SHAPE OPTIMIZATION OF CRASHWORTHY STRUCTURES

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Abbreviations:
HEEDS – Hierarchical Evolutionary Engineering Design System

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ABSTRACT

Crashworthiness problems, which are highly dynamic and nonlinear, do not lend themselves well to classical gradient optimization techniques. Evolutionary-based design approaches that employ a form of guided stochastic search algorithm have been successfully applied to these problems. While many design optimization approaches are limited to a small number of continuous design variables, the approach described here can productively search over hundreds at a time. The power of classical evolutionary algorithms can be increased by allowing flexible design variable decomposition and incorporating classical local optimization methods and/or by embedding them within adaptive agents, which communicate but work semi-independently on a common problem. The authors have developed a system that allows for flexible design variable decomposition while combining evolutionary algorithms with local optimization. Within this approach, autonomous agents break down a problem hierarchically, using problem-specific divide-and-conquer rules to organize design variables and design criteria into a set of highly decomposed, overlapped relationships. These agents simultaneously search a discretized design space at various levels of resolution and use different design variable representations, performance measures (combinations of objectives and constraints), and local search methods. The agents exchange information about the decomposed solution space with each other, helping them jointly to satisfy multiple constraints and objectives. This technology has been implemented into a software code called HEEDS (Hierarchical Evolutionary Engineering Design System), which can be run on a single processor or in a networked computing environment, including clusters of personal computers or simple networks of workstations. Using LS-DYNA explicit as the finite element solver within the HEEDS optimization environment, this process has been applied to several automotive lower compartment rail designs, resulting in significant gains in performance along with up to 20% reductions in mass compared to baseline rails designed by experienced engineers. An example application of this method is described herein.

INTRODUCTION

The design of modern vehicle structures is driven by many competing criteria: improved safety and fuel efficiency, lower cost, enhanced performance, and increased styling flexibility. In addition, the introduction of new manufacturing processes and materials significantly increases the available design space, or the set of all possible designs for a problem. In order to explore this large design space more effectively while trying to reduce design cycle times, engineers often try to take advantage of automated design optimization and simulation software tools. These tools can greatly decrease the time required to identify a set of feasible, or even near-optimal, designs prior to building and testing the first prototype.

Optimizing multifunctional, energy-absorbing structures in a vehicle proves to be a major challenge to safety engineers and to automated design techniques. For example, energy-absorbing structures should maintain their rigidity while carrying the anticipated in-service loads and while serving as primary mounting locations for numerous functional devices and attachments, such as the engine in an automobile or a passenger seat in a helicopter. Yet these same structures must collapse in a prescribed manner during a crash to maximize the amount of energy absorbed by the structure and to limit the forces transmitted to passengers.

Objectives and constraints related to crash energy management, stiffness, strength, and packaging are joined by additional requirements on manufacturability, noise and vibration, mass reduction, and robustness against process and material variation. These objectives compete strongly against one another, making this a very challenging multi-objective optimization problem.

Energy-absorbing structures often take the form of thin-walled tubular metallic structures subjected to dynamic compressive loads. In this case, energy is absorbed primarily through plastic deformation of the material and friction due to surface contact. The ideal mode of failure is one of progressive short-column buckling, which maximizes plastic material deformation and folding contact.

Stability or buckling behavior can be very sensitive to geometrical and material imperfections, which may prevent a part from failing in the way it was intended. Therefore, it is not sufficient to find a design that performs well under a set of narrowly defined objectives, constraints, and loading conditions. The structure should be somewhat insensitive to variations in the objective measures, constraints, and loadings, to eliminate such variations as additional causes of failure. The design of energy-absorbing tubular structures must ensure that their collapse or buckling mode is not sensitive to expected variations in material properties, wall section thickness, cross-sectional shapes, or overall tube curvature. The structure should also be robust enough to absorb similar amounts of energy under a wide variety of off-axis dynamic loading scenarios.

