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DESIGN OF COMPUTER EXPERIMENTS FOR IMPROVING AN IMPACT TEST SIMULATION

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ABSTRACT

This paper gives an overall presentation of a research project pursued at Los Alamos National Laboratory for the validation of numerical simulations for engineering structural dynamics. An impact experiment used to develop and test the model validation methodology is presented. Design of experiments techniques are implemented to perform parametric studies using the numerical model and improve its predictive quality. The analysis relies on correlation study where input parameters responsible for explaining the total variability of the numerical experiment are identified, then, updated. The quality of the model is assessed via its ability to reproduce the same statistics as those inferred from the experiment data sets. Throughout the paper, a particular emphasis is placed on presenting the contribution to this project of Amanda Wilson, undergraduate student at Texas Tech University, and research assistant at Los Alamos in the summer of 2000 in conjunction with the Los Alamos Dynamics Summer School. The model validation project is described in greater details in the companion paper [1].

NOMENCLATURE

The recommended "Standard Notation for Modal Testing & Analysis" is used throughout this paper [2].

1. INTRODUCTION

Current model updating and refinement methods in structural dynamics are generally based on linear assumptions and do not provide quantifiable confidence intervals for model components. Updating techniques commonly attempt to map the experimental information to the model space. This results in a confounding of system information through the data expansion or condensation. There is normally little evaluation from either a design of experiments or statistical approach to quantify the model updating mechanism for a range of applications and confidence intervals.

This research aims at exploring pattern recognition and Design of Experiment (DoE) techniques to improve the predictive quality of numerical models via model updating and refinement. Here, the emphasis is placed on presenting the contribution to this project of Amanda Wilson, undergraduate student at Texas Tech University, Lubbock, Texas, and research assistant at Los Alamos National Laboratory (LANL) in the summer of 2000 in conjunction with the Los Alamos Dynamics Summer School. A complete description of the model validation project can be obtained from paper [1]. After a brief description of the impact test in section 2, the test data variability is discussed (section 3) and the features or output parameters of interest are presented (section 4). A description of the numerical model follows in section 5. Sensitivity studies and statistical effect analyses are contrasted in sections 6 and 7, respectively. The generation of statistical meta-models from the computer experiment's output and the optimization of fast-running models are presented briefly in section 8. Finally, key enabling software aspects are discussed in section 9.

2. IMPACT EXPERIMENT

In this section, a brief description of the impact experiment performed in the summer of 1999 at LANL is provided. The application is a high-frequency shock that features a component characterized by a nonlinear, visco-elastic material behavior. Details can be obtained from Reference [3]. Issues such as the variability of the experiment, the model-based sensitivity study, the statistical parameter effect analysis and the optimization of the numerical model are discussed in the following sections.

2.1 Experiment Setup

The impact test consists of dropping from various heights a carriage (drop table) to which are attached a layer of hyper-elastic material and a steel cylinder. Upon impact on a concrete floor, a shock wave is generated that propagates to the hyper-elastic layer. It compresses the

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steel cylinder to cause elastic and plastic strains during a few milli-seconds. Figure 1 illustrates the cylinder/pad/carriage assembly. A photograph of the test setup is shown in Figure 2.

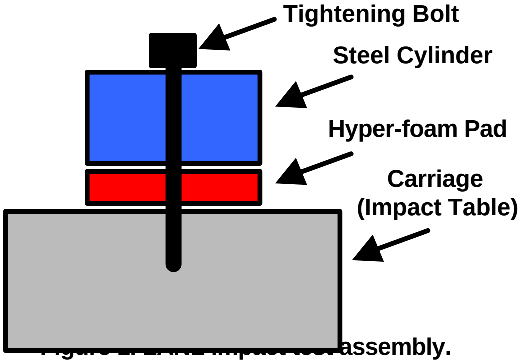

Figure 1. LANL impact test assembly.

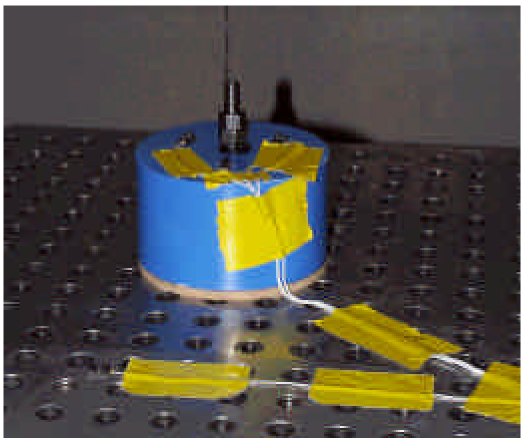

Figure 2. LANL impact test setup.

