APPLICATION OF DESCRIPTIVE SAMPLING AND METAMODELING METHODS FOR OPTIMAL DESIGN AND ROBUSTNESS OF VEHICLE STRUCTURES

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Abstract

The application of well established technologies such as Numerical Optimization and Monte Carlo simulation to a realistic vehicle system impact problem is addressed. An investigation of a limited set of design space metamodeling and sampling procedures is performed. The complete study is performed in a High Performance Computing (HPC) environment thereby addressing several of the high fidelity simulation, problem dimensionality, and computational infrastructure bottlenecks in engineering design. The recent advancements in HPC technology, especially massively concurrent processing, is enabling effective deployment of simpler procedures for design optimization and robustness studies of large-scale, vehicle systems. In addition, the low cost of HPC technology combined with the superior value derived from application of these design methodologies mandates their usage as a natural component of a vehicle system “best” design practice.

Very often, an optimization problem is expressed in terms of finding the best setting of design parameters that minimize or maximize an objective function, such as weight, cost or elapsed time to reach a target, while satisfying the specified constraints. The classical example of such an optimization in structures is the one of finding the lightest structure that can withstand a given load. Robustness design involves accounting for uncertainty in the design parameters and making the design work in the presence of uncertainties. In other words, a robust design is not necessarily an optimal design but is one that is insensitive to the design variations. Thus robustness design is synonymous with high quality or high reliability design.

While numerical optimization strategies involving nonlinear programming methods have been extensively used to solve general optimization problems, stochastic design methods, based on Monte Carlo techniques, have long been used to address design decisions under uncertainty. Both approaches require a significant number of analyses (for example, explicit finite element analysis to evaluate the vehicle behavior under impact conditions) making the solution time very long, if not prohibitive. Superior methods, involving a combination of high performance computing with a large number of compute processors as well as sufficiently accurate surrogate models for high fidelity simulations, become critical for design optimization or robustness solutions involving complex, high-fidelity analysis codes.

The focus of this work is on design optimization and robustness of vehicle systems, involving:

1.0 Introduction:

Designing and delivering high quality products at low cost has become critical in today’s globally competitive economy. The manufacturing industry is increasingly focusing on structured design methods for optimization and robustness of product designs. Several approaches including those based on numerical optimization strategies and Monte Carlo simulations are available for such optimization and robustness solutions.
1. Investigation of Monte Carlo and Numerical Optimization based design strategies;
2. Investigation of specific surrogate modeling and sampling procedures for use with above strategies; and,
3. Use of high performance computing, specifically massively concurrent computing, for high throughput.

The application problem is an automotive vehicle design under side impact involving high fidelity modeling and compute intensive finite element impact simulation.

2.0 Theoretical Aspects and Solution Procedure:

The key solution components of this study include:

- Surrogate (approximation) models;
- High Performance computing; and,
- Numerical Optimization & Monte Carlo simulation.

2.1 Surrogate (approximation) models:

Vehicle impact, which is the application focus of this paper, is a nonlinear event in terms of the structural and dummy responses. Crash analysis, using explicit finite element based methods, is extensively used by automotive companies for improving the vehicle structural design for crashworthiness and passenger safety. With increasing fidelity of the vehicle and dummy models, over half a million degrees of freedom, a single crash analysis can require several hours of computing time on a state-of-the-art compute server with multiple processors. Even employing multiple processors with each crash simulation, the computational cost of these analyses along with the iterative nature of design optimization procedures prohibits rigorous optimization and robustness studies. In addition, crash analysis is unstable since several runs corresponding to design perturbations will fail due to modeling and element penetration issues. Hence it is critical that surrogate models (i.e. approximations) be constructed apriori using the results from a number of actual crash simulations for use with crashworthiness optimization solution. Several considerations are involved in the construction of surrogate model for such high fidelity, nonlinear simulations, including:

- Choice of sampling procedure for generating the data (fractional factorial, orthogonal arrays, central composite design, D-optimal, Latin Hypercube experimental design, random sampling, descriptive/stratified sampling, etc…),
- Choice of a suitable approximation model to represent the data (linear, quadratic, cubic, exponential, gaussian, radial basis, network of neurons, etc…), and,
- Choice of an approximation model fitting procedure (polynomial response surface models based on least squares regression, Kriging response surface models based on maximum likelihood estimates, Neural Network response surface models based on backpropagation learning,…).

