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High-Performance Computing and Surrogate Modeling for Rapid Visualization with Multidisciplinary Optimization

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The use of high-performance computing for rapid visualization of design alternatives and the subsequent use of such visualization for design steering during the multidisciplinary optimization (MDO) process are investigated. Surrogate models based on polynomial response surfaces and message-passing-interface-based parallel programming models are used for rapid visualization of the physical model behavior responses corresponding to changes in the design variables. Application of the proposed procedure for vehicle structure impact design optimization is investigated involving both sizing and shape design variables. Mesh morphing is used in conjunction with the shape design changes. Rapid visualization of physical model behavior for changes in design variables during the MDO process facilitates collaboration of discipline experts that in turn facilitate steering of the design and enhances efficiency of the MDO process.

Introduction

MULTIDISCIPLINARY design optimization (MDO) embodies a set of methodologies that provide a means of coordinating efforts and possibly conflicting recommendations of various disciplinary design teams with well-established analytical tools and expertise.[1,2] MDO involves multiple disciplines, engineering, business and program management, often with multiple, competing objectives. These disciplines might just be analysis codes, which contain a body of physical principles, or, in addition, they can possess some intelligent decision-making capabilities. In an attempt to address the issues involved with the MDO process, formal methods have been derived, making use of consistent mathematical concepts, unique data structures, and alternative system representation techniques.[3]

Simulation-based detailed design of complex systems, more specifically, aerospace and automotive systems, is increasingly becoming a distributed design activity involving multiple decision teams each with very high-fidelity models and analysis tools as well as heterogeneous computing environments. Hence MDO processes will need to be executed in a flexible environment that would support the following:

1) Provide easy access to remote analysis tools and bring together multiple analysis tools into an integrated system analysis while hiding the details of data management from the user.

2) Surrogate models (also referred to approximate models) are used for design responses. Because these surrogate models are inexpensive to evaluate for a new set of data or values assigned to design variables, we can afford to evaluate approximate responses many more times without having to worry about the elapsed computing time required to perform the full analysis.

3) Rapid visualization of the design changes during the multidisciplinary design improvement stages to visually steer the design.

4) High-performance computing (HPC) can provide the aggregate computing powers necessary for rapid visual design steering and solving large-scale, multidisciplinary optimization problems. Such HPC servers with a large number of processors enable multiple levels of parallelism (coarse and fine grained) resulting in higher throughput and faster solution turn around times.

The preceding key points emphasize the need for MDO solutions to be performed in a flexible, interactive manner that can facilitate "expert-in-the-loop" through advanced visualization and utilize the domain experts knowledge to steer the design improvement process as opposed to solving such complex problems in a "black-box" mode.

While the state of the art in visualization of the optimization process is presently emerging, some of the existing approaches and those presently being researched offer a credible foundation. Although there are numerous research efforts and publications on visual design steering, this work is limited to the use of rapid visualization of the physical designs in the optimization process. Commercial frameworks, such as iSIGHT,[4] provide the capability to view in real-time two- and three-dimensional plots of the design space as the optimization progresses. The user could stop the process, modify the design optimization task, and restart the process from the current design point. Some of the methods presently being researched include visual design steering based on graph morphing[5] and the physical-programming-based visualization of the optimization process.[6] With the graph morphing approach, two- and three-dimensional plots are used to view the design objective contours and design constraint boundaries and how changing a variable in the n-dimensional design space will impact the objectives and constraints. With the physical-programming-based visualization, color-coded plots, two-dimensional plots depicting differing degrees of desirability of a selected design metrics are used to facilitate decision making and monitor the optimization process.

The primary focus of this work is on the use of HPC for rapid visualization of the physical design changes during optimization and the subsequent use of such visualization for design steering with the MDO process. Accordingly, visualization is used both to

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track the changes in the physical design as well as to provide a better understanding of the design space during the MDO solution process instead of simply providing a numerical solution. The current state of the art in HPC and graphics hardware makes real-time visualization a viable option. A second focus of this work is to develop a robust procedure for rapidly updating and visualizing the behavior responses of the physical design corresponding to changes in design variables. For example, updating the deformations of a vehicle system under impact loads, corresponding to changes in design variables, is a highly computer-intensive task when dealing with high-fidelity models and analysis. In this work, the rapid visualization of such system behavior responses is enabled using surrogate modeling methods in conjunction with message-passing-interface (MPI)-based parallel programming model. This capability to rapidly update the physical system behavior responses is used with the MDO process to steer the solution as well as provide for a stand-alone visual tool for engineers to conduct design trades. Details of the proposed method and its application to vehicle design are outlined in the following sections. Both sizing design variables as well as shape design variables using mesh morphing are considered in this study.

Multidisciplinary Design Optimization

Formal MDO methods are intended for the synthesis of multidisciplinary engineering systems, such as an aircraft or automotive or a weapons system, whose design is governed by multiple disciplines, such as engineering, manufacturing processes, cost, etc., often with multiple, competing objectives. These disciplines might just be an analysis code, which contains a body of physical principles, or in addition, they might possess some intelligent decision-making capabilities. The general system optimization problem is stated in the following form:

Given a set of design variables $\boldsymbol{X}$,

Find:

$$\Delta \boldsymbol{X} \tag{1a}$$

Minimize:

$$F[\boldsymbol{X}, Y(\boldsymbol{X})] \tag{1b}$$

Satisfy:

$$G[\boldsymbol{X}, Y(\boldsymbol{X})] \tag{1c}$$

$$\text{Bounds on } \boldsymbol{X} \tag{1d}$$

In the mathematical programming problem defined by Eqs. (1), $Y(\boldsymbol{X})$ represents the behavior (state) variables, F represents the design objective function, and G represents the design constraints.