It can be observed from Figure 2 that four acceleration measurements are collected during each test. The input acceleration is measured on the top surface of the carriage and three output accelerations are measured on top of the steel cylinder. Another important feature of the experiment is the double bolt used to tighten the cylinder and hyper-foam pad to the carriage (see Figure 2). This assembly technique generates a pre-load that depends on the amount of torque applied. As explained in the following, the pre-load value turns out to be a critical parameter of the numerical simulation. Unfortunately, it was not possible to measure the amount of torque applied during the experiments, therefore, defining an important source of uncertainty and variability.

2.2 Purpose of the Experiment

The primary purpose of this test is to infer from the measured input/output acceleration data the "best possible" material model. Figure 3 pictures the result of an optimization where the material model is optimized until the acceleration response predicted by the numerical model "matches" the measured data.

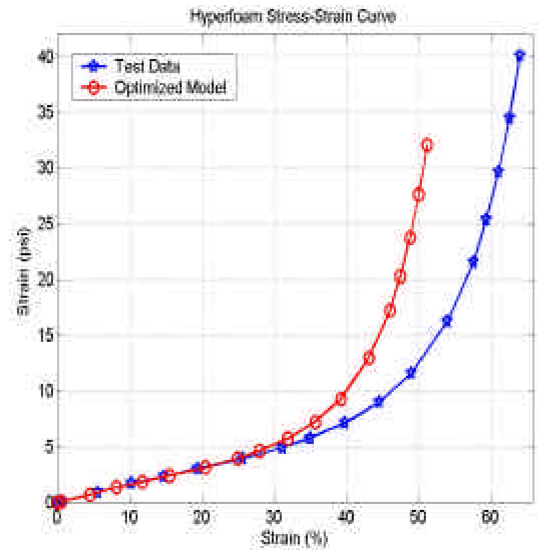

Figure 3. Initial (*) and optimized (o) strain-stress curves of the hyper-foam pad.

The difficulty of recasting this inverse problem as a conventional finite element model updating problem comes from the following facts:

1) Nonlinearity such as the hyper-foam material and contact must be handled by defining appropriate "features" from the system's response;

2) Parameter variability and uncertainty about the experiment must be identified and propagated throughout the forward calculations;

3) Prior to performing any optimization of the numerical model, the expensive computer simulations must be replaced by equivalent, fast running "meta-models" that capture all dominant parameter effects yet remain computationally simple.

3. TEST DATA VARIABILITY

Since we were concerned with environmental variability and we suspected that several sources of uncertainty would contaminate the experiment, the impact tests were repeated several times to collect multiple data sets from which the repeatability could be assessed. Acceleration signals measured during these tests are depicted in Figures 4-5. The carriage is dropped from an initial height of 13 inches (0.33 meters) and the hyper-foam pad used in this configuration is 0.25 inch thick (6.3 mm). A blow-up of the peak acceleration signals collected during ten "identical" tests at output sensor #1 is shown in Figure 5. This sensor is one of the three located on top of the steel cylinder.

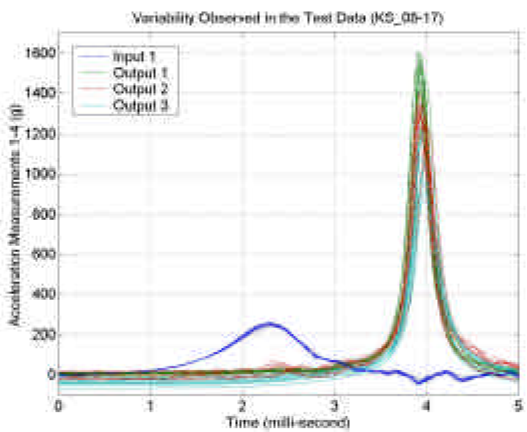

Figure 4. Accelerations measured during a low velocity impact on a thin layer of material.

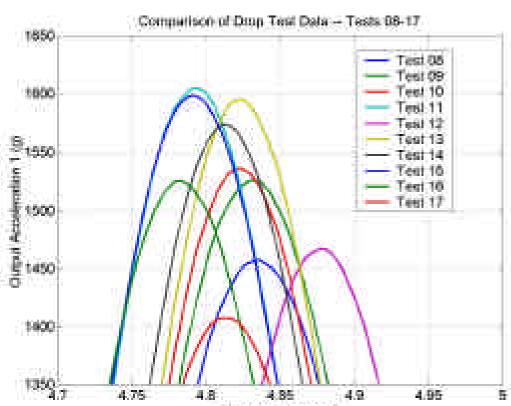

Figure 5. Variability of the acceleration response.

