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Multi-Model Uncertainty Quantification and Model Updating for the TMD Research Challenge

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ABSTRACT
In 2021, a group of organizers released the Tribomechadynamics (TMD) Research Challenge requesting blind predictions for the nonlinear modal characteristics of a jointed structure with expected geometric nonlinearity. Various institutions submitted computations of the desired quantities of interest, namely amplitude dependent frequency and damping curves for the fundamental mode, prior to an experimental campaign to provide the corresponding test data. The analysis team from Sandia National Laboratories provided predictions using both a low- and high-fidelity finite element model. The current research builds upon this study by developing a multi-model simulation framework that leverages the efficiency of the low-fidelity model combined with the accuracy of the high-fidelity model to create a surrogate model. The resulting surrogate model is capable of parametrically predicting the nonlinear frequency and damping curves while providing a measure of uncertainty associated with its prediction. The multi-model framework is utilized to compute the bounds of the predictions based on the epistemic uncertainty while providing an efficient framework to perform model updating with the provided experimental data.

Keywords: nonlinear modal analysis, backbone curves, finite element analysis, multi-model uncertainty quantification, model updating

INTRODUCTION

The 2021 Tribomechadynamics (TMD) Research Challenge invited various researchers from different institutions to make blind predictions of the nonlinear resonant behavior of a bolted structure [1]. An image of the TMD structure is shown in Fig. 1, where the system consists of a thin panel, a support structure, and two blades to compress the ends of the blade using bolted connections [2]. A slight angle at the support interfaces produces a slight arch in the blade following the preload, resulting in a non-flat panel when in its assembled state. The benchmark was designed to induce both geometric nonlinearity due to the bending-axial coupling, as well as frictional contact nonlinearity within the bolted interfaces. As a result of the challenge, several groups submitted predictions for the first five linear modes of the system as well as the nonlinear frequency and damping backbone curves of the fundamental mode. The comparison of results revealed the variability in the predicted modal characteristics, most notably in the nonlinear damping backbone of the first mode [1].

As a follow-on to the research challenge, a group of researchers conducted experiments on the benchmark structure during the 2022 TMD Research Camp. In preparation for the experimental results, the research team at Sandia National Laboratories worked to develop a multi-model uncertainty quantification framework that leverages both the low- and high-fidelity models developed originally for the challenge. These models were parameterized based on the largest expected sources of uncertainty, and were utilized to generate a surrogate model built from simulations of both models. The method leverages the efficiency of the low-fidelity model while applying corrections from the samples obtained from the high-fidelity model. The surrogate model allows for fast predictions of the frequency and damping backbone curves for the purpose of model calibration to the experimental data. The details of the modeling approach are summarized in this extended abstract.

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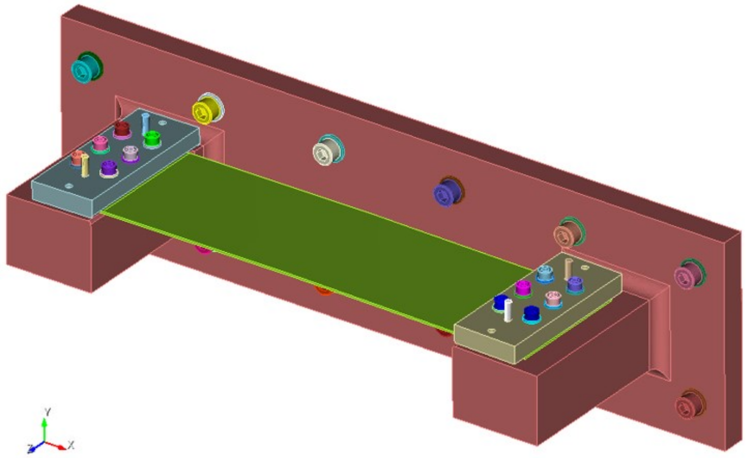

Figure 1: CAD image of the TMD benchmark structure.

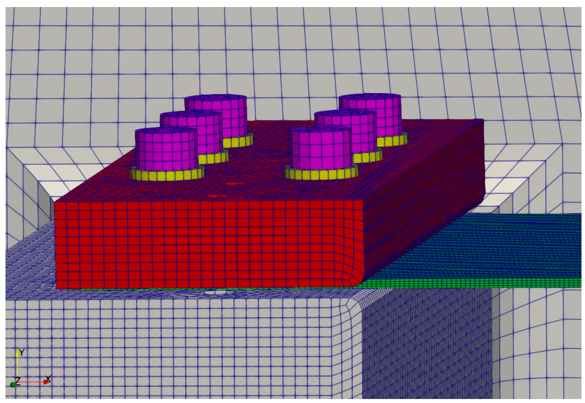

Figure 2: Close-up image of the high-fidelity finite element mesh.