The key components of MDO include 1) engineering tools/process integration including geographically distributed collaboration, 2) design optimization methods and strategies, and 3) advanced visualization methods.

For high-fidelity MDO solutions, other additional requirements involve 1) high productivity (throughput) computing, and 2) simulation data management. Simulation-based detailed design of complex systems is increasingly becoming a geographically distributed design activity involving multiple decision teams each with high-fidelity models and analysis tools as well as heterogeneous computing environments. Hence MDO processes will need the ability to easily access remote analysis tools and bring together multiple analysis tools into an integrated system analysis while hiding the details of data management from the user. The engineering tools/process integration can involve linking a set of analysis tools ranging from tools such as commercial-off-the-shelf software, legacy (in-house) codes, spreadsheets, databases, as well as tools to capture user's knowledge (Fig. 1). The integrated environment should provide for efficient transfer, storage, and access of data, including analysis responses as well as behavior sensitivities. An additional benefit to integrating distributed, dissimilar simulation components for analysis is that all aspects of performance can be evaluated, and the sensitivity of system and subsystem components can be quickly traded off.

Problem-solving methods involves a variety of solution procedures including numerical optimization techniques, design space sampling and approximation methods, robustness design methods, and tradeoff analyses. Although numerical optimization strategies involving nonlinear programming and evolutionary computing methods (genetic algorithms) have been extensively used to solve multidisciplinary optimization problems, robustness design methods, based on Monte Carlo techniques, Taguchi methods, and reliability-based design techniques, have been used to address design decisions under uncertainty. With increasing fidelity of the analysis models, a single analysis can require several hours of computing time on a state-of-the-art computer server with multiple processors. Even employing multiple processors with each crash simulation, the computational cost of these analyses along with the iterative nature of these design procedures prohibits rigorous optimization and robustness studies. Hence it is critical that surrogate models (i.e., lower-fidelity models or approximations) be constructed a priori using the results from a number of actual simulations for use with the

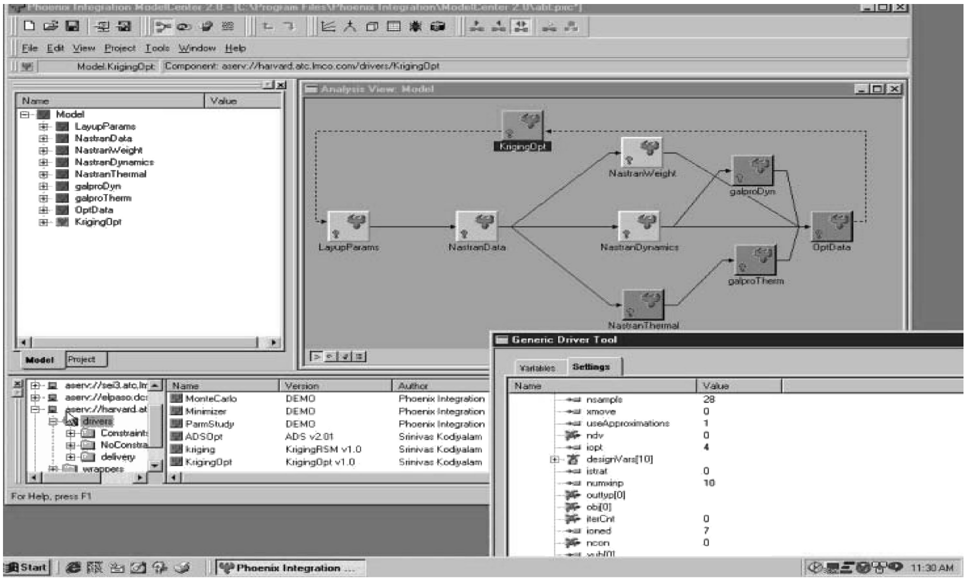

Fig. 1 Engineering tools integration with MDO.

optimization solution. In addition, these surrogate models can improve convergence for "noisy" computational tools by smoothing the response function.

Visualization of the MDO process not only provides for valuable design insight and design directions but also enables exploitation of the domain specialists' knowledge to aid the design process. Visualization in the context of MDO involves visualization of design data at run time and postprocessing stages as well as group visualization for collaborative design and engineering. The rapid advances in visualization technology over the last decade have made the effective use of high-end graphics and visualization a critical element of the simulation-based design process. In particular, advances in virtual reality and related environments have made group visualization extremely effective to the product design process. In general, visualization leverages a natural tendency to collaborate and hence facilitate insight/interactions and drive design decisions especially when dealing with large data and provide for improved collaboration and communication between teams of disciplinary experts.

HPC with high throughput is mandatory because most vehicle system optimization and robustness design studies are multidisciplinary involving a heterogeneous mix of analysis codes, including high-fidelity analyses codes. 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 nonthroughput mode. However, this is usually not the case because 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, enabling many runs to be made concurrently in a short amount of time as required in Monte Carlo simulation and in the construction of the surrogate models for design optimization.