Overall, it can be seen that peak values vary by 4.4% while the corresponding times of arrival vary by 0.6% only. (These percentages are defined as the ratios of standard deviations to mean values.) Although small, ignoring this variability of the peak response may result into predictions erroneous by several hundred g's, which may yield catastrophic consequences.

In addition to repeating the "same" test several times, various configurations were tested. Table 1 summarizes the test matrix where, essentially, the drop height and the foam thickness were varied. The reason why less data sets are available at high impact velocity is because these tests proved to be destructive to the hyper-foam material and could not be repeated to study the variability of the acceleration response.

Table 1. Data collected with the impact testbed.

Number of Data Sets Collected	**Low Velocity Impact** (13in./0.3m)	**High Velocity Impact** (155in./4.0m)
Thin Layer (0.25in./6.3mm)	10 Tests	5 Tests
Thick Layer (0.50in./12.6mm)	10 Tests	5 Tests

More important than developing a numerical model that reproduces the measured response, it must be assured that the variability featured in Figures 4-5 is captured. This matters because a numerical simulation is often developed for studying the system's reliability in which case it must be able to represent the total variability of the experiment and responses located in the tails of the statistical distributions rather than mean responses.

4. CHARACTERIZATION OF THE RESPONSE

It can be observed from Figures 4-5 that over a thousand g's are measured on top of the impact cylinder, which yields large deformations in the hyper-foam layer. The time scale also indicates that the associated strain rates are important. Clearly, modal superposition techniques would fail modeling this system because of the following reasons:

1) Contact can not be represented efficiently from linear mode shapes;

2) Nonlinear hyper-foam models, that possibly include visco-elasticity, are needed to represent the foam's hardening behavior at high strain rates;

3) Very refined meshes would be required to capture the frequency content well over 10,000 Hertz.

These remarks introduce the general problem of "feature extraction." In other words, which quantities (features) can be extracted from the data sets to characterize the response of this nonlinear system? Several features have been proposed in the literature, a recent review of which can be found in Reference [4]. Among them, we cite the principal component (Karhunen-Loeve) decomposition; the coefficients or control charts obtained from fitting AR, ARX or ARMA models to time-domain data; the shock response spectrum; the spectral density function; the joint probability density function of the output feature; and higher-order statistical moments.

For analyzing the drop test experiment, we essentially focused on the peak acceleration and time of arrival. The reason is because these are the quantities of interest to the analyst. Actually, the impulse is so short in time that matching these two features is sufficient to capture the response's energy content. Nevertheless, feature extraction is one of the most critical aspects of model validation for nonlinear systems.

5. NUMERICAL MODELING AND ANALYSIS

In an effort to match the test data, several finite element models were developed by varying, among other things, the angles of impact, the amount of bolt pre-load, the material's constitutive law and the amount of friction at the interface between various components. Introducing two independent angles of impact was important for capturing the response's asymmetry. (A small free-play in the alignment of the central collar had to be introduced in the numerical model to simulate the same time-lags of peak accelerations as the ones observed from test data.) Table 2 summarizes the input parameters that define the numerical simulation. They consist of physical, deterministic quantities such as the material model; physical, stochastic quantities (such as the bolt pre-load); and numerical coefficients (such as the bulk viscosity that controls the rate of deformation of the volume elements used in the discretization).

Table 2. Input parameters of the model.

Identifier	Definition	Unit
1 or A	Angle of Impact 1	degree
2 or B	Angle of Impact 2	degree
3 or C	Bolt Pre-load	psi (N/m^2)
4 or D	Material Coefficient 1	N/A
5 or E	Material Coefficient 2	N/A
6 or F	Input Scaling	N/A
7 or G	Friction Coefficient	N/A
8 or H	Bulk Viscosity Coefficient	N/A

Figure 6 illustrates the finite element model used for numerical simulation. The analysis program used for these calculations is HKS/Abaqus®-Explicit, a general-purpose package for finite element modeling of nonlinear structural dynamics [5]. It features an explicit time integration algorithm, which is convenient when dealing with nonlinear material behavior, potential sources of impact or contact, and high frequency excitations. The model is composed of 963 nodes, 544 C3D8R volume elements and two contact pairs located at the cylinder/pad interface and the pad/carriage interface. This modeling yields a total of 2,889 degrees of freedom composed of structural translations in three directions and Lagrange multipliers defined for handling the contact constraints. A typical analysis running on a single processor of the ASCI platform is executed in approximately 10 minutes of CPU time. (The computing module of the ASCI, Accelerated Strategic Computing Initiative, platform at LANL is a cluster of 64 Silicon Graphics Origin2000 nodes, each composed of 128 R10010 chips.)