Crashworthiness problems, which are highly dynamic, are characterized by a very complex design space with many peaks and valleys. These classes of structural design problems, which have a very multi-modal, non-convex design spaces do not lend themselves well to classical gradient techniques. Evolutionary-based design approaches that employ a form of guided stochastic search algorithm have been successfully applied to these problems. While many design optimization approaches are limited to a small number of continuous design variables, the approach described here can productively search over hundreds at a time.

The power of classical evolutionary algorithms can be increased by allowing flexible design variable decomposition and incorporating classical local optimization methods and/or by embedding them within adaptive agents, which communicate but work semi-independently on a common problem. The authors have developed a system that allows for flexible design variable decomposition while combining evolutionary algorithms with local optimization. Within this approach, autonomous agents break down a problem hierarchically, using problem-specific divide-and-conquer rules to organize design variables and design criteria into a set of highly decomposed, overlapped relationships. These agents simultaneously search a discretized design space at various levels of resolution and use different design variable representations, performance measures (combinations of objectives and constraints), and local search methods. The agents exchange information about the decomposed solution space with each other, helping them jointly to satisfy multiple constraints and objectives.

This technology has been implemented into a software product called HEEDS (Hierarchical Evolutionary Engineering Design System), which can be run on a single processor or in a networked computing environment, including clusters of personal computers or simple networks of workstations. Various agents can evaluate potential designs with different design variable representations and performance measures. Each design variable representation can employ a different number of design variables of the overall problem while each performance measure might use only a subset of the technical objectives and constraints. For example, this approach has the capability to seek independently a set of good designs for each single technical objective and constraint set with a small number of coarse design variables, while aggregating sets of sub-optimal solutions for all performance measures in a stochastic manner, allowing economical emergence of solutions with a larger number of design variables that satisfy all constraints and are driven by all technical objectives.

Using LS-DYNA explicit as the finite element solver within the HEEDS optimization environment, this process has been applied to several automotive lower compartment rail designs, resulting in significant gains in performance along with up to 20% reductions in mass compared to baseline rails designed by experienced engineers. These achievements were realized through cross-sectional shape, material, and spot-weld optimization. In contrast, optimization of only material properties, spot welds, and section thickness in a rail with fixed cross-sectional shape will typically yield much lower performance improvements, even if mass is not reduced. An example application is described herein.

APPROACH

HEEDS was used to design several automotive lower compartment rails using LS-DYNA explicit as the finite element solver. HEEDS found cross-sectional shape, material, and spot-weld placements that dramatically increased the amount of crush-zone energy in the front of the rail for direct and offset crash scenarios with inequality constraints on the peak rigid wall force and on the mass. First, component level simulations of a vehicle front rail were developed for direct and offset crash scenarios. HEEDS was then used to automate the creation and evaluation of each potential design to perform design optimization.

Component Level Simulation of Vehicle Front Rail

A component level simulation of a vehicle front rail for multiple crash scenarios was performed with LS-DYNA (LSTC, 2000). A lumped mass was placed at various offset positions at the rear of the rail structure to allow simulation of multiple crash scenarios (see Figure 1). The rail structure and mass were given an initial velocity and crushed into a rigid stationary wall as depicted in Figure 1. The crush-zone energy, peak rigid wall force, and mass were computed with LS-DYNA.