2.1.1 Sampling Procedures:

The sampling procedures considered in this work include:

- Descriptive Sampling
- Latin Hypercube sampling

A simple random sampling involves usually much more than a desirable number of sample points and often impractical for complex, time-consuming analyses. Certain importance/descriptive sampling methods have been developed to reduce the sample size without sacrificing the quality of the statistical properties of the output behavior variables. In the descriptive sampling technique [1], the space defined by each random variable is divided into subsets of equal probability and the analysis is performed with each subset of each random variable only once.

The Latin Hypercube experimental design procedure is similar to the descriptive sampling and it ensures that the entire range of each variable is sampled. The range of probable values for each parameter is divided into M segments of equal probability. A parameter space consisting of N parameters is thus partitioned into M^N cells.

2.1.2 Approximation Model Construction:

Two methods are considered in this work for generating sufficiently accurate approximations of vehicle impact responses.

2.1.2.1 Kriging Metamodel:

The mathematics of Kriging includes a combination of a global model of the design space as well as local deviations so that the Kriging interpolates the sampled data points [2, 3]. The principal differences between the reference and this work are in the implementation [4], specifically, (i) the procedure for updating the models, (ii) optimization algorithm used for solving the n-
dimensional unconstrained optimal fitting problem, and
(iii) scaling of the variables.

Based on the work reported in Reference [4], the
following can be stated about Kriging metamodels:

• Provide for sufficiently accurate approximations to
  vehicle impact responses;
• Capable of modeling nonlinear responses which are
difficult to approximate by a second order response
  surface polynomial;
• Maintains acceptable level of accuracy in the
  neighborhood of the sample set of data points and
  passes through the given sample set of point
  exactly.

2.1.2.2 Polynomial based Regression Models:

Gu investigated a polynomial-based subset selection
regression model for vehicle safety analysis. The
criterion used for the choice of best fitting polynomials
is the Residual Sum of Squares (RSS). The method that
is recommended in Reference [5] is the sequential
replacement algorithm in subset selection.

The basic idea of the sequential replacement
algorithm is that once two or more terms have been
selected, it is determined that any of those terms can be
replaced with another that gives a smaller RSS [6]. The
procedure must converge as each replacement reduces
the RSS that is bounded below. In practice, the
procedure usually converges very rapidly. Sequential
replacement algorithm is normally used in conjunction
with stepwise selection. It can be obtained by taking the
stepwise selection and applying a replacement
procedure after each new term is added. Results of
sequential replacement are usually better than those
from stepwise selection [6]. Sequential replacement
requires more computational time than that required by
stepwise selection but it is feasible to apply to problems
with several hundreds terms in the solution sets when
subset of 20-30 terms are required. Another advantage
for sequential replacement algorithm is that it does not
have artificial parameters to be tuned.

Gu showed that, with limited number of samplings, the
second order polynomial regression models are good
enough for dummy responses such as V*C (viscous
criterion), rib deflection, pelvis force and abdomen load
in vehicle side impact analysis.

2.2 Robustness Design methods:

A suite of methods is available for robust design,
including the traditional Monte Carlo Simulation
approach, Taguchi techniques and Reliability based
design optimization methods. With Monte Carlo
Simulation, a defined number of system simulations that
are to be analyzed are generated by sampling values of
the random variables (uncertain inputs) following their
probabilistic distributions. The Taguchi approach to
robust design is based on design of experiments (DOE).
With the reliability based design optimization methods,
either a conventional reliability index approach or a more
recent and robust performance measure approach [7]
can be employed. With the performance measure
approach the reliability constraint is defined from the
design perspective (rather than the reliability analysis
perspective) to measure the design constraint violation.
The prescribed reliability requirement (such as six-sigma
design) is assumed to be satisfied and the probabilistic
performance measure that satisfies this prescribed
reliability requirement is used to measure the degree of
the reliability constraint violation.

In this work, Monte Carlo Simulation as
implemented in ST-ORM (Stochastic Optimization and
Robustness Management) software [8] is used.

2.3 High Performance Computing:

Design optimization and robustness studies being
iterative requires a significant amount of computational
time especially when confronted with high fidelity
models and analysis tools. The state-of-the-art in High
Performance Computing, specifically, massively
concurrent computing, facilitates performing such
studies within an acceptable time duration for the
solutions to impact the design cycle.

