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VALIDATION OF TRANSIENT STRUCTURAL DYNAMICS SIMULATIONS: AN EXAMPLE

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1 INTRODUCTION

The field of computational structural dynamics is on the threshold of revolutionary change. The ever-increasing costs of physical experiments coupled with advances in massively parallel computer architecture are steering the engineering analyst to be more and more reliant on numerical calculations with little to no data available for experimental confirmation.

New areas of research in engineering analysis have come about as a result of the changing roles of computations and experiments. Whereas in the past the primary function of physical experiments has been to confirm or "prove" the accuracy of a computational simulation, the new environment of engineering is forcing engineers to allocate precious experimental resources differently. Rather than trying to "prove" whether a calculation is correct, the focus is on learning how to use experimental data to "improve" the accuracy of computational simulations. This process of improving the accuracy of calculations through the use of experimental data is termed "model validation."

Model validation emphasises the need for quantitative techniques of assessing the accuracy of a computational prediction with respect to experimental measurements, taking into account that both the prediction and the measurement have uncertainties associated with them. The "vugraph norm," where one overlays transparencies of simulated data and experimental data in an attempt to show consistency, is no longer an adequate means of demonstrating validity of predictions.

To approach this problem, a paradigm from the field of statistical pattern recognition has been adopted [1]. This paradigm generalises the extraction of corresponding "features" from the experimental data and the simulated data, and treats the comparison of these sets of features as a statistical test. The parameters that influence the output of the simulation (such as equation parameters, initial and boundary conditions, etc.) can then be adjusted to minimise the distance between the data sets as measured via the statistical test. However, the simple adjustment of parameters to calibrate the simulation to the test data does not fully accomplish the goal of "improving" the ability to model effectively, as there is no indication that the model will maintain accuracy at any other experimental data points.

Effective model validation requires "uncertainty quantification" to ensure that the adequate agreement achieved between the numerical prediction and the experimental measurement is robust to changes in the experimental conditions. Uncertainty quantification refers to the exploration and understanding of the sources of uncertainty in a simulation:

- Solution uncertainties, such as errors introduced by spatial and temporal discretization, as well as model form errors

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- Parametric uncertainties, such as distributions on simulation inputs and the propagation of these distributions to the simulation outputs
- Relationship between simulation inputs and outputs, such as the generation of reduced-order models (response surfaces) using design of experiments sampling techniques

The contents of this paper will illustrate the pursuit of a systematic treatment of this problem via an example. The validation of transmission of shock energy through a complex, jointed structural assembly is the problem of interest, and the solution uncertainty is neglected for the purposes of the example. (This neglecting is legitimate, as the uncertainties introduced via simulation parameters are typically much more significant in structural mechanics applications.)

2 EXAMPLE APPLICATION

Quantifying shock transmission through complex, jointed structures has traditionally been possible only with experimental methods. These experiments are expensive and time-consuming and thus only a few cases can be studied. With the advent of large scale computing capabilities estimation of the shock transmission with numerical models has become a tractable problem. A primary advantage of these models is that, when validated, parametric studies can be efficiently performed to evaluate the effects of different input loads and variations to the structure’s design or to load path changes caused by ageing. The U.S. Department of Energy's Accelerated Strategic Computing Initiative (ASCI) is developing massively parallel hardware and software environments for modelling these types of problems.

The ASCI computing environment is being used at Los Alamos to study the transmission of shock through a complex, jointed structure. A three-dimensional explicit finite element model has been developed that includes a detailed representation of the geometry and contact surfaces including preloading effects. A series of full-scale experiments has been performed to provide data for model validation and uncertainty quantification.

Several issues of open research are addressed in this example. First, large computer simulations tend to generate enormous amounts of output that must be synthesised into a small number of indicators for the analysis. This step is referred to as data reduction or feature extraction [1]. These features are typically used to define the test-analysis correlation metrics optimised to improve the predictive accuracy of the model. The main issue in feature extraction is to define indicators that provide meaningful insight regarding the ability of the model to capture the dynamics investigated.

Second, efficient numerical optimisation requires that the correlation between the model’s input variables and output features be assessed with adequate accuracy. Statistical response surface models (RSM) must be generated to replace the expensive, large-scale simulations. One difficulty of fitting RSM’s is efficient sampling, i.e. the generation of sufficient information in regions where representative variation in the features of interest will be observed.