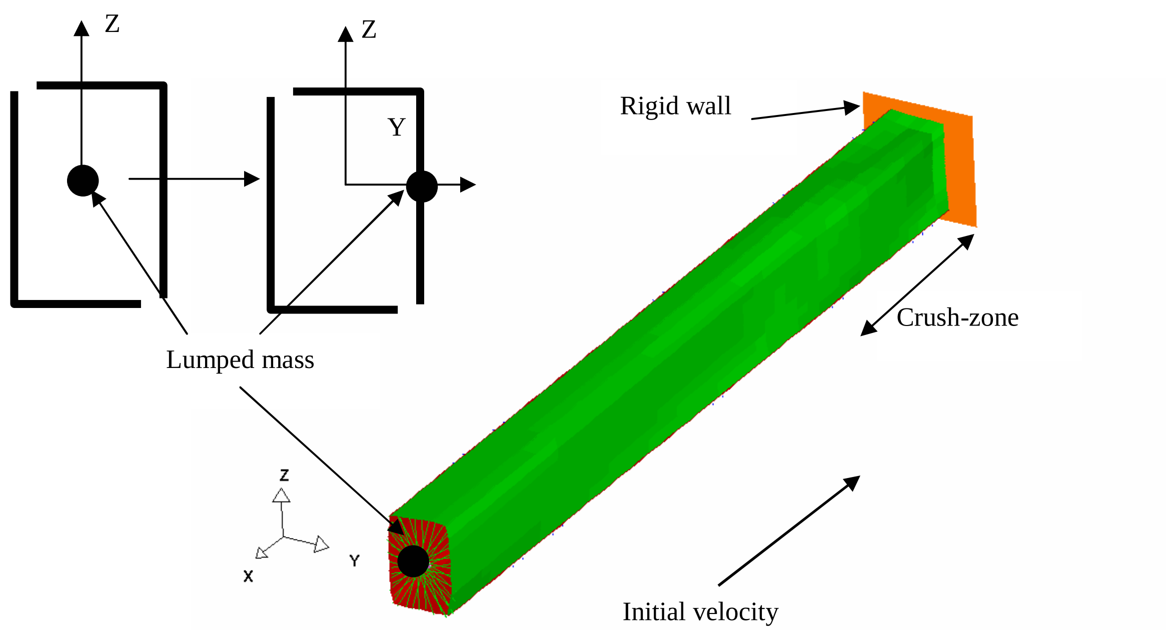

Figure 1. Two open "L" shaped surfaces are welded together to create a closed surface. The rail structure is crushed into the rigid wall due to the initial velocity of the system. The lumped mass is positioned at the end of the structure at various "Y" offsets to create the direct and the offset cases. The peak crush force is measured at the rigid wall while the internal energy is measured in the crush-zone.

Design Optimization with HEEDS

Many optimization studies have shown that no single optimization approach performs best on all classes of problems, but combining a set of global and local optimization techniques often yields good results (Koch et al., 2002). This situation often creates significant confusion and can be misleading to inexperienced users of optimization software. In addition, for problems that contain many design variables and criteria, it is often helpful to decompose the overall problem into a set of smaller, more tractable problems to obtain improved results with reasonable computational resources. The software package, HEEDS (ACD Associates, 2002), has been constructed to hierarchically decompose problems while automatically combining the strengths of global exploration and local optimization algorithms. HEEDS combines the strengths of genetic algorithms (Holland, 1975), simulated annealing (Ruthenbar, 1989), sequential quadratic programming (Schittkowski, 1985), design of experiments (Cochran *et al.*., 1992), response surface methodology (Khuri *et al.*, 1996), and neural networks (Masters, 1993).

HEEDS creates adaptive autonomous agents that communicate but work semi-independently on a common problem, employing a communication topology determined by default settings or custom tailored by the user. Each agent (or group of agents) can employ specialized search heuristics that seek to maximize the performance of its representation of the problem. For instance, Figure 2 depicts a topological structure composed of nine agents that share information in a hierarchical manner. They independently seek a set of good designs for each single technical objective and constraint set with a small number of coarse design variables, while aggregating sets of sub-optimal solutions for all performance measures in a stochastic manner, allowing economical emergence of solutions with a larger number of design variables that satisfy all constraints and are driven by all technical objectives. Each agent was executed as a separate computer process on a loosely coupled network of personal computers (550 MHz). Designs are shared periodically in a structured manner from agent-to-agent according to the arrows in Figure 2.