MODELING APPROACH

Two different models were developed for the original submission of the research challenge, as discussed in [3]. A low- and high-fidelity model were created to account for the geometric and frictional contact nonlinearity in the system. The high-fidelity FEM is presumed to be highly accurate due to the explicit and detailed representation of the geometry and the physics. On the other hand, the low-fidelity model is a simplification of the physics in the structure, such as contact, and the exclusion of three-dimensional stress states. An initial sensitivity analysis was performed using the low-fidelity model, which revealed that the angle and thickness of the thin panel, as well as the coefficient of static friction, were the most sensitive parameters to the nonlinear backbone curves. As a result of this finding, these three variables were chosen to parameterize the high-fidelity model.

A high-fidelity finite element mesh of the TMD structure was developed in Cubit [4], where a close-up of the mesh is provided in Fig. 2. A selective deviatoric element formulation was utilized for all the analyses with the high-fidelity model. Sierra Solid Mechanics (Sierra/SM) [5] and Sierra Structural Dynamics (Sierra/SD) [6] finite element software is used to perform the high-fidelity simulations. The procedure utilizes a hand-off workflow for a variant of quasi-static modal analysis [7] [8], with the only difference being the release of the modal force in the final step and the transient ring-down of the structure is simulated. Initial preloading is completed in Sierra/SM, followed by a linearized modal analysis in Sierra/SD, which is then used to perform a nonlinear ring-down in Sierra/SM using the applied modal forcing vector as the excitation source. An explicit time integration scheme was used for the nonlinear modeling.

A low-fidelity model of the curved plate was developed in Matlab using a two-dimensional corotational beam element formulation [9] [10] to capture the geometric nonlinearity. Two-dimensional Jenkins elements [11] with variable normal load were added to the beam elements at the location of the bolted interface in order to capture the effects of frictional contact. It was assumed that the normal force from the bolt preload was uniformly distributed, allowing the nodes with friction elements to be

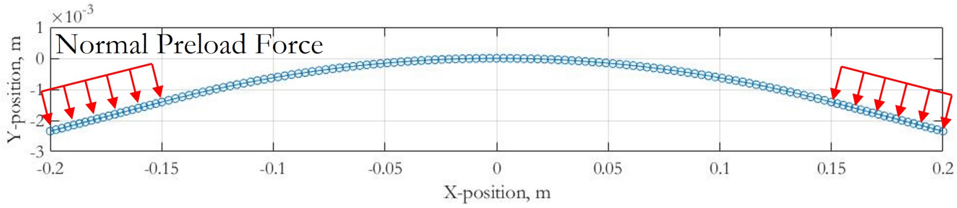

Figure 3: Schematic of the low-fidelity model of the TMD benchmark structure.

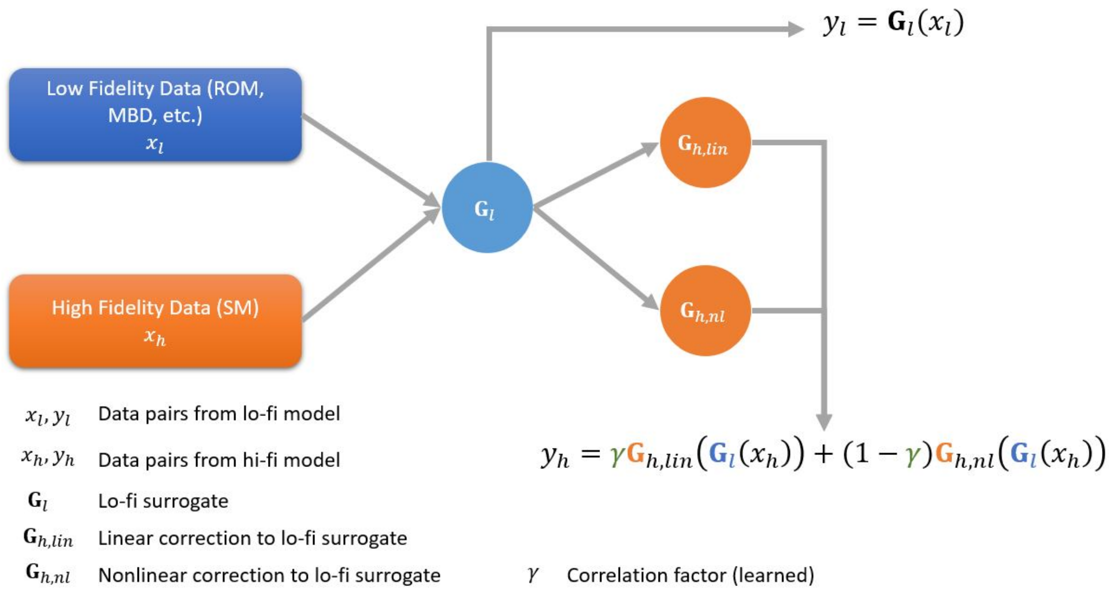

Figure 4: Diagram of MMUQ workflow.

preloaded prior to the dynamic simulation. The low-fidelity model consists of only 136 beam elements, making it efficient to perform the preload, linearized modal, and nonlinear ring-down analysis. A schematic of the low-fidelity model is shown in Fig. 3.