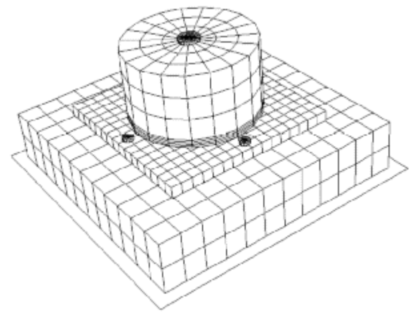

Figure 6. 3D model of the LANL drop test.

Figure 7 illustrates the total variability observed when the eight variables defined in Table 2 are varied. To analyze the variability, a fully populated factorial design of computer experiments is simulated where each variable is set either to its lower bound or to its upper bound and all possible combinations of input variables are defined. Therefore, a total of $2^8 = 256$ numerical simulations must be analyzed.

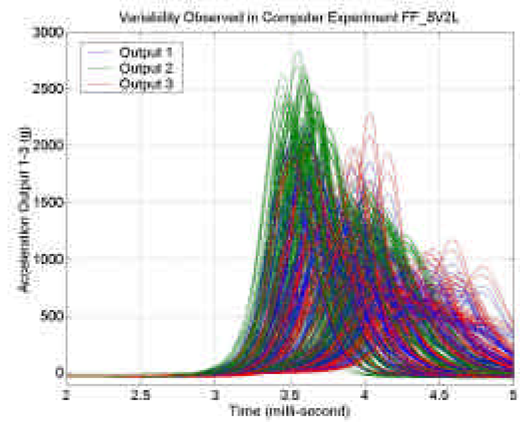

Figure 7. Full factorial design of computer experiments (8 variables, 2 levels).

It is clear from Figures 4 and 7 that the variability of the numerical simulation is much greater than the variability observed during testing. As a result, the first step of test-analysis correlation consists of designing a "screening" experiment that must achieve the following two objectives. First, the range of variation of each input parameter must be narrowed down in a manner that stays consistent with test results. Second, the main effects of the experiment must be identified in a statistical manner as opposed to performing a local sensitivity study.

It is emphasized that multi-level full factorial analyses would typically not be accessible for complex engineering applications due to the lack of time or computational power. An example is the ASCI experiment performed at LANL for a complex threaded joint subjected to explosive loading [6]. To predict with adequate accuracy the attenuation of the shock wave through various joints and components of the structure, a detailed finite element model that counts over 6 million degrees of freedom had to be developed and analyzed. The search space for this simulation is composed of 11 input parameters that describe the pre-load and friction properties of the assembly. Obviously, achieving a full description of such input space is impossible. For example, a full factorial DoE featuring three levels only would require a total of 3^{11} = 177,147 simulations. For this particular application, they would be executed in roughly 40.4 years assuming that 504 processors of today's most powerful ASCI platform are available! This is the reason why other DoE's are investigated in the following sections. The Taguchi, orthogonal array designs used below provide essentially the same information at a fraction of the computational requirement [7].

6. SENSITIVITY STUDY

The tool commonly used for identifying the dominant parameter effects in structural dynamics is sensitivity study. We wish to identify the input parameters to which the output features (peak acceleration and time of arrival) seem to be the most sensitive. Because of the strong sources of nonlinearity involved, centered finite differences are implemented to estimate these sensitivities with respect to each of the eight input parameters. We emphasize that we are fully aware of the adverse mathematical implications of approximating discontinuous functions with finite differences but we choose to proceed anyway to illustrate the drawbacks of this popular engineering practice.

A sample of the results obtained is presented in Figures 8 and 9. Figure 8 shows the sensitivity of the peak acceleration when the input parameters are set to their upper bounds. It illustrates that the most sensitive parameter is the 5^{th} one, the second material constant. However, a different parameter is identified as being the most sensitive one when the study is performed at the input parameter's lower bounds (Figure 9). Since the "true" combination of input parameters is unknown prior to test-analysis correlation, drawing a conclusion regarding which one of these parameters should be kept in the analysis is not possible.