Efficient and robust procedures for simulation data management are critical for design process applications such as MDO because these involve the execution of many simulations (or analyses) with multiple applications. A single analysis can require several days to complete and can require huge amounts of compute resources, including disk capacity, memory and I/O bandwidth. Because of the comparatively large number of simulations that a high-fidelity MDO solution typically requires, creation of a consistent and appropriate data management capability is essential. In addition, because the MDO process flow can involve large data files (several hundred gigabytes) on multiple server and workstation environments the need for unified access to these simulation data at or near local disk speeds is also essential.

MDO Environments Where HPC and Advanced Visualization Are Beneficial

The design of complex structures and vehicles, such as in the automotive and aerospace industries, results in a simulation environment with the following characteristics[7]: 1) high number of design variables; 2) substantial number of design subsystems and engineering disciplines; 3) interdependency and interaction between the subsystems; 4) large, complex models across all engineering disciplines; and 5) iterative design and analyses processes. These attributes are representative of an environment that would benefit from the use of MDO techniques. Because of the level of complexity and dimensionality, high-performance-computing systems are critical for large-scale MDO in order to impact the product development cycle. In addition, a heterogeneous mix of simulations is common with MDO. These various kinds of simulations put different strains on the compute systems. Some are I/O intensive, whereas others require fast CPUs with high CPU-to-memory bandwidth. Because all of these simulations need to be conducted simultaneously to impact the design cycle, the computing environment must be capable of effectively running the complete mix of simulations.

Advanced visualization systems and methods facilitate better design decisions especially when dealing with high-fidelity models and large amounts of data as well as provide for improved collaboration and communication between teams of disciplinary experts. Both of these are critical for MDO. The representation methods available today for use with the MDO process involve methods to visualize the progress of the optimization solution, including 1) tables (numerical), 2) two-/three-dimensional design space plots (curves and surfaces), 3) animations (time dependent), and 4) virtual reality and related environments.

High-performance visualization systems are mandatory to support the following:

1) Visualize high-fidelity computer-aided engineering (CAE) models for results postprocessing. This could involve models [such as in normal modes finite element analysis, impact finite element analysis, and computational fluid dynamics] having several million degrees of freedom, several 100s or even 1000s of mode shapes, several local and global modes, etc. Even with a very fast workstation, trying to load and render 100s of mode shapes is very time consuming and mentally exhausting.

2) Visualize precomputed data vs dynamic steering of computer-intensive simulations. This requires great deal of resources, such as large memories, massive data stores, network bandwidth, massively concurrent processing, etc.

3) Visualize rapidly design alternatives for effective collaboration and steer the design with iterative design and optimization process.

4) Explore different views simultaneously for multiple disciplinary experts. The different participants can be working on the same aggregate information but exploring different views. For example, an aerodynamic expert visualizing the flowfield on an aerospace structure while the structural designer looking at the stress contours for the same configuration.

For high-fidelity models, advanced visualization systems such as the Onyx4,[§] which based on a high-bandwidth, scalable, shared memory architecture along with industry standard graphics components, enables visualization at higher interactive speeds.

Proposed Method for Rapid Visualization of Design Alternatives and Design Steering

The unique elements of the proposed method for rapid visualization of design alternatives include the following:

1) The first element is surrogate model construction for the physical system behavior responses (for example, several 100,000s of nodal displacement responses for each time step in a transient simulation), using polynomial response surfaces[8] with subset selection.[9,10]

2) The second is use of MPI-based parallel programming models for rapid construction of the surrogate models. MPI is a component of the Message Passing Toolkit, which is a software package that supports parallel programming across a network of computer systems through a technique referred to as message passing. The interface establishes a practical, portable, efficient, and flexible standard for message passing. The surrogate model construction is performed concurrently for all of the responses (for example, all of the nodal displacements) on an HPC server with a large number of compute processors.

3) The third element is subsequent use of the surrogate models for rapidly updating and visualizing the physical system behavior, including transient animations, for changes in design variables during the optimization process. This is again accomplished using parallel programming models and HPC systems with a large number of compute processors.

4) The last one is further use of the rapid visualization capability for discipline expert collaboration and design steering.

The mathematical and implementation details of the proposed methodology are provided in the following sections.

Surrogate Model Construction Based on Polynomial Response Surfaces with Subset Selection

The key considerations that are involved in the construction of surrogate model for high-fidelity, nonlinear simulations, include the following:

1) The first consideration is the choice of sampling procedure for generating the data points [design of experiments (DOE) based,

[§]Data available online at http://www.sgi.com/visualization/onyx4/overview.html.

orthogonal arrays, central composite design, Latin hypercube design, random sampling, descriptive sampling, etc.].

2) The second is the choice of a suitable approximation model to represent the data (linear, quadratic, cubic, exponential, Gaussian, radial basis, network of neurons, etc.).

3) The last is the 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, etc.).

The methodology implemented in this work is based on polynomial response surfaces. In particular, a polynomial response surface model with subset selection is used. The subset selection is advantageous over a complete set polynomial model for a few reasons including variance reduction and simplicity. Each additional coefficient that is estimated adds to the variance of the regression equation.