This work aims to combine the advantages of both fidelity models by finding linear and nonlinear correlations between the two. To this end, a multi-fidelity surrogate model is constructed from a hierarchical stacking of surrogate submodels as shown in Fig. 4. This process is known as the multi-model uncertainty quantification (MMUQ) workflow. This work builds upon previous research focused on efficient additive manufacturing modeling [12]. A neural network is trained to act as surrogate of the low-fidelity model (G_l) from a rich dataset generated by the low-fidelity model, which is efficient to evaluate. A much more sparse dataset of high-fidelity model evaluation is then used to learn a correction for the G_l surrogate. Two neural networks are used to learn the linear ($G_{h,lin}$) and nonlinear ($G_{h,nl}$) correction mapping. A correlation factor γ dictating the contribution of the linear versus nonlinear correction is also learned during the training process. The end result is a surrogate model that has accuracy on the order of the high-fidelity model and is faster to evaluate than the low-fidelity model.

ANALYSIS

As a demonstration of the MMUQ workflow, the surrogate was trained on data from a ”low-fidelity” and a ”high-fidelity” version of the low-fidelity model with corotational beam elements. The lo-fi model had only 10 elements along the beam arc, and 8 elements along the flat part, while the hi-fi model had 98 and 38 elements, respectively. For the training, 60 samples were generated from the lo-fi model, and 15 samples from the hi-fi model. The parameters that were varied for training were the following: the plate angle, initial preload, friction coefficient, and plate thickness. The surrogate was trained with these data and then used to predict the response of a new test parameter set. Figure 5 shows these results. As illustrated, the lo-fi prediction (red line) is different from the actual result (black). However, the surrogate is able to correct this discrepancy resulting in an

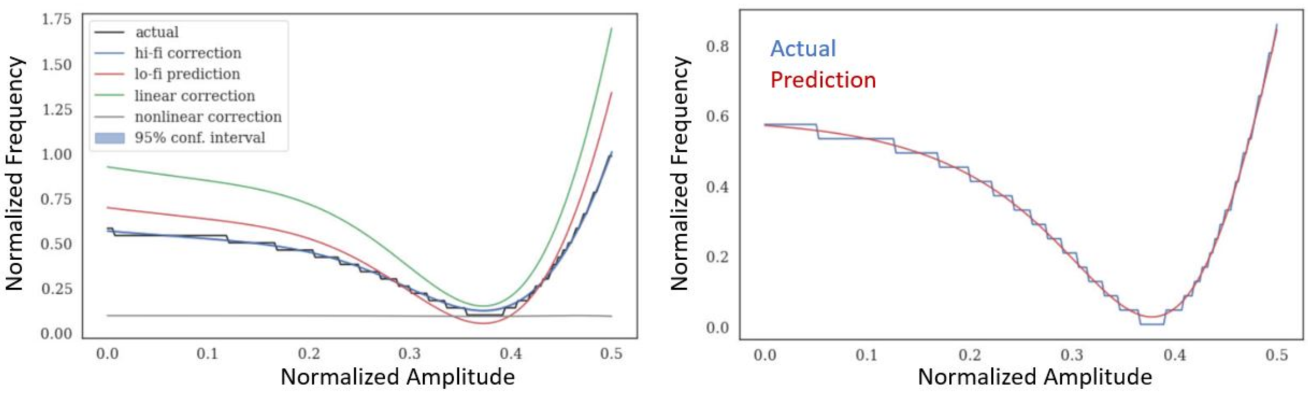

Figure 5: Surrogate model intermediate (left) and final (right) predictions.

accurate reconstruction of the actual data. A 95% confidence interval produced by the surrogate is included but it is shown to be really narrow indicating the high confidence associated with the model prediction.

CONCLUSION

The low- and high-fidelity models of the TMD benchmark structure have been developed and parameterized based on the variables that are most sensitive to the nonlinear frequency and damping backbones of the fundamental mode of vibration. A multi-model uncertainty quantification framework has been developed to leverage both low- and high-fidelity model simulations to train a surrogate model, leading to an efficient means to parameterize the quantities of interest. The methodology leverages the speed of the low-fidelity model to allow for many samples to be drawn, while the high-fidelity model provides higher accuracy that corrects the errors inherent to the low-fidelity model. As future work, the high-fidelity finite element model will be included in the workflow to update the surrogate model, allowing for parameterization of the nonlinear backbone curves and enabling model calibration to the experimental data obtained on the TMD structure.

ACKNOWLEDGEMENTS

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