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Input-dependence effects in dynamics model calibration

Ghina N. Absi, Sankaran Mahadevan *

Vanderbilt University, Nashville, TN, USA

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ABSTRACT

This paper investigates the use of non-linear structural dynamics computational models with multiple levels of fidelity for the calibration of input-dependent model parameters. Non-linear behavior complicates the calibration of model parameters that are input-dependent (i.e., functions of temperature, loading, etc.). Different types of models may also be available for the estimation of unmeasured system properties, with different levels of physics fidelity, mesh resolution and boundary condition assumptions. To infer these system properties, Bayesian calibration can be used to combine information from multiple sources (such as experimental data and prior knowledge) and comprehensively quantify the uncertainty in the model parameters. Estimating the posterior distributions 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 pursues a multi-fidelity approach for input-dependent model parameter calibration with a surrogate of the low-fidelity model corrected using higher fidelity simulation data. The effects of non-linear behavior and input-dependence of model parameters and measurements are systematically organized and distinguished using a Bayesian network. The methodology is illustrated with a curved panel, subjected to acoustic and thermal loading, where the damping properties of the panel could be functions of the acoustic loading and temperature magnitudes. Two models (a frequency response analysis and a full time history analysis) are combined to estimate the damping characteristics of the panel. The effect of the temperature on the performance of the strain gages and therefore on the calibration results is also studied.

1. Introduction

With advances in computational technology, there is increasing opportunity and demand for high-fidelity dynamic simulations that allow performance prediction under normal as well as extreme operating conditions. In hypersonic aircraft simulations for example, Candler et al. [1–2], Higgins and Schmidt [3], and others have explored high-fidelity models. Substantial work has also been reported in developing reduced-order models that are cheaper and faster to run [4–6]. These high-fidelity simulations, as well as the reduced-order models, are useful only when they accurately represent the actual physics that cause the observed behavior [7]. This is of particular concern in the presence of non-linear behavior [8–9]. Attempts at developing non-linear reduced-order models have been reported [10]. For example, Perez and Mignolet [11]

* Corresponding author.
E-mail address: sankaran.mahadevan@vanderbilt.edu (S. Mahadevan).

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used a non-linear static analysis at specific input conditions to capture geometrical non-linearity in panels subjected to acoustic and thermal loading. On the other hand, high-fidelity non-linear analyses are often prohibitively expensive to run.

One necessary step in obtaining a model that accurately represents reality is model calibration, i.e., quantifying the errors and estimating the unknown model parameters to minimize the difference between the model outputs and experimental observations. Christie et al. [12] argue that knowledge about the state of a complex system and the governing physical processes is often incomplete and/or erroneous, and propose building error models. Uncertainty in model prediction arises from multiple sources: (1) natural variability (irreducible, aleatory uncertainty), generally modeled by assigning probability distributions to the variables, (2) statistical uncertainty (reducible, epistemic uncertainty) arising from sparse and/or imprecise data, and (3) model uncertainty (reducible, epistemic uncertainty), which is due to uncertainty in model parameters, model form error, and solution approximations [13]. The solution approximation errors arise due to reduced order models, surrogate models, discretization errors, truncation and round off. Liang and Mahadevan [14] proposed a systematic methodology to quantify various error and uncertainty sources in model prediction. Three approaches are generally used in the calibration of model parameters with input-output data: least squares, maximum likelihood, and Bayesian calibration. Bayesian calibration combines both prior (subjective) information and experimental data, and quantifies the epistemic uncertainty in the calibration result. Kennedy and O'Hagan [15] included a discrepancy function between the model prediction and the experimental data during Bayesian calibration. Including appropriate model discrepancy functions has been shown to improve the calibration of model parameters [16].

Bayesian model calibration is often numerically accomplished with Markov Chain Monte Carlo (MCMC) sampling when analytical solutions are not available, which requires thousands of samples. The cost is further amplified for problems with a large number of parameters, or when the model output is far from the experimental data (thus requiring a large number of samples to achieve convergence). Therefore, an inexpensive surrogate model is often used to replace the original simulation model and reduce the computational expense in Bayesian calibration. However, building a surrogate model requires training points, which are generated by running the original model at a certain number of input conditions. If the original high-fidelity model is expensive, this may limit the number of training points, thus reducing the accuracy of the surrogate model. On the other hand, if a lower fidelity model is available, this may help to generate many training points, but the accuracy of the resulting surrogate model would be questionable due to the use of the lower fidelity model runs.

Fusion of information from models of different fidelity has been significantly investigated in forward problems and in optimization frameworks. Haftka [17] and Hutchison et al. [18] scaled the low fidelity data with a high to low fidelity ratio to improve the low fidelity surrogate model. Kennedy and O'Hagan [19] combined surrogate models of different fidelity using an autoregressive approach. Leary et al. [20] trained local artificial neural networks and kriging interpolations using the distance between the high fidelity and low fidelity data. Robinson et al. [21] investigated fusing information from models of different fidelity for optimizing the surrogate model using a trust-region approach. The focus in our paper is on calibration within the multi-fidelity framework. In the context of model calibration, Absi and Mahadevan [22] fused information from models of different fidelities in the calibration of system parameters. The approach consists of first correcting a low-fidelity surrogate model using a small number of high-fidelity simulations, thus effectively creating physics-informed stronger priors from that correction to use in the final calibration with experimental data.

Further complications in calibration arise in the presence of nonlinear behavior. Typical sources of non-linearity in structural dynamics are geometric non-linearity (due to large deformations), material non-linearity (non-linear stress/strain constitutive law, strain hardening), damping dissipation (dry friction – contact and sliding between bodies, and hysteretic damping [23] effects), boundary conditions (e.g., surface/fluid interactions), external non-linear body forces (e.g., hydrodynamic forces, temperature), etc. [24]. Model parameters in such situations could be input-dependent. Calibration considering input-dependent system parameters has been referred to as functional calibration. Pourhabib and Balasundaram [25] showed that calibration of parameters that are input-dependent is a curve-to-surface matching problem, and used a sum of splines to represent that relationship. Plumlee et al. [26] considered calibration parameters as analytical functions of inputs to replace previously used empirical definitions (data fitting by least squares) in the ion channel models of cardiac cells. Brown and Atamturktur [27] used a nonparametric approach to calibrate input-dependent system parameters, in which a Gaussian Process (GP) model is used to represent the relationship between the parameters and the input.

In real application problems, many challenges arise in the experimental, modeling and calibration stages. In experiments, replicating the natural phenomena in laboratory settings while preserving the quality of the recorded data is difficult, especially in the presence of high temperature, which could negatively affect the recording devices such as strain gages. Modeling the experimental setting also brings high uncertainty in capturing all the present physical phenomena. The increased number of parameters makes effective calibration hard, especially when a low number of experimental data is available. Complex interactions can lead to having nonlinearity and input-dependence simultaneously active, thus there is a need to distinguish between these effects in the calibration process.

The aim of this study is to extend our approach of fusing information from models of different levels of fidelity to Bayesian calibration of input-dependent model parameters. In this paper, we consider geometric nonlinearity (effect of large deformations) and material non-linearity (nonlinear stress-strain relationships that can also be temperature dependent) in the modeling phase that are distinguished from the input-dependence of the parameters. We assume a functional dependence between the inputs and the parameters, organize them in a Bayesian network, and use a multi-fidelity calibration approach to update the coefficients of these functional relations (i.e., the hyper-parameters). We also include the effect of different types of inputs on the sensors (i.e., strain gages) and use realistic experimental data to illustrate the benefits of this approach.