Many of the criteria that have been suggested in the literature to identify the best subset are monotone functions of the residual sum of squares (rss) for subsets with the same number of independent variables.[9] Hence, the problem of finding the best polynomial can often be reduced to the problem of finding those polynomials of size p with minimum RSS. The RSS is given by

$$RSS = \sum_{i=1}^{m} (y_i - \bar{y}_i)^2 \qquad (m > p) \tag{2}$$

In Eq. (2), y is the response to be approximated by a polynomial, and m is the total number of sample points ($m > p$) for a polynomial of size p (p can also be referred to as the number of fitting terms).

Most procedures that produce statistical inference depend heavily on the relation between the total and regression sums of squares. In the case of linear regression by linear polynomial, the relationship can be simplified as follows:

$$\sum_{i=1}^{m} (y_i - \bar{y})^2 = \sum_{i=1}^{m} (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^{m} (y_i - \hat{y}_i)^2 \tag{3}$$

where $\bar{y}$ is the mean of y_i, and $y_i = y(\boldsymbol{x}_i)$. Equation (3) represents the following conceptual identity[9]:

(Total variability) = (Variability explained)

+ (Variability unexplained)

The coefficient of determination, often referred to as R^2, is given by Eq. (4):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{4}$$

R^2 is surely a measure of the model's capability to fit the sampling data. The insertion of any new regressor into a model cannot bring about a decrease in R^2. Though there are rules and algorithms that allow for selection of best model, the statistic itself is not conceptually prediction oriented. It is not recommended as a sole criterion for choosing the best prediction model from a set of candidate models.[9]

The adjusted R^2, denoted by $\bar{R}^2$, is used by many researchers as a criterion for identifying the best prediction models in subset selection. The $\bar{R}^2$ can guard against overfitting by including marginally important model terms at the expense of error degrees of freedom. Adjusted R^2 is given by[9]

$$\bar{R}^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \times \frac{(m-1)}{(m-p)} \tag{5}$$

The quantity of $m - p$ of Eq. (5) represents the residual degrees of freedom for the p-term model. One can easily notice that $\bar{R}^2$ represents the proportion of variation in the response data that is explained by the model. Clearly $0 \le \bar{R}^2 \le 1$, and the upper bound is achieved when the fit of the model to the data is perfect. $\bar{R}^2$ is used as the criterion to find best subset in the applications later.

For subset selection, the method that is recommended in Ref. 10 is the sequential replacement algorithm. 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 an improved $\bar{R}^2$. In practice, the procedure usually converges very rapidly. Although sequential replacement algorithm requires more computational time, it is feasible to apply to problems with several hundreds of terms in the solution set when subset of 20 to 30 terms are required. Another advantage of the sequential replacement algorithm is that it does not have any artificial parameters to be tuned.

The sequential replacement algorithm can be briefly outlined as follows. The starting subset for sequential replacement algorithm could be a linear polynomial of the form

$$y = a_0 + a_1 x_1 + \cdots + a_n x_n \tag{6a}$$

with replacement candidates as

$$x_1^2, x_2^2, \ldots, x_n^2, x_1x_2, x_1x_3, \ldots, x_1x_n, x_2x_3, \ldots, x_{n-1}x_n \tag{6b}$$

In the sequence of steps with the sequential replacement algorithm, there are q iterations involved for determining each term, where $q = (n+1)^* n/2$ and n is the number of design variables.

Reference 10 provides a detailed study of subset selection and with different subset terms in the regression model for transient impact-type simulations. The error between the surrogate model prediction and a detailed explicit finite analysis, for intrusion (displacement)-type responses that have a nonlinear relation with the design variables, is generally within an acceptable range of 10%.

The surrogate modeling method just proposed is next discussed in the context of an automotive vehicle design for impact behavior. Surrogate models are constructed for each nodal displacement degree of freedom of a finite element model for every animation time step over the complete impact simulation time interval.

In an automotive vehicle design, the car-body structure analysis involves compute intensive disciplines, such as impact and noise-vibration harshness. In particular, vehicle impact is a nonlinear event in terms of the structural and dummy responses. Impact (crashworthiness) 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 a million degrees of freedom, a single crash analysis can require several hours of computing time on a state-of-the-art computer server with multiple processors. Table 1 provides elapsed times on a SGI Origin 3800 server for crash simulations using explicit finite element code, RADIOSS, on industry standard models. In addition, impact analysis is still not robust enough because occasionally runs corresponding to large design perturbations fail as a result of modeling and element penetration issues. Hence it is critical that surrogate models constructed a priori using the results from a number of actual crash simulations be used both for rigorous optimization studies as well as for rapid visualization of vehicle impact responses corresponding to design perturbations.

As an example, consider a relatively small model of about 100,000 nodes and a simulation time interval of $t = 0$ to 100 ms, with animation time step of every 10 ms. This would result in construction of

Table 1 Vehicle impact (crashworthiness) simulations and compute resources

Impact condition	Model size and simulation time	Elapsed time, h	Number of CPUs per simulation
Full frontal	136,000 elements 120 ms	0.830	8
50% offset	178,000 elements 140 ms	1530	8
Roof crush	150,000 elements 200 ms	0.710	16
Side impact	142,000 elements 80 ms	0.630	8

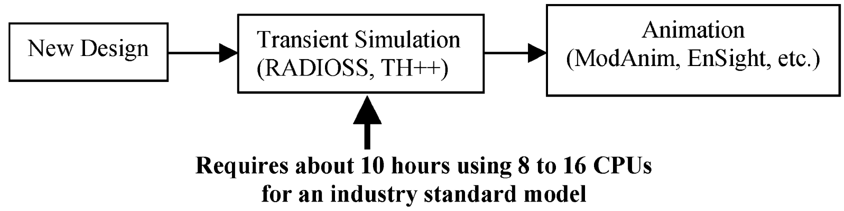

Fig. 2a Visualization of crash mode deformations: conventional process.