This example demonstrates that performing a sensitivity study may not provide the analyst with any useful information, especially when the dynamics of the response is significantly nonlinear. The main reason is because sensitivity provides information local in nature (sensitivity coefficients are computed at a design point, in a particular direction of the search space) as opposed to a global assessment of the effect of each input parameter over the entire design space.

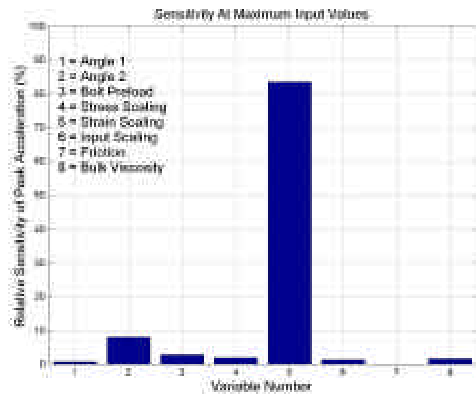

Figure 8. Sensitivity of the peak acceleration at the parameter's upper bounds.

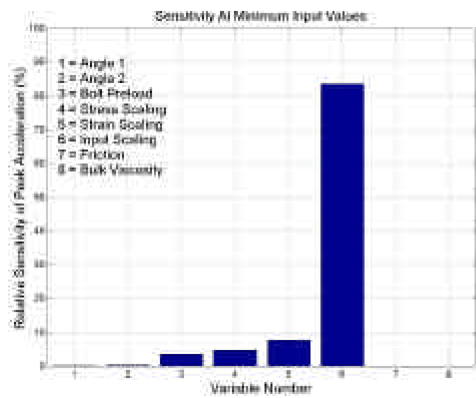

Figure 9. Sensitivity of the peak acceleration at the parameter's lower bounds.

Another drawback of conventional sensitivity study is the computational cost. In this case where finite differences are involved, each sensitivity coefficient requires one analysis at the design point p_i followed with two analyses for each input parameter at points (p_i+dp_i) and (p_i-dp_i) where dp_i denotes a "small" increment. Therefore, a total of (1 + 2x8) = 17 computer runs are required to generate all sensitivity coefficients at a single point of the design space. Estimating them during parameter optimization or over the entire design space yields prohibitive computational requirements even in the case of such a small model.

7. STATISTICAL EFFECT ANALYSIS

Instead of relying on local information, it appears more efficient to perform a statistical effect analysis that quantifies the global influence and interaction between input parameters over the entire design space. Here, we wish to identify the subset of input parameters responsible for producing the total variability observed in Figure 7. In doing so in the context of inverse problem solving, the focus is shifted from iteratively providing an optimization algorithm with accurate sensitivity data to designing upfront a computer experiment that provides the information necessary to the effect analysis.

First, a design of computer experiments is selected. Issues are the number of simulations to execute (depending on the time and computer resource available) and the avoidance of aliasing that may bias the subsequent statistical analysis. Alias in statistical modeling is caused by a too sparse sampling of the input space and it results in the contamination of the main effects investigated by higher-order effects. For example, a DOE designed to study linear interactions between input parameters and output features may yield erroneous conclusions because predictions are aliased by quadratic interactions. Design matrices used are typically full factorial designs, partial factorial designs, Taguchi orthogonal arrays or sampling techniques among which we cite the Latin Hypercube sampling and the orthogonal array sampling [7-8]. After defining a computer experiment, the finite element package is run at the corresponding combinations of input parameters and results are gathered for feature extraction. Then, statistical tests are implemented to assess the global contribution of each input parameter to the total variability observed from the computer simulations. A popular example is the R-square (R^2) statistics that estimates Pierson's correlation ratio. It is defined as the ratio between the variance that can be attributed to a given effect and the total variance of the data set. Mathematically, the R^2 is a normalized quantity (between 0 and 1) calculated as

$$R^2 = 1 - \frac{\sum_{l=1\cdots N_{level}} \sum_{j=1\cdots N_{data}^{(l)}} \left(y_j^{(l)} - \bar{y}^{(l)}\right)^2}{\sum_{j=1\cdots N_{data}} \left(y_j - \bar{y}\right)^2} \quad (1)$$

where y_j denotes the output data feature of interest. Clearly, values close to one indicate a variable or an effect (p_i^2, p_i*p_j, $p_i*p_j*p_k$, etc.) that contributes in a significant manner to the total variability of the responses. Details about the procedure can be obtained from Reference [8].