Since most vehicle optimization and robustness
studies are multidisciplinary involving a heterogeneous
mix of analysis codes, the need for high throughput
computing is mandatory. Throughput is usually defined
as a rate of execution, for example the number of jobs
run per unit of time. In an ideal situation, one would like
to see the solution time of each analysis in throughput
mode to be the same as that run in a non-throughput
mode. However, this is usually not the case since each
job must compete with the other jobs for available
resources such as memory, disk and processors. High
throughput efficiency on a multiprocessor system
allows for fast turnaround times of multiple jobs, enablings
many runs to be made concurrently in a short
amount of time as required in Monte Carlo simulation
and in the construction of the approximations/metamodels for numerical optimization.
SGI Origin 3800 HPC server is used for all the computations. The Origin 3800 is a cache-coherent non-uniform access multiprocessor (ccNUMA) architecture where the memory is physically distributed among the nodes but is globally addressable to all the processors through the interconnection network. The Origin 3800 configuration used in this study involves 128, 400 MHz IP35 processors, with MIPS R12000 processor chip, main memory size of 131 Gbytes, instruction and data cache size of 32 Kbytes and secondary cache size equal to 8 Mbytes.

2.4 Solution Procedure:

The solution procedure used in this work is briefly outlined below.

1) Generate a set of sample points through either descriptive sampling or Latin Hypercube sampling technique.

2) Perform side impact analyses of the sample set design points concurrently on the SGI Origin 3000 server, with 128 processors, using RADIOSS explicit finite element code (for example, 15 concurrent RADIOSS analysis using 8 processors per analysis). Compute the design objectives and constraints as required for the side impact optimization problem.

3) For numerical optimization based solution strategies, construct an approximation model using the either Kriging or Polynomial regression approach. (For Monte Carlo simulation with STORM, approximation models are not used).

4) Perform the optimization problem solution based on the approximation model of Step 3. (For Monte Carlo simulation, identify the design point closest to the defined design targets).

5) Perform verification RADIOSS analysis on the optimal design obtained in Step 4. Check for satisfaction of constraints and relative changes in the objective function.

6) Perform any necessary modifications to the model, optimization problem formulation, etc... based on engineer’s interpretation of solution from Step 5.

7) If not converged, revise the design move-limits and generate a new set of sample design points that is now centered at optimal point of Step 6. (For Monte Carlo simulation, a new set of samples is generated around the best point identified in Step 4). Go to Step 2 and repeat the process till convergence. Convergence criteria include engineering judgement, constraint satisfaction and point of diminishing returns with respect to design objectives.

The solution procedure outlined above is simple and is similar to the one published in Reference [9].

3.0 Application – Automotive Vehicle Side Impact:

The automotive vehicle design should meet a variety of safety requirements for the National Highway Traffic Safety Administration (NHTSA). One particular safety requirement addressed in this paper is the side impact procedure based on either the Federal Motor Vehicle Safety Standards 214 or European Enhanced Vehicle-Safety Committee (EEVC). In our study, the EEVC side impact test configuration is used. The dummy performance is the main concern in side impact, which includes head injury criterion (HIC), chest V*C's (viscous criterion) and rib deflections (upper, middle and lower). These dummy responses must at least meet EEVC requirements. The finite element vehicle model along with moving deformable barrier model is shown in Figure 1. A finite element dummy model is also employed for prediction. Other concerns in side impact design are the velocity of B-Pillar at middle point and the velocity of front door at B-Pillar. The total number of elements in this model is about 100,000.

The moving deformable barrier position is defined in the EEVC side impact procedure. All nodes of the moving barrier are assigned an initial velocity equal to 50 km/h. For side impact, the increase of gage design variables tends to a get better dummy performance. However, it also increases vehicle weight, which is undesirable. Therefore, a balance must be sought between weight reduction and safety concerns. The objective is to reduce the weight while imposing safety constraints on the dummy. The dummy safety performance is usually measured by EEVC side impact safety rating score. In the EEVC side impact safety rating system, the safety rating score depends on four measurements of the dummy: HIC, abdomen load, rib deflection or V*C, and pubic symphysis force.
The design task is to find the set of design variables, that:

Minimizes Vehicle Weight
Subject to

Abdomen Load ≤ 1.0 KN
V*C ≤ 0.32 m/s
D_{urd} (Upper Rib Deflection) ≤ 32 mm
D_{mrd} (Middle Rib Deflection) ≤ 32 mm
D_{lrd} (Lower Rib Deflection) ≤ 32 mm
Pubic Symphysis Force F ≤ 4.0 KN
Velocity of B-pillar at mid-pt.: V_{B-Pillar} ≤ 9.9 mm/ms.
Velocity of front door at B-pillar: V_{front door} ≤ 15.70 mm/ms

The design variables are sizing and material parameters, including thickness of B-pillar (inner and reinforcement), thickness of floor side, thickness of cross member, thickness of door beam, thickness of door belt line reinforcement, thickness of roof rail, and material of B-pillar (inner) and floor side (inner). A total of 9 design variables are considered.