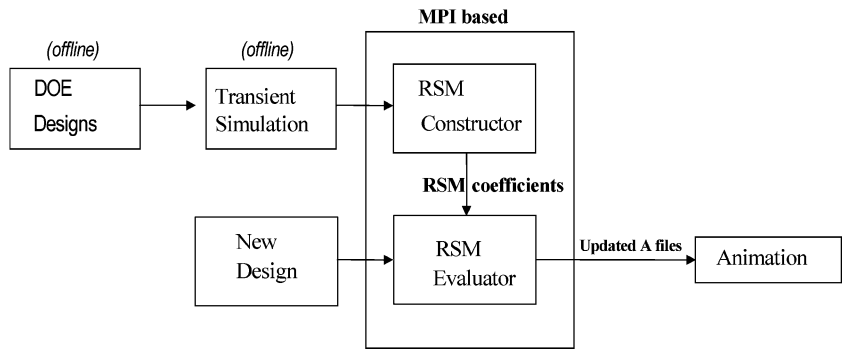

Fig. 2b Visualization of crash mode deformations: response surface models + MPI-based process.

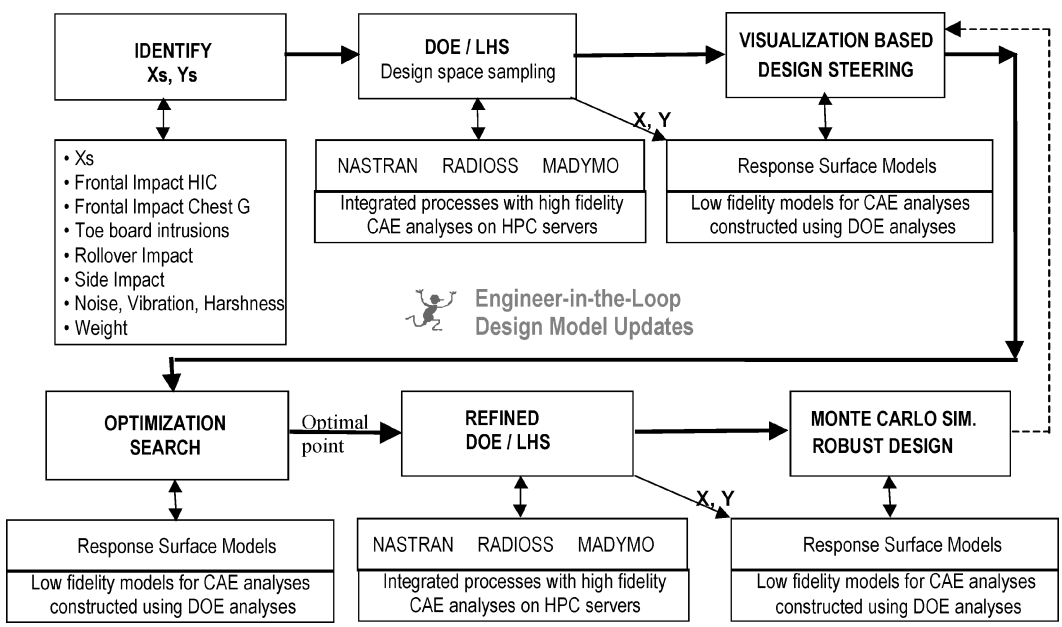

Fig. 3 MDO process with rapid visualization for design steering.

over three million surrogate models for each of the nodal displacements (x, y, z direction) as a function of the design variables:

$$100{,}000 \text{ nodes} \times 3(x, y, z) \text{ degrees of freedom} = 300{,}000$$

ten animation steps over the simulation time interval [generates 11 animation files (A files)]; the total number of displacement responses to be approximated as a function of the design variables equals $300{,}000 \times 10 = 3{,}000{,}000$.

Although this is a computationally intensive task, the process of generating these surrogate models for each nodal degree of freedom is completely independent of the other degrees of freedom and hence is highly parallel. The MPI parallel programming model is used to utilize all of the processors in a multiprocessor server with hundreds of processors to minimize the elapsed time of constructing these surrogate models and update the crash deformation modes for changes in design variables.

A flowchart of the conventional and the new procedures are provided in Fig. 2a and 2b. The conventional procedure of Fig. 2a involves running the computer-intensive full transient analysis with RADIOSS code, typically for tens of hours using 8 to 16 CPUs on an HPC server. The time histories resulting from the transient simulation are postprocessed using an appropriate postprocessing tool, such as ModAnim or EnSight. With the conventional process, the rapid visualization of crash mode deformations for large models corresponding to changes in design variables is therefore not feasible. The procedure just outlined based on the use of surrogate models to approximate each displacement degree of freedom for every animation time step overcomes this drawback. The surrogate model construction for each displacement degree of freedom is done a priori. For rapid visualization of design alternatives, the surrogate models in conjunction with MPI-based parallel programming are used to approximate each displacement degree of freedom corresponding to the new design variables and write out the updated animation files. The animation files are subsequently postprocessed for display using ModAnim or EnSight. Figure 2b shows the new procedure.