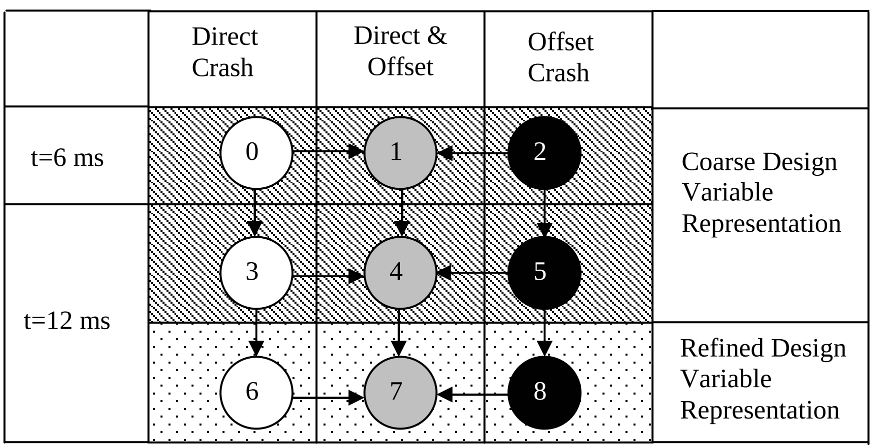

Figure 2. A HEEDS agent topology that decomposes the problem in terms of total number of design variables, total crush time, and design criteria. Designs are shared periodically from agent to agent according to the arrows. Each agent is executed on a separate personal computer within a network. This topology employs search agents that independently seek a set of good designs for each design criterion with a small number of coarse design variables, while aggregating sets of sub-optimal solutions for all performance measures in a stochastic manner, allowing economical emergence of high performing solutions with a larger number of design variables.

Agents 0 through 5 represent the overall problem with a total of 42 design variables (24 control points, 12 spot-welds, 4 material properties, and 2 gage thicknesses, see Figure 3). Agents 6 through 9 represent the overall problem with 78 design variables (60 control points, 12 spot-welds, 4 material properties, and 2 gage thicknesses, see Figure 4). A mapping of the control point design variable decomposition is depicted in Figure 5.

Agents 0 through 2 seek to maximize the amount of crush-zone energy in the front of the rail for crash scenarios with inequality constraints on the peak rigid wall force and the mass, considering a small period of crush time (6 ms); while agents 4 through 9 consider a larger period of time (12 ms). The agents are grouped such that agents 0, 3, and 6 consider only the direct load case crash scenario (lumped mass is placed directly behind the rail) with deterministic design variables. Agents 2, 5, and 8 consider only the offset load case crash scenario (lumped mass is placed behind the rail at an offset) with deterministic design variables. Agents 1, 4, and 7 consider each load case as a stochastic variable and allow each design variable to behave in a stochastic manner. In essence, this topology's agents seek to maximize the performance of the rail structure while avoiding designs that are sensitive to variation of the design variables and load cases.

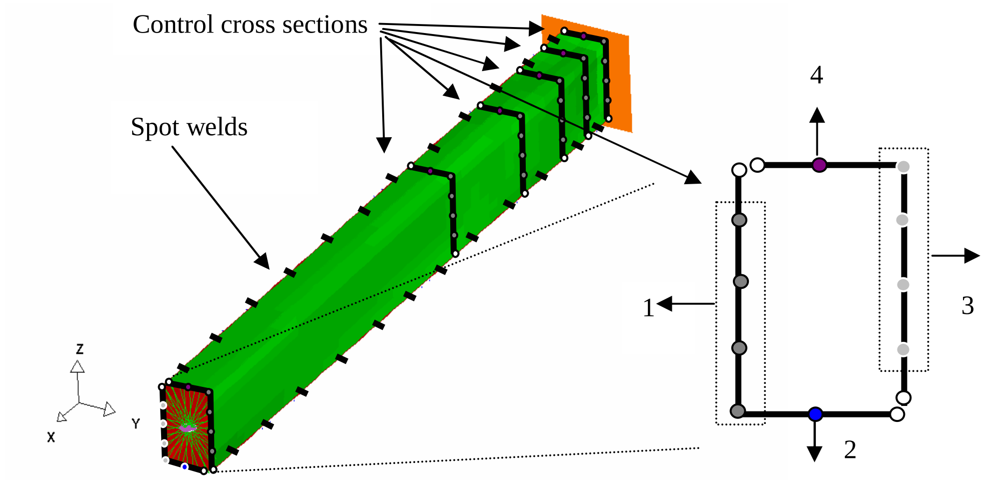

Figure 3. Coarse representation of two "L" shaped spot welded open surfaces depicted with six control cross-sections per open surface. Control points surrounded by a box define master-slave conditions (which can be used to impose desired symmetries or equality constraints on the problem). Due to the master-slave conditions defined, there are four control point design variables for each control cross-section (a total of twenty-four control point design variables). The two "L"-shaped open surfaces have different gauge thicknesses, Young's moduli, and yield strengths (six additional design variables). Twelve sets of spot weld design variables have been defined and depicted as short dark lines at various points along the length of the rail structure at the seams of the two open surfaces (twelve additional design variables).

