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Uncertainty quantification and propagation in dynamic models using ambient vibration measurements, application to a 10-story building

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ABSTRACT

This paper investigates the application of Hierarchical Bayesian model updating for uncertainty quantification and response prediction of civil structures. In this updating framework, structural parameters of an initial finite element (FE) model (e.g., stiffness or mass) are calibrated by minimizing error functions between the identified modal parameters and the corresponding parameters of the model. These error functions are assumed to have Gaussian probability distributions with unknown parameters to be determined. The estimated parameters of error functions represent the uncertainty of the calibrated model in predicting building's response (modal parameters here). The focus of this paper is to answer whether the quantified model uncertainties using dynamic measurement at building's reference/calibration state can be used to improve the model prediction accuracies at a different structural state, e.g., damaged structure. Also, the effects of prediction error bias on the uncertainty of the predicted values is studied. The test structure considered here is a ten-story concrete building located in Utica, NY. The modal parameters of the building at its reference state are identified from ambient vibration data and used to calibrate parameters of the initial FE model as well as the error functions. Before demolishing the building, six of its exterior walls were removed and ambient vibration measurements were also collected from the structure after the wall removal. These data are not used to calibrate the model; they are only used to assess the predicted results. The model updating framework proposed in this paper is applied to estimate the modal parameters of the building at its reference state as well as two damaged states: moderate damage (removal of four walls) and severe damage (removal of six walls). Good agreement is observed between the model-predicted modal parameters and those identified from vibration tests. Moreover, it is shown that including prediction error bias in the updating process instead of commonly-used zero-mean error function can significantly reduce the prediction uncertainties.

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1. Introduction

The dynamic response of civil structures to external loadings is often predicted using finite element (FE) models. Examples include prediction of structural response to wind or seismic loads. It is common to validate linear FE models by comparing their response or features extracted from response such as modal parameters with the ones identified from vibration data [1–6]. The FE models of civil structures are often associated with many sources of uncertainty and modeling errors; Haukaas and Gardoni [7] provide a discussion on different sources of uncertainty in FE structural models. These uncertainty sources affect the design and performance assessment of civil structures when these FE models are used for predicting a quantity of interest [2,8–17]. Calibration/updating of the FE models [18,19] using static and/or dynamic data can reduce some of these uncertainties [20–22]. In the model updating process, selected parameters of the model are adjusted so that the model-predicted response time histories, modal parameters, or frequency response functions best match the corresponding quantities obtained from the test data. In most cases, the updated FE models still have bias in predicting the data that are used for model calibration [4,20,23–26]. This problem is not limited to the deterministic model updating frameworks; the accuracy of probabilistic updating frameworks, as presented in [12,27,28], has been discussed by a number of researchers. In [29], the effects of weighting factors (or prediction error variances) on the model updating results in the presence of modeling errors are studied, and Pareto optimal models are used to provide more robust identifications in the presence of modeling errors. Ching and Beck [30] report modeling errors to be the major source of inaccurate damage identification results in their case study. In [31–34], the authors propose model falsification instead of model identification to overcome the challenges of accounting for modeling errors in model identification. One major argument in the last three studies is that the estimated structural parameters from Bayesian updating techniques are biased from their true values in the presence of modeling errors. They also discuss that models cannot be fully validated, and therefore, they utilize the concept of model falsification as an alternative approach to handle the uncertainty of FE models. Prediction error bias is one of the major drawbacks of Bayesian identifications. Goller and Schueller [23] investigate this problem through Bayesian model updating using zero-mean Gaussian error functions and conclude that the prediction bias of the updated FE models should be considered when the model is used for predictions.

This paper presents an improved model identification technique that aims to quantify the uncertainty of a model in predicting a specific quantity of interest. The estimated uncertainty of the model is then propagated in model-predicted quantities. To this end, the Hierarchical Bayesian Modeling [35–37] is used to calibrate the initial FE model of a 10-story concrete building using identified natural frequencies and mode shapes of the building extracted from ambient vibration measurements. A probability distribution with unknown mean and covariance matrix is considered for the error function between the identifiable modal parameters and those of the model. Parameters of the probability distribution are considered as updating parameters. The effects of prediction error bias are studied by considering an error function once as zero-mean and once as non-zero mean random variable. The calibrated FE model and the prediction error model are used to predict the natural frequencies of the building at different states, i.e., after removing four and six of its exterior walls, respectively. It is shown that considering the mean of error functions as updating parameters reduces the prediction error variances and the commonly-used zero-mean error function may result in large prediction uncertainty. This paper is the extension of the work presented by the authors in conference paper [38].

2. Model calibration in the presence of modeling errors

Model calibration aims to reduce the discrepancy between model-predicted features (here natural frequencies and mode shapes) and their experimentally-identified counterparts by tuning a set of model parameters. As it has been discussed in past studies, tuning structural parameters alone may not fully eliminate the misfit between the data and model predictions (i.e., bias) because of modeling error effects [7,23,27,31]. The probabilistic FE model calibration method used in this study includes the structural updating parameters as well as modeling error parameters to capture the remaining misfit between identified and model-predicted response features. The following error functions are defined for the natural frequency and model shape of mode m:

$$e_{\omega_{tm}} = \frac{\omega_m^2(\boldsymbol{\theta}_t) - \tilde{\omega}_{tm}^2}{\bar{\tilde{\omega}}_m^2} \quad m = 1 : N_m \tag{1}$$

$$\mathbf{e}_{\boldsymbol{\Phi}_{tm}} = \cos(\varphi_{tm}) \frac{\boldsymbol{\Gamma}\boldsymbol{\Phi}_m(\boldsymbol{\theta}_t)}{\|\boldsymbol{\Gamma}\boldsymbol{\Phi}_m(\boldsymbol{\theta}_t)\|} - \frac{\tilde{\boldsymbol{\Phi}}_{tm}}{\|\tilde{\boldsymbol{\Phi}}_{tm}\|} \tag{2}$$

In Eqs. (1) and (2) $\tilde{\boldsymbol{\omega}}_{tm}$ and $\tilde{\boldsymbol{\Phi}}_{tm}$ are the circular natural frequency and mode shape of mode m identified using data set t, and $\bar{\tilde{\omega}}_m$ is the average of identified natural frequencies over all data sets. $\omega_m(\boldsymbol{\theta}_t)$ and $\boldsymbol{\Phi}_m(\boldsymbol{\theta}_t)$ are the model-calculated natural frequency and mode shape of mode m given $\boldsymbol{\theta}_t$, where $\boldsymbol{\theta}_t$ is the vector of structural parameters corresponding to data set t. N_m is the number of identified modes, matrix $\boldsymbol{\Gamma}$ picks the measured mode shape components, and φ_{tm} is the angle between identified and model-calculated mode shapes which can be estimated using Eq. (3).