MDO Process with Rapid Visualization-Based Design Steering

The MDO process implemented in this study is shown in Fig. 3. Although the process is generic, the figure shows a specific example of an automotive vehicle MDO for crashworthiness safety, noise-vibration-harshness and weight requirements. The key steps of the process include the following:

1) Capture the customer and design requirements: This step primarily involves the problem formulation phase, where capturing the critical customer requirements as well design and quality requirements are mandatory. The problem formulation involves identifying the design variables, design constraints and objectives, system decomposition, coupling variables, disciplinary analysis tools and methods, and other related parameters.

2) Screen the design space through design of experiments: Typically a realistic vehicle design optimization task involves several hundreds of design variables and a large number of design requirements (constraints and objectives). A screening design of experiment study, using Latin hypercube sampling, is performed on the full set of design variables to identify key design variables based on their influence of the design objectives and constraints for optimization search.

3) Construct surrogate models (response surfaces): A response surface model, based on the methodology just described, is constructed for each behavior response. These are constructed as a function of the key design variables identified in the screening phase.

4) Steer the design with rapid visualization of physical model changes and experts in the loop: This phase, in general, refers to the use of rapid visualization of the physical model changes to steer the design process. Specifically it refers to the use of visualization within the MDO process to facilitate domain knowledge capture and steer the solution toward an improved design. The sequence of actions in this step include the following:

a) Visualize the design space (objective and constraint contours) and locate key areas to explore.

b) Request an enhanced rendering from the server of behavior responses at the design point of interest. This is accomplished either through the use of surrogate models for computer-intensive analysis or playback of large stores of precomputed data.

c) Recommend changes in configuration and design optimization model based on disciplines' data visualization and expert's domain knowledge.

5) Perform full analyses of the design with recommended changes. Based on the analysis solution, accept or reject the changes and proceed with the numerical optimization search.

6) Perform a rigorous numerical optimization based search of the design space in conjunction with the surrogate models for improved designs.

7) Perform a refined design of experiments (Latin hypercube sampling) at the vicinity of the optimization solution arrived from the preceding step. Update the surrogate models using the analysis data from the refined DOE study.

8) Perform Monte Carlo simulation to obtain a robust (minimum variance) design solution. The result of the Monte Carlo robustness study could be in terms of acceptable sigma level (three-sigma designs, etc.).

9) Check convergence to an acceptable solution using engineering judgement.

Clearly the MDO process just outlined is not a black-box methodology, but instead involves significant human interactions and is not automated across the complete process. Steps 6 and 8 are automated to perform the optimization search with surrogate models and Monte Carlo simulations, but the rest of the process is driven manually by the engineer, so that the user can stop the process when the solution is good enough before more computations are performed or can interrupt the process to change the design optimization model when the design is progressing in the wrong direction.

Applications

Two applications involving high-fidelity finite element models are considered. The first application is using sizing design variables only while the second application uses both sizing and shape design variables along with mesh morphing technique.

Crashworthiness Design Optimization with Sizing Variables

A 50% offset frontal impact car crash finite element model is shown in Fig. 4. The model contains about 100,000 elements. It crashes into a rigid 90-deg fixed barrier with 50% offset at the speed of 40 mph. Frontal crash is commonly used to design and validate the vehicle front structures. Federal Motor Vehicle Safety Standards 208 (FMVSS 208) specifies the safety regulations and test configuration for full frontal crash test. The Insurance Institute of Highway Safety has specified test configuration for frontal offset impact. The key output from the 50% frontal offset impact simulation is the toe-board intrusion. The design target for toe-board intrusion is set to be less than 10 in. (0.254 m). The focus of this design study is to reduce the toe-board intrusion and to increase the crash energy absorption of the front rail. The front rail, shown in Fig. 5, is located behind the bumper and extends to the rocker of a car. The key design variables x_i used are sizing variables that define the thickness of the three parts in the front rail as shown in Fig. 5.

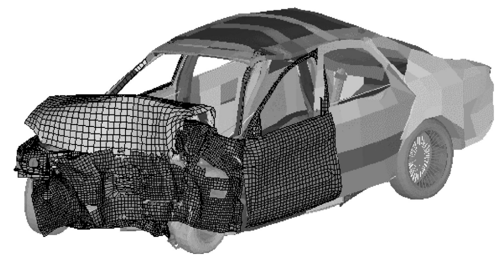

Fig. 4 The 50% vehicle frontal offset impact model.

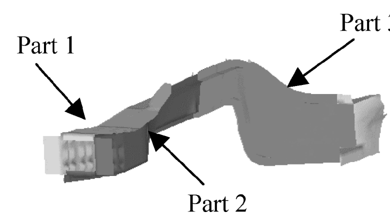

Fig. 5 Front rail.

The formal design optimization problem is defined as follows.