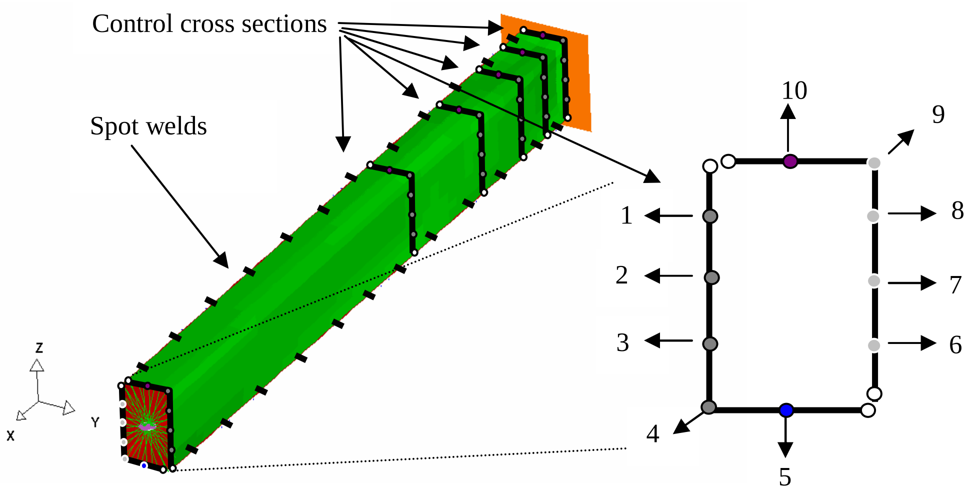

Figure 4. Refined representation of two "L" shaped spot welded open surfaces depicted with six control cross-sections per open surface. There are ten control point design variables for each control cross-section (a total of sixty control point design variables). The two "L"-shaped open surfaces have different gauge thicknesses, Young's moduli, and yield strengths (six additional design variables). Twelve sets of spot weld design variables have been defined and depicted as short dark lines at various points along the length rail structure at the seams of the two open surfaces (twelve additional design variables).

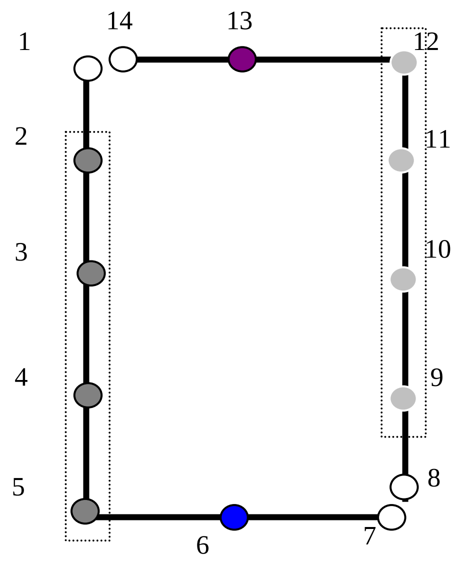

Figure 5. A planar view of the control cross-sections of each open surface with labeled control points. For this example, control points 1, 7, 8, and 14 remain fixed. The dotted boxes around the control points show the master-slave conditions imposed on the control points in the coarse design representation. In the coarse representation, control points 3, 4, and 5 are slaves to master control point 2 – *i.e.*, they are displaced identically to point 2. Similarly, control points 10, 11, and 12 are slaves to master control point 9 in the coarse representation. Control points 2-6 and 9-13 are offset independently in the refined representation.

