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Multi-fidelity approach to dynamics model calibration

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ABSTRACT

This paper investigates the use of structural dynamics computational models with multiple levels of fidelity in the calibration of system parameters. Different types of models may be available for the estimation of unmeasured system properties, with different levels of physics fidelity, mesh resolution and boundary condition assumptions. In order to infer these system properties, Bayesian calibration uses information from multiple sources (including experimental data and prior knowledge), and comprehensively quantifies the uncertainty in the calibration parameters. Estimating the posteriors is done using Markov Chain Monte Carlo sampling, which requires a large number of computations, thus making the use of a high-fidelity model for calibration prohibitively expensive. On the other hand, use of a low-fidelity model could lead to significant error in calibration and prediction. Therefore, this paper develops an approach for model parameter calibration with a low-fidelity model corrected using higher fidelity simulations, and investigates the trade-off between accuracy and computational effort. The methodology is illustrated for a curved panel located in the vicinity of a hypersonic aircraft engine, subjected to acoustic loading. Two models (a frequency response analysis and a full time history analysis) are combined to calibrate the damping characteristics of the panel.

1. Introduction

With the continuous development of faster and more efficient computational capabilities, higher fidelity computer simulations are increasingly being used to try to predict the behavior of systems. Specifically in dynamics problems, being able to forecast the response of a structure over time is an important need. High fidelity dynamic simulation allows the prediction of performance not only under normal operating conditions but also during startup, shutdown and abnormal conditions, especially when behavior is highly non-linear, and linear low fidelity models are inaccurate [1]. In hypersonic aircraft simulations for example, Candler et al. [2,3], Higgins and Schmidt [4], and many others have investigated high fidelity analyses. Considerable effort has also been reported in developing reduced-order models that are cheaper and faster to run [5–7]. These high fidelity simulations, as well as the reduced-order models, are useful only when they are good representations of the actual structure and the underlying physics that cause the observed behaviors are taken into account [8].

In order to obtain a model that is structurally equivalent to an experimental setup, one necessary step is model calibration: quantifying the errors and adjusting the unknown model parameters to minimize the difference between the model output and the experimental data. Errors arise in the numerical methods used to solve the problem, but also in the

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limitations of the available experimental data. Christie et al. [9] argue that knowledge about the state of a complex phenomenon system and the governing physical processes is often limited and/or inaccurate, and propose building error models. These error models aim to provide an independent estimate of the known shortcomings of the simulations, and define quantitative bounds of the possible errors. However, they are not necessarily used to increase the accuracy of the simulation.

Uncertainty in simulations has multiple sources:

(1) Natural variability (aleatoric uncertainty) which is not reducible, but generally modeled by assigning probability distributions to the variables.
(2) Statistical uncertainty (reducible, epistemic uncertainty). It arises from sparse and/or imprecise data.
(3) Model uncertainty (reducible, epistemic uncertainty), which is due to uncertainty in model parameters, model form error, and solution approximations [10]. The solution approximation errors arise due to reduced order models, surrogate models, discretization errors, truncation and round off.

Mottershead and Friswell [11] offer a similar grouping of modeling errors into three types: (a) model form errors (due to assumptions regarding the underlying physics of the problem, especially with strongly nonlinear behavior); (b) model parameter uncertainty (due to assumptions regarding boundary conditions, parameter distributions and simplifying assumptions); and (c) model order errors (arising from the discretization of complex geometry and loading). Liang and Mahadevan [12] proposed a systematic methodology to quantify various error and uncertainty sources in model prediction.

Three types of modeling approaches have been pursued in structural dynamics for complicated mechanical systems: (1) finite element models; (2) reduced order models and (3) surrogate models. Finite element analysis (FEA) is commonly used in the dynamics modeling of engineering structures with complicated geometry and under complex loading conditions. Construction of the FEA model incorporates many assumptions by the analyst about the system properties and excitation. Two principal qualities are desired in a functional finite element model of structural dynamics [13]: (1) physical significance, i.e., the model should properly represent how the mass, stiffness and damping are distributed, and (2) correctness, i.e., the observations from dynamics experiments are accurately predicted by the model. High-fidelity dynamic finite element analysis of complex mechanical systems is quite expensive, and considerable research has been done to construct cheaper and simpler surrogate models, equivalent static models, or reduced-order models. However, the errors and uncertainties in calibration and prediction increase with the reduction in model fidelity. Computationally efficient models have to be cheap enough to allow multiple repetitions of the simulations, but also retain precious information available from rigorous but more expensive models.

Many studies have concentrated on developing reduced-order models (ROM) to replace full fidelity dynamic analyses. McEwan et al. [14,15] proposed the Implicit Condensation (IC) method that included the non-linear terms of the equation of motion, but restricted the nonlinear function to cubic stiffness terms. The IC method can only predict the displacements covered by the bending modes. Other methods explicitly include additional equations to calculate the membrane displacements in the ROM, such as those by Rizzi et al. [16,17] and Mignolet et al. [18,19]. The effectiveness of these reduced order models is directly related to their ability to predict the trends in higher fidelity models and/or experimental data [20].

Several studies have replaced the expensive computational model with surrogate models such as Polynomial Chaos Expansion (PCE), Gaussian process models, etc. This approach facilitates running inexpensive simulations. Dynamic finite element models are particularly expensive to run, and Hemez et al. [21] also used a polynomial surrogate to reduce the computational cost in calibrating the parameters of a transient dynamics problem.

Different methodologies have also been presented to deal with multi-fidelity surrogate modeling, where codes and/or models of different complexities are available. Haftka [22] and Hutchison et al. [23] calculated a high to low fidelity ratio, and applied it as a scaling factor to the low fidelity data to refine the low fidelity surrogate model. Kennedy and O'Hagan [24] developed an autoregressive approach to combine surrogate models of different fidelities. Leary et al. [25] use the difference between the high fidelity and low fidelity data at certain locations to train artificial neural networks and kriging interpolation. Forrester et al. [26] considered partially converged simulations from a high fidelity model as low fidelity data.

In order to improve the performance of simulation models, model calibration, commonly known as model updating in dynamics literature, has been extensively investigated. The distance between the measured data and the model prediction is computed. The goal is to minimize this distance (using least squares, for example) by varying the design parameters. Direct updating methods have been proposed by computing closed-form solutions for the global stiffness and mass matrices using the structural equations of motion [27,28]. The generated matrices are faithful to modal analyses, but do not always maintain structural connectivity, and may not retain physical significance. Other iterative methods study the changes in model parameterization to evaluate the type and the location of the erroneous parameters, and vary these parameters in an effort to minimize the difference between the experimental data and the FE model predictions [29]. Datta et al. [30] used complex mode data to update FEA models with validated models and synthetic data, however performing complex mode identification tests is difficult. Other studies propose updating different parameters separately, in a two-step method. Arora et al. [31] update mass and stiffness matrices in the first step, and then use the updated results in the second step to update the damping matrix. Yuan and Yu [32] claim that the difference in scale between the parameters (elastic moduli and