Minimize:

Toe-board intrusions at several predefined locations

Subject to:

Vehicle weight

Head-injury criteria (HIC) < 450

Chest G < 45

$$x_i^l \le x_i \le x_i^u, \qquad i = 1, 3$$

The explicit finite element analysis software RADIOSS is used for the crashworthiness analysis with the following finite element model details:

NUMMAT: NUMBER OF MATERIALS: 117
NUMNOD: NUMBER OF NODAL POINTS: 100932
NUMELS: NUMBER OF 3D SOLID ELEMENTS: 400
NUMELC: NUMBER OF 3D SHELL ELEMENTS (4-NODES): 101709
NUMELT: NUMBER OF 3D TRUSS ELEMENTS: 199
NUMGEO: NUMBER OF PROPERTY SETS: 431
NUMELP: NUMBER OF 3D BEAM ELEMENTS: 75
NUMELR: NUMBER OF 3D SPRING ELEMENTS: 3616

The design of experiment method used to sample the design space is the Latin hypercube sampling with a uniform distribution. A total of 10 finite element simulations are performed to build the response surface as a function of the three front-rail design variables. Each RADIOSS simulation requires about 27 h of elapsed time on a SGI Origin 3800 HPC server using a single processor. With a MPI-based implementation, the surrogate model construction of three million displacement responses requires a little over 5 min on the same Origin 3800 server using eight CPUs. The elapsed time for surrogate model construction does not include the 10 RADIOSS performed a priori based on a uniform design sampling of three-dimensional design space. Using the rapid visualization process discussed in the earlier section, the rail deformation for a new design can be updated and displayed on the screen in a few minutes. The visual tool enables the engineer to perform parametric trades and simultaneously visualize the structural behavior changes (deformations) as compared to solely working with updated numerical quantities (head injury criterion, maximum intrusion, etc.). Under frontal impact it is not desirable to see much bending of the rail (Fig. 6); instead, it is desirable to see progressive crash that increases energy absorption. Such critical information can be readily obtained from this rapid visualization tool.

The design optimization for the gauges of the parts resulted in successfully reducing the toe-board intrusions by 25% without increasing the vehicle weight. The final deformations of the rail at time $t = 70$ ms for both baseline design and optimal design are shown in Fig. 6.

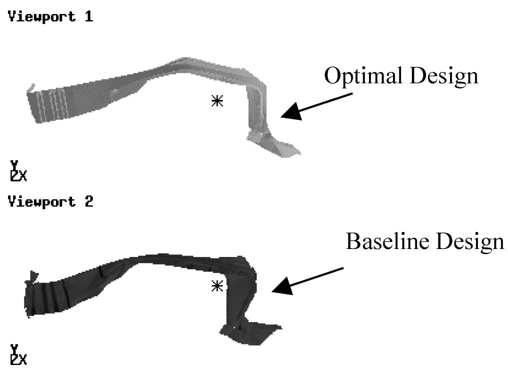

Fig. 6 Deformation of front rail.

Crashworthiness Design Optimization with Sizing and Shape Variables Using Mesh Morphing

Traditionally, when a vehicle model is changed, such as changes to new body profile, a new CAD geometric model has to be created and then meshed to generate the discretized finite element model. This process usually takes a long time and significant effort, particularly for large-scale complex subsystems and assemblies. With the morphing technique, the new finite element model can be built directly from the old one by modifying the finite element mesh to fit the new profile. With morphing, an existing design can be taken and transformed into a new design by using the new engineering criteria and available design information. For example, if a new product, such as a door from a newly developed concept, is to be designed, morphing will aid in transforming the styled door into a fully engineered, production ready door. Morphing allows engineers to quickly parameterize models and stretch finite element meshes when the geometry of the structure is changed. It can be accomplished either through a combination of Laplacian smoothing techniques and mesh quality measures.[11] Several commercial software such as HyperMesh and Meshworks/Morpher are available

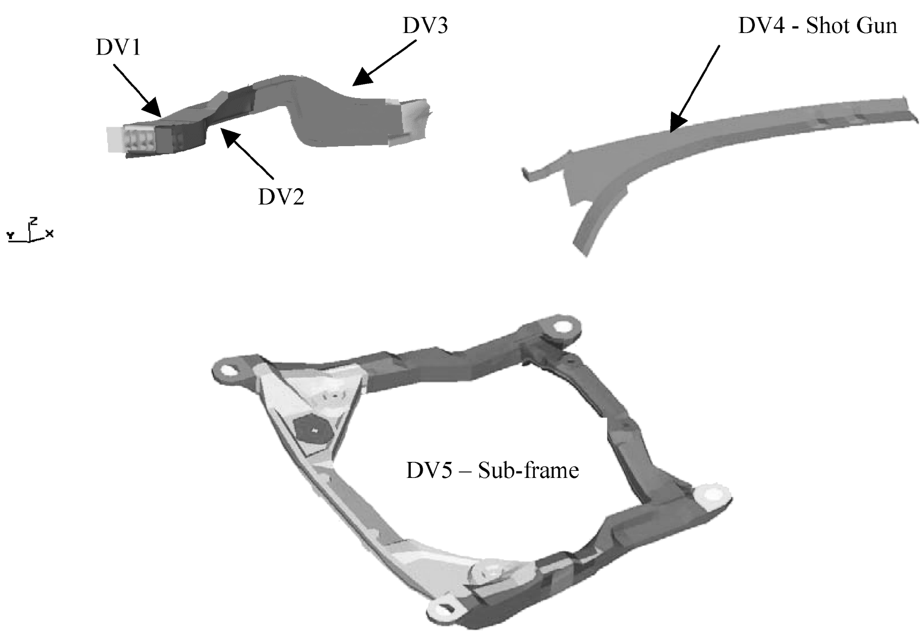

Fig. 7 Sizing design variables.