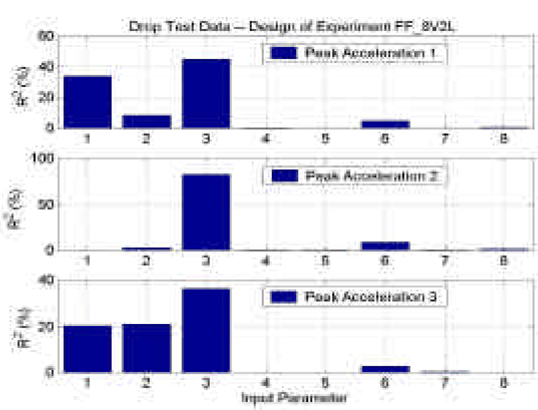

Figure 10. R^2 analysis for main, linear effects.

Figure 10 represents the R^2 statistics obtained for each one of the eight input parameters when analyzing the peak acceleration response at output sensors #1-3. Variables #1-3 (the two angles of impact and the bolt pre-load) are identified as being the most critical for predicting the total variability observed in Figure 7. Similarly, the analysis of coupled effects p_i*p_j can be carried out to identify the most influential cross-terms provided that enough data are available to minimize the effects of aliasing. The results of a cross-term analysis are presented in Figure 11. Again, coupling terms that feature an interaction with variable #3 (the bolt pre-load) are shown to be dominant.

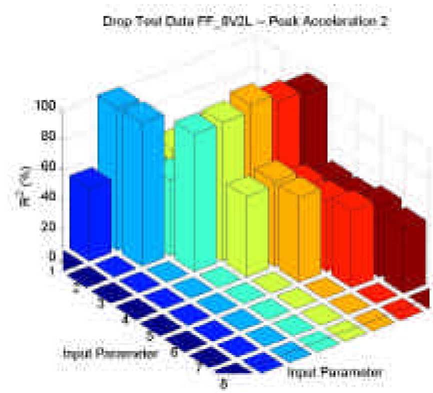

Figure 11. R^2 analysis for quadratic interactions.

The main conclusion that can be drawn from the statistical effect analysis is that the material model does not explain the variability nearly as much as the bolt pre-load does. It means that the original material model obtained by performing a static compression test on a sample of material is a good starting point for the optimization. Indeed, it can be seen from Figure 3 that the final, optimized model is not significantly different from the original model.

8. NUMERICAL OPTIMIZATION

The final step is to infer from test data the optimal values of the input parameters. We briefly introduce the procedure followed when the investigation is restricted to four parameters: the two angles of impact, the bolt pre-load and the input scaling. Other models are shown in Reference [1] that provide similar or better results.

8.1 Fitting Meta-models to the Simulation Data

Since a smaller number of input parameters are retained (4 out of 8), a localized computer experiment can be designed to provide a better resolution in the area of interest. The area of interest is here defined as the region in the multi-dimensional search space where features extracted from the test data sets are located. A full factorial DOE matrix with 4 levels for each input parameter is defined which results into the analysis of 4^4 = 256 designs. Then, fast running models are fit to the simulation data following the procedure detailed in Reference [1]. Equation (2) illustrates a possible model for the peak acceleration response at sensor #2:

$$\ddot{x}_2^{peak} = \begin{Bmatrix} -1{,}538.2 \\ 43.6 \\ 288.4 \\ 2.4 \\ 2{,}552.8 \\ -391.3 \\ -307.1 \\ -0.0006 \\ 665.7 \\ -0.5 \\ -452.4 \\ 1.5 \end{Bmatrix}^T \begin{Bmatrix} 1 \\ a_1 \\ a_2 \\ P_{bolt} \\ s_I \\ a_1^2 \\ a_2^2 \\ P_{bolt}^2 \\ a_1 * a_2 \\ a_2 * P_{bolt} \\ a_2 * s_I \\ P_{bolt} * s_I \end{Bmatrix} \tag{2}$$

Instead of fitting multi-dimensional polynomials, statistical models are preferred because in addition to yielding computationally efficient meta-models, they also provide confidence intervals that can be used for assessing the model's goodness-of-fit. For example, each coefficient of the polynomial shown in equation (2) is associated with a statistics that shows how dominant the corresponding effect is. Statistical significance in this case refers to those parameters whose effect on the response feature variability is greater than would be explained by a normal distribution of noise. Table 3 shows the +/-95% confidence interval bounds obtained for each coefficient of model (2). Also shown are the values of the F-statistics, a test that measures the degree of significance of each contribution kept in the model [9]. Typically, a value of the F-statistics smaller than 5% indicates that the corresponding model term is significant. It can be concluded from Table 3 that the statistical model (2) exhibits a remarkable fit to the simulation data defined by our 4-variable, 4-level full factorial DOE.