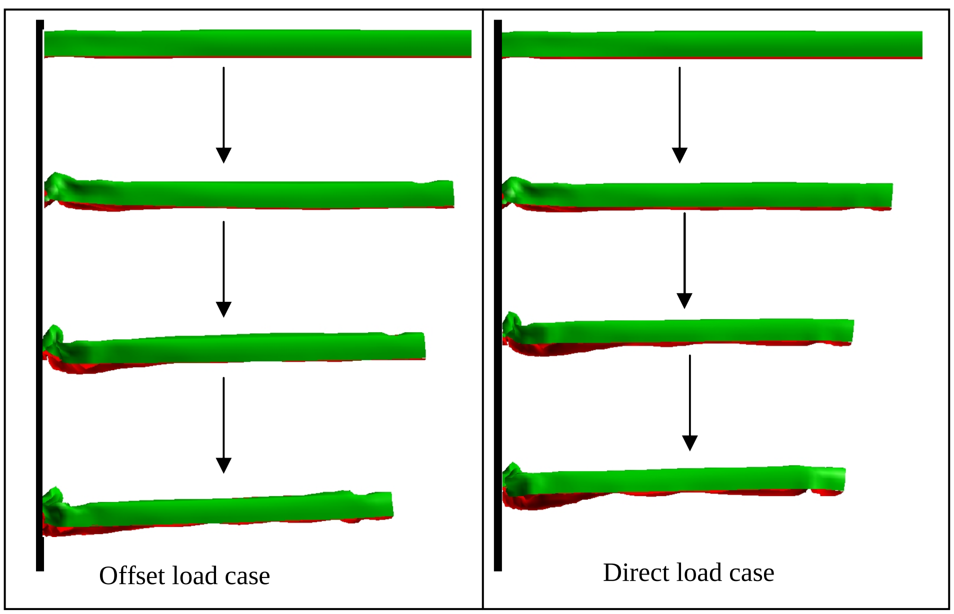

Figure 6. These progressive short-column buckling modes of crush depicted are inherently robust against off-axis dynamic load cases. Energy is absorbed primarily through plastic deformation of the material and friction due to surface contact through the progressive accordion-like deformation. These accordion-like deformation modes help to maximize the plastic material deformation and folding contact during off-axis and direct axis crash scenarios.

DISCUSSION OF RESULTS

Many high-performance designs were found during the run, since HEEDS evolves a set of designs over a period of generations. Figure 6 depicts the animation of crush for the best overall design found by HEEDS for the direct and offset load cases. For both the direct and offset load cases, the design crushes progressively in an "accordion" fashion from the front to the rear of the structure, primarily due to the structure's shape. These progressive short-column buckling modes of crush depicted in Figures 6 are inherently robust against off-axis dynamic load cases. Energy is absorbed primarily through plastic deformation of the material and friction due to surface contact through the progressive accordion-like deformation. These deformation modes help to maximize the plastic material deformation and folding contact during off-axis and direct axis crash scenarios.

SUMMARY

HEEDS was applied to a crashworthiness problem, using various search agents to evaluate potential designs with different design variable representations and performance measures. Each successive design variable representation increased the total number of design variables of the overall problem, while each performance measure used a subset of the technical objectives and constraints.

For this example, HEEDS created search agents that independently sought a set of good designs for each single technical objective and constraint set with a small number of coarse design variables, while aggregating sets of sub-optimal solutions for all performance measures in a stochastic manner, allowing economical emergence of solutions with a large number of design variables that satisfy all constraints and are driven by all technical objectives.

Agents in the HEEDS topology (see Figure 2) maximized the amount of crush-zone energy in the front of the rail for stochastic crash scenarios with inequality constraints on the peak rigid wall force and on the mass. In essence, the agents in the HEEDS topology sought to maximize the performance of the rail structure while avoiding designs that are sensitive to variation of the design variables and load cases.

It is not sufficient to find a design that performs well under a set of narrowly defined objectives, constraints, and loading conditions. The structure should be somewhat insensitive to these variations, to eliminate these as major factors in the failure.

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