Response Surface Model Updating (GRSMU)* – consists of three steps of RS model construction, evaluation, and optimization. Through these three steps, with assumption of known input, and using least square techniques [33], accurate RS models are constructed at every time step of the analysis and minimization problem of parameter estimation is solved iteratively in the length of the time history of the responses of the system. The performance of GRSMU was previously validated through a numerical cases study of a nonlinear frame under sinusoidal loading [32].

As noise contamination is unavoidable in any measurement procedure, which may heavily influence the interpretation of the data, a reliable parameter estimation technique should be robust to measurement noise. Therefore, this paper primarily evaluates the sensitivity of GRSMU estimates to the measurement noise. Moreover, the effect of input excitation frequency content and further application of this method in updating a nonlinear frame under seismic loading are investigated.

The outline of this paper is as follows. In the next section, the algorithm developed to accomplish nonlinear FE model updating using RS models is briefly presented. Afterward, the sensitivity of the proposed algorithm to measurement noise is studied followed by simulated case studies of single – and multi-DOF nonlinear models updated in cases with different assumptions for the frequency of input excitation and noise contamination level. Subsequently, application of this method in estimation of the parameters of a nonlinear steel frame under seismic loading is investigated in different scenarios. Finally, a summary of the paper and conclusions are presented.

2. Generalized Response Surface Model Updating (GRSMU)

In RS-based FE model updating, RS models replace the full FE model in a pre-selected domain of unknown model parameters, here called RS domain. These RS models are constructed using least square techniques [33] by regressing a polynomial function on a set of points sampled from the RS domain. Techniques of designs of experiments [34] can be employed in order to sample these points. However, finding the appropriate model order associated with each parameter and design of model parameters' levels that produce accurate RS models, require a number of trials and errors which may contradict the primary motivation for using the RS models to decrease the computational cost of FE model analyses in model calibration.

GRSMU was previously proposed to systematically design the levels and model order of the RS models, and extend the application of RS modeling for nonlinear model updating in time through RS model construction and optimization iteratively at every time step of the analysis. In order to construct accurate RS models capable of predicting the response of the FE model throughout the RS domain, GRSMU adopts a full factorial design with minimum number of levels and linear RS models. This procedure is subsequently followed by evaluation of the regressed RS models in terms of accuracy and predictability, and increasing the model order or number of levels associated with each model parameter, when required. Fig. 1 presents the flowchart of GRSMU. Eq. (1) formulates the optimization problem of model updating using GRSMU at the l^{th} time step of the nonlinear dynamic analysis.

$$\begin{aligned}&\min_{\theta_j}\quad f_1=\sqrt{\sum_{i=1}^{s}\left(\frac{RS_{il}(\theta_1,\theta_2,\ldots,\theta_m)-Y_{expil}}{Y_{expil}}\right)^2}\quad i=1,2,\ldots,s\\&s.t.\quad \theta_{jlb}\leqslant\theta_j\leqslant\theta_{jub}\quad j=1,2,\ldots,m\end{aligned}\tag{1}$$

In Eq. (1) $RS_{il}(\theta_1,\theta_2,\ldots,\theta_m)$ denotes the RS model associated with the l^{th} time step of the analysis representing the i^{th} analytical response feature, as a function of the pre-selected uncertain model parameters $(\theta_1,\theta_2,\ldots,\theta_m)$, θ_{jlb} and θ_{jub} represent the lower and upper bounds of the j^{th} model parameter in the RS domain, and y_{expil} is the i^{th} response feature measured at the l^{th} time step of the experiment. Any nonlinear constrained optimization algorithm can be readily adopted to solve this explicitly formulated FE model updating problem.

3. Sensitivity of the GRSMU estimates to measurement noise

This section investigates the effect of measurement noise on the parameter estimation results of GRSMU. This study simulates the measurement error as White Gaussian noise in which the values at any pair of time instances in the noise signal are statistically independent and identically distributed with a zero-mean normal probability distribution.

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