Table 3. Statistical significance of model (2).

Effect Kept	-95% CI Bound	Value Used	+95% CI Bound	F-test Value
1	-1,597.6	-1,538.2	-1,478.8	0.01%
a_1	11.1	43.6	76.1	0.43%
a_2	208.5	288.4	368.3	0.01%
P_{bolt}	2.3	2.4	2.6	0.01%
s_I	2,351.0	2,552.8	2,754.6	0.01%
a_1^2	-436.5	-391.3	-346.1	0.01%
a_2^2	-352.3	-307.1	-261.9	0.01%
P_{bolt}^2	-0.0008	-0.0006	-0.0004	0.01%
a_1*a_2	629.5	665.7	701.9	0.01%
a_2*P_{bolt}	-0.6	-0.5	-0.4	0.01%
a_2*s_I	-633.4	-452.4	-271.5	0.01%
$P_{bolt}*s_I$	1.1	1.5	1.9	0.01%

It is emphasized that equation (2) defines a family of models that could be re-sampled to account for omitted sources of uncertainty (round-off errors, environmental variability, etc.). Table 3 shows in column 3 the values used for defining our model in equation (2). However, any other model synthesized from coefficient values randomly selected within their [-95%; +95%] confidence intervals would also be consistent with the data sets provided by the DOE. Re-sampling this model would essentially mean that decisions are based on properties of ensembles rather than a single model. This can be exploited advantageously to include omitted sources of variability or to identify areas of the design space that require further refinement. Optimizing the statistical significance of each individual effect contribution may be as important than maximizing the overall goodness-of-fit to the experimental or computer data [10].

8.2 Optimization of Input Parameters

Figure 12 illustrates a 2D response surface obtained from equation (2). The mean acceleration response obtained from the data collected at output sensor #2 is shown as a star. A straightforward optimization provides the optimal values of the input parameters. In this case, a pre-load equal to 200 psi (1.38 x 10^6 N/m^2) is obtained together with an impact angle equal to 0.7 degrees. Note that such an approach provides an optimized model capable of reproducing the mean response obtained from test data. It does not guarantee that the variance or other higher statistical moments are captured. Other optimization strategies are discussed in Reference [1] to address this important issue. In particular, it is shown that the optimized model can reproduce the variability measured during the experiments. This demonstrates that the adequate sources of variability and correct statistical distributions of input parameters have been included in our model.

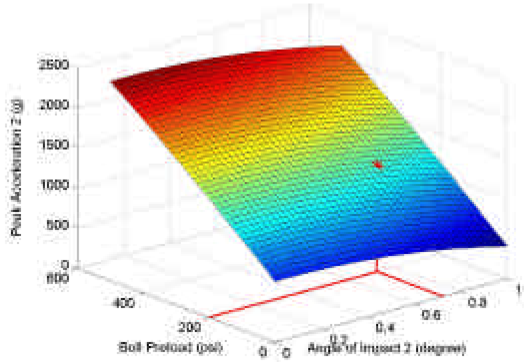

Figure 12. Optimization of the meta-model.

Obviously, the value of 200 psi for the bolt pre-load could not be verified and it was likely to have varied somewhat from test to test. The values of (0.0; 0.7) degrees for the impact angles were confirmed by an independent investigation. The measured acceleration signals were integrated numerically to provide the time-history of displacement at three locations on top of the steel cylinder. Then, fitting a plane to these data did confirm that the rotation was located around the second axis with an approximate value of 0.7 degrees.

8.3 Independent Validation of the Model

The most critical issue in model validation is to assess the domain of predictability of the optimized model. Too often, a model will not be predictive away from the dynamic range spanned by the test data used for numerical optimization or model updating. It may be because the physics of the system is not understood; the model form is incorrect; or the simulation does not capture the total variability. However, this issue is critical because the purpose of numerical models is to make predictions in situations for which test data are not available, for example, for predicting rare or catastrophic events. Practices generally encountered in model validation are to:

1) Perform independent optimizations using, for example, various features and metrics, and assess the consistency between the models obtained;

2) Validate the predictive quality of the numerical model using test data sets not used during the optimization.