In this paper, the design variable changes within an assumed interval will be treated as random variables with uniform distribution and the influence of such changes on the probabilistic distribution of design responses will be evaluated. The uniform distribution, as opposed to all other distributions having tails, would favor designs that are not necessarily close to the mean.

Three different solution strategies are presently being investigated including, (i) Monte Carlo Simulation using ST-ORM, (ii) Numerical Optimization with Regression approach, and (iii) Numerical Optimization with Kriging metamodels.

For Case 1 (Monte Carlo approach), 15 samples are generated using ST-ORM around the “best” design for each cycle. These sample points are analyzed concurrently using RADIOSS explicit finite element solver on a SGI Origin 3800 compute server with 128 processors. Each sample point analysis is performed using 8 processors. For Case 2 (Numerical Optimization with Regression approach), the initial set of sample points are generated using an in-house Latin Hypercube sampling algorithm and the crash analyses performed using RADIOSS on the Origin server. For Case 3 (Numerical Optimization with Kriging metamodels), the same 15 sample points used with Case 1, are used for the first cycle. For successive cycles with Case 3, a varying number of new sample points are generated using the sampling algorithm.

Numerical results are provided in Table 1 below. The results include design objective, number of cycles performed with each approach (each cycle corresponds to 1 pass of the steps 1 to 6 listed in section 2.4), as well as the total number of RADIOSS crash analyses performed with each approach. All of approaches arrive at a feasible design solution. The regression based numerical optimization approach is able to find a slightly superior solution in terms of the design objective. In terms of comparing the three approaches, the differences are primarily in:

(i) the “robustness” of the sampling scheme used to generate the sample design points within each approach; robustness here refers to the generation of a sample set that would provide adequate knowledge of the design space;

(ii) the procedure for choosing of the “best” design point at the end of each design cycle.

For the numerical optimization based approaches (Case 2 and 3), the best point corresponds to the surrogate model based optimal solution. For Monte Carlo simulation based Case 1, the best point corresponds to the design sample that is closest to the target objectives. It is noteworthy that the “best” design point shifts the means of the variables for the successive cycle of Monte Carlo sampling while it becomes the starting point for the next cycle with the numerical optimization based approaches.

The optimization-based approaches for this problem require less number of design iterations and hence less number of crash analyses. This could be partially attributed to the manner by which the “best” design point at the end of each iteration is obtained –
through the solution of an optimization problem formulated to satisfy the design objectives and constraints. Whereas in the Monte Carlo based approach, this is not the case. It is important to point out that through the use of HPC servers with a large number of processors, analyses of the sample points can be performed concurrently. Hence, a high number of sample points for each design iteration is permissible and even becomes attractive towards acquiring adequate knowledge of the design space.

5.0 Summary:

Rigorous optimization and robustness design strategies are critical to delivering high quality products at low cost. While both Numerical Optimization and Monte Carlo Simulation are very generic and powerful solution methodologies, their effective implementation for multidisciplinary design optimization and robustness design studies demands the engineering process integration across a heterogeneous computing environment as well as the availability of HPC resources for concurrent processing. In this study, both design strategies provided for a feasible vehicle design while lowering the design objective (weight).

It is concluded that the recent advancements in HPC technology, especially massively concurrent processing, is enabling effective deployment of “simpler” procedures for design optimization and robustness studies of large-scale, vehicle systems.

6.0 References


Table 1: Vehicle Impact Design – Numerical Results

<table>
<thead>
<tr>
<th>Case</th>
<th>Design Objective (Weight, Kg)</th>
<th>Design Status (Feasible/Infeasible)</th>
<th># of Cycles</th>
<th># of RADIOSS analyses</th>
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<tbody>
<tr>
<td>Baseline</td>
<td>1922.2</td>
<td>Infeasible</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Monte Carlo Simulation (ST-ORM)</td>
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<td>Feasible</td>
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<td>75</td>
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<tr>
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<td>36</td>
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<tr>
<td>Numerical Opt. (w/ Kriging)</td>
<td>1918.6</td>
<td>Feasible</td>
<td>3</td>
<td>30</td>
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