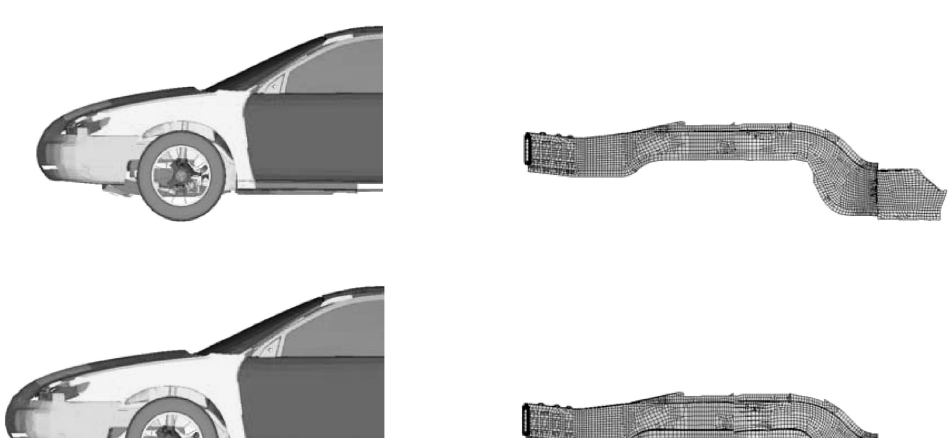

Fig. 8 Shape design variables.

for mesh morphing today.[¶,**] Mesh morphing has the potential to reduce design and engineering costs as existing meshes can be quickly morphed to hypothetical design considerations, without remeshing, for evaluation while preserving the model integrity and connectivity. This eliminates the need to continuously work back through the CAD tool to evaluate design considerations.

With the advancement of computer hardware and software, morphing technique has become more practical for industry applications. Morphing can be used in two key areas: shape optimization and preliminary simulation after changes to the model. For shape optimization, the feasible shapes need to be characterized by parameters, such as length, height, width, angle, and profile curves. The specific shape can easily be generated using a morphing tool with parametric data. The optimal shape is achieved after certain iterations with the model generation process embedded into the optimization loop. The shape design variables can be either vehicle level or component level parameters.

In this application, the same 50% offset frontal impact model, used with the previous application, is considered with the addition of two shape design variables, and two more gauges are added to the original three gauge variables for design optimization. The first shape variable corresponds to the length of extension of the front portion of the vehicle (in front of the vehicle A pillar). This variable is a vehicle-level parameter. The second shape variable corresponds to the height extension of the rail. When applying extension to the front portion of the vehicle, all nodes in that region are displaced accordingly. For rail height extension, only nodes of rail components are moved while the rest of the structure is fixed. The five sizing design variables include rail inner and outer, shotgun and subframe and are shown in Fig. 7 and the shape variables are shown in Fig. 8.

The formal design optimization problem is defined as follows.

Minimize:

Toe-board intrusions at several predefined locations

Subject to:

Vehicle weight

HIC < 450

Chest G < 45

$$x_i^l \leq x_i \leq x_i^u, \qquad i = 1, 7$$

As before, the explicit finite element analysis software RADIOSS is used for the crashworthiness analysis. A Latin hypercube sampling with a uniform distribution is used to generate 24 designs for constructing the response surfaces for the nodal displacements. A total of 25 finite element simulations are performed to build the response surface as a function of the seven sizing and shape design variables. Each RADIOSS simulation requires about 6 h 20 min of elapsed time on a SGI Origin 3800 HPC server using eight processors. Using the rapid visualization process discussed in the earlier section, the rail deformation for a new design can be updated and displayed on the screen in a few minutes. The maximum intrusion was successfully reduced to the desirable levels without increasing the vehicle weight using the MDO process outlined earlier.

Summary

Visualization and HPC systems are critical in competitive environments, where processing data faster has a significant return on investment. It maximizes the engineer's capacity to absorb and process data and transform it to knowledge. The result is greater insight, better decisions, superior designs, and competitive advantage.

In this work, high-fidelity MDO using industry standard vehicle models and computer-intensive analyses is presented. Such MDO tasks necessitate the use of robust methods and HPC with the solution process. A novel MDO process is proposed that involves surrogate modeling methods, HPC for rapid visualization of the physical model changes and its behavior responses, and use of rapid visualization to facilitate human collaboration and steering of the design optimization solution. The process emphasizes the need for such solutions to be performed in a flexible environment that can provide a better understanding of the design space instead of simply providing a numerical solution.

From the two-vehicle design optimization applications, it is observed that visualization of the system behavior and integration of visualization procedures with the MDO process enables discipline experts to provide design insights and thereby increase the efficiency of the iterative design optimization process. More specifically, the engineering judgement and expert inputs are used to appropriately modify and enhance the design model with each cycle of the MDO process and achieve a superior design faster.

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[¶] Data available online at http://www.altair.com/software/hw-hm.htm.

[**] Data available online at http://www.depusa.com/morpher.html.