With the impact experiment, two independent features (peak acceleration and time of arrival) are optimized for each sensor. It has been verified that consistent models are obtained when the correlation between test data and model predictions is optimized based on independent features. Obtaining consistent models is nevertheless not sufficient because the optimized models could all be wrong. Data sets from our test matrix (Table 1) are used for validating the model's predictions in configurations other than the one used during statistical effect analysis and model updating. Preliminary results on the thick pad/low impact velocity configuration tend to confirm the conclusion presented in Reference [3]. That is, computer simulations with the previously optimized input parameters reproduce the test data of a different setup with very good accuracy.

9. SOFTWARE INTEGRATION

In this section, we emphasize some of the key points contributed to by Amanda Wilson during the summer of 2000 in terms of software development and integration. The computing environment and the interaction between various software is briefly described.

As mentioned previously, the modeling and analysis package used for this research is Abaqus™. Generating and processing efficiently the large amount of data from a DoE requires that multiple analyses be executed with minimum involvement from the analyst. To fulfill this goal, drivers are written with the language Python® [11]. The Python® scripts parameterize Abaqus™ input decks and run multiple analyses without having to type in the commands one by one. Generating the Python® scripts themselves is performed via a user interface in MATLAB™. Essentially, all pre and post-processing are handled within MATLAB™ as much as possible.

An illustration is provided below. The hyper-elastic constitutive model of an Abaqus™ input deck can, for example, be defined through the following commands:

```
(1)  *HYPERELASTIC, POLYNOMIAL, N=1
(2)  0.6, 1.7, 0.8, 20.0
```

where the key word "*HYPERELASTIC" refers to a particular model form and the coefficients provided on the second line define the material. A parameterization of the first two variables can be achieved with:

```
(1)  *PARAMETER
(2)  var1 = 0.6
(3)  var2 = 1.7
(4)  *HYPERELASTIC, POLYNOMIAL, N=1
(5)  <var1>, <var2>, 0.8, 20.0
```

Each Abaqus™ input deck of the DoE would typically be assigned different values for variables 1 and 2 and the role of the Python® script file is to set up the multiple input decks according to the analyst's instructions. For example, defining two analyses at the design points (0.6; 1.7) and (0.8; 2.3) can be handled by the following Python® script file:

```
(1)  DoE = parStudy(par=['var1','var2'])
(2)  DoE.define(DISCRETE, par='var1',
(3)  domain=(0.6,0.8))
(4)  DoE.define(DISCRETE, par='var2',
(5)  domain=(1.7,2.3))
(6)  DoE.sample(INTERVAL, par='var1',
(7)  interval=1)
(8)  DoE.sample(INTERVAL, par='var2',
(9)  interval=1)
```

```
(10) DoE.combine(TUPLE)
(11) DoE.generate(template='abaqus.inp')
(12) exit()
```

where file "`abaqus.inp`" is a generic Abaqus™ input deck that contains the problem definition. The generic input deck must be parameterized with variables 1 and 2 identified by "`<var1>`" and "`<var2>`", respectively, as shown before. A 2-level factorial analysis is obtained by changing the key word "`TUPLE`" on line 10 into "`MESH`". Then, a total of four models are analyzed at the design points (0.6; 1.7), (0.6; 2.3), (0.8; 1.7) and (0.8; 2.3) for variables 1 and 2. Parameters can also be defined as strings of alpha-numeric characters which is convenient for varying element types, contact conditions, solver algorithms, etc.

After the parametric Abaqus™ input decks and DoE's design points have been defined, the Python® script is linked to Abaqus™ and executed on one of the available computing platforms. The multiple binary result files are gathered by another MATLAB™ function with very little involvement from the analyst. According to the output requested by the user, the MATLAB™ function imports, compiles and executes the adequate Abaqus™ utilities used to convert and extract the results. The MATLAB™ environment then makes it easy to extract features from time series, implement the statistical effect analysis and optimize meta-models. Fitting statistical models to the DoE's output is currently performed with the Design-Expert® software [9] and it has not yet been interfaced with our MATLAB™ library of functions.

10. CONCLUSION

An overall presentation is given of the on-going research pursued at Los Alamos National Laboratory for the validation of numerical simulations for engineering structural dynamics. An impact experiment used to develop the model validation methodology is presented. Design of experiments techniques are implemented to perform parametric studies using the numerical model and improve its predictive quality. An application of this methodology to a more complex engineering simulation is discussed in a companion paper [6] presented at the IMAC-XIX conference.

Future work includes the development of a complete array of features or test-analysis correlation metrics; the comparison of different sampling techniques; and the implementation of statistical model updating procedures capable of refining estimates of the input parameter's variance and higher-order statistical moments.

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