The test article used for the experiments and subsequent analyses consists of several components fabricated from a variety of materials. A titanium component designated the "mount" to which all other components are attached is shown in Figure 1. Two payload mass simulators and two aluminium shells attach to this mount. For the experiments the test article was suspended using wire rope creating a pendulum with a length of about 1m. An impulse of a few microseconds in duration was delivered to the assembly using an explosive charge. A total of four experiments were performed. SRI International performed these tests at their Menlo Park, California facility.

Figure 1: Titanium Mount (left) and Experimental Test Configuration (right)

The explicit finite element model (FEM) of the test article was developed using the ParaDyn finite element code [2]. The resulting model had approximately 1.4 million 8-node hexahedral elements, 56,000 4-node shell elements, and 1.8 million node points. The finite element model was run on 504 processors on the Los Alamos Blue Mountain computer. Using this number of processors resulted in 1.3 CPU hours for each ms of the simulation. A typical response of the model after a short increment of time is shown in Figure 2.

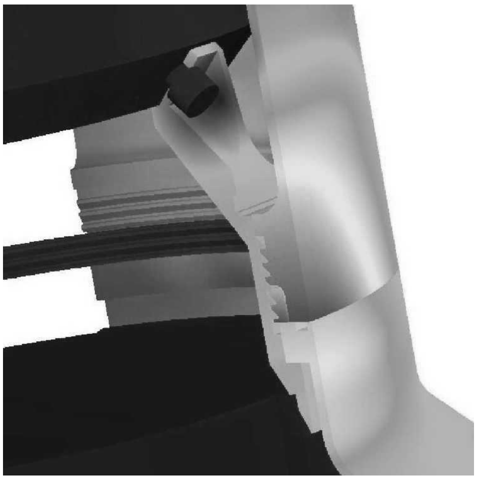

Figure 2: Displacement Contours of the Mount ParaDyn Model

3 PARAMETER SCREENING: FEATURE SELECTION & MAIN EFFECTS ANALYSIS

To quantify and understand the influence of each of the simulation model parameters on the model response, a higher-order RSM must be constructed. Because of the large number of simulation runs required (to cover many levels of each parameter), and the length of time required to run each simulation, the number of parameters must be limited to about 5.

Based on the judgement of the engineering analysts, a total of twelve parameters in the finite element model were selected as being of possible importance to the response and also having a relatively high uncertainty associated with their value. These parameters consist of three component preloads, four static and four kinetic coefficients of friction, and the magnitude of the explosive impulse. So the first step in the model validation/uncertainty quantification process was to build a multidimensional linear RSM of the response features of interest over the parameter space of interest to screen the total number of parameters from 12 to about 5. For the 12 parameters of interest, 4 had 2 levels of interest while 8 had 3 levels. The total number of runs to build a full factorial RSM was therefore 104,976. To limit the required simulation time, a first set of 48 runs was completed from parameter samples selected using the Taguchi Orthogonal Array technique [3].

Because the transmission of shock across the mount to the payload components was the primary event of interest, errors between the predicted and measured statistical moments of the time history, shock response spectrum (SRS) and power spectral density (PSD) at each accelerometer location were used as features of interest. An analysis-of-variance analysis was performed on the 48 runs for each feature to compute the influence of each parameter on each feature. The features were evaluated based on whether a) the total contribution of the individual parameters was significant (e.g. the feature was significantly sensitive to at least 1 of the parameters) and b) whether the feature was amenable to a linear RSM fit (i.e. the linear fit had a high R^2 value).

A few of the features either were not amenable to linear screening or did not demonstrate significant sensitivity to any of the parameters. Generally, however, a trend was observed for features from all sensors indicating significant effects due to the following five parameters: one preload, three kinetic coefficients of friction, and the impulse magnitude. Thus the parameter space of interest was reduced from dimension 12 to dimension 5, allowing realistic generation of a higher-order RSM.

4 CONCLUSION/FUTURE WORK

Work to date has indicated that it is possible to reduce a high-dimension parameter space to a reasonable dimension using a moderate number of runs of a very large finite element model of a transient structural dynamics event. A higher-order RSM will be created using this lower dimension parameter space for the purposes of understanding the sensitivity of the response features to each of these parameters, and for the optimisation of these parameters to adequately represent the measurements from the actual test article. A second round of validation experiments will then be designed to further explore the parameter space and define the regime of validity of the model. The validated model can then be used with some confidence to predict events outside the regime of practical testing.

5 REFERENCES

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