Design Optimization of Hydroformed Crashworthy Automotive Body Structures

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Summary

While many design optimization approaches are limited to a small number of design variables, the approach described here leads to a productive search over hundreds of variables at a time. This capability has been implemented in a software product called HEEDS (Hierarchical Evolutionary Engineering Design System). HEEDS uses multiple autonomous agents to hierarchically decompose a problem into subsets with highly decomposed overlapped relationships. Decomposition is effected by using different numbers of design variables, different levels of design variable discretization, and/or other problem-specific divide-and-conquer rules. The system combines evolutionary search algorithms with local optimization techniques. Using explicit finite element codes such as LS-DYNA as the finite element solver within the HEEDS optimization environment, this process has been applied to several automotive rail designs, resulting in significant gains in performance in addition to substantial reductions in mass compared to baseline rails designed by experienced engineers. Two example applications of this method are described herein.

Keywords

Crashworthiness, Safety, Optimization, Shape, Hydroforming, Spot weld

1. Introduction

The design of modern vehicle structures is driven by many competing criteria, such as improved safety and fuel efficiency, lower cost, enhanced performance, and increased style 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 can now 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. Moreover, these tools also overcome the limitations of human intuition and allow the designers freedom to seek creative solutions that are not obvious to even the most experienced engineer. This is true in general but particularly true with shape optimization problems, which can involve potentially hundreds of design variables.

Crashworthiness problems are characterized by a very complex design space with many peaks and valleys due to their highly dynamic nature. These classes of structural design problems have a very multi-modal, non-convex design space and do not lend themselves well to classical gradient techniques. Moreover, 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. Finally, the structure should be somewhat insensitive to slight variations in design variables. For example, in problems involving stability or buckling, behavior can be very sensitive to geometrical and material imperfections, which may prevent a part from failing in the way that 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.

Because complete system finite element models of automotive vehicles contain a very large number of elements (0.5 – 2.5 million), performing optimization on a complete system model is difficult and expensive. Due to their long run times and high usage of computing resources, only a limited number of system level simulations can be performed using these very large models. Hence, it is not currently practical to perform high fidelity design optimization at the component level using a system model.

However, it is necessary to incorporate the interactions between overall system performance and components in crashworthiness simulation studies. Using legacy knowledge and an understanding of how each component or sub-system behaves and contributes to the energy management strategy allows component-level design studies to be used effectively during the design of automotive structural systems. In this approach, the system model is decomposed by allocating requirements for loads, energy absorption, noise and vibration, mass, etc. to the main components. In this way, a high fidelity design optimization can be performed for each component, yielding a high level of structural efficiency at both the component and the system level.

2. Optimization Strategy

Many optimization studies and even mathematical proofs have shown that no single optimization approach performs best on all classes of problems, while combining a set of global and local optimization techniques often yields improved results. In addition, for problems that contain many design variables and criteria, it is sometimes necessary to decompose the overall problem into a set of smaller, more tractable problems to obtain improved results with reasonable computational resources. This capability has been implemented in a software package called HEEDS (Hierarchical Evolutionary Engineering Design System). HEEDS has been constructed to allow hierarchical decomposition of problems while automatically combining the strengths of global exploration and local optimization algorithms. It combines the strengths of genetic algorithms (Holland, 1975), simulated annealing (Ruthenbar, 1989), sequential quadratic programming (Schittkowski, 1985), design of experiments (Cochran et al., 1992), and response surface methodology (Khuri et al., 1996), which jointly allow it to efficiently solve a wide class of problems.

HEEDS employs adaptive autonomous agents that communicate but work semi-independently on a common problem. Each agent uses one or more search methods to intelligently scan a part (or all) of the design space in search of optimal solutions. Using this methodology, the overall problem can be hierarchically decomposed so as to provide most agents with different, smaller representations of the problem. A set of design variables at a given level of discretization constitutes one representation of the problem. Each agent (or a group of agents) can use a different representation of the problem to increase the efficiency of the design search. Furthermore, each agent (or group of agents) can employ specialized search heuristics that seek to maximize the performance of its representation of the problem. This approach combines the evolutionary search methods with the traditional local search methods to increase the effectiveness of the search process for a broad class of problems. Using this approach, agents can search for good designs in different representations of the design space and/or using different sets of constraints and objectives, communicating with each other to identify more globally optimal designs through structured sharing of information. The hierarchical decomposition allows a complex problem to be discretized into a set of highly decomposed, overlapping relationships, which have a reduced design space that is relatively easy to search. The agents seeking good designs for these smaller problems provide information to the agents searching the complete design space with all the objectives and constraints, resulting in an economically efficient search process. This approach significantly reduces the total number of design iterations required for finding excellent solutions, and allows efficient handling of very complex optimization problems, which would otherwise be impractical to solve.

By using a stochastic strategy during the search for an optimal design, HEEDS is able to account for slight variations in design variables, thus insuring robustness and reliability. This results in designs that are tolerant of slight changes in the design parameters without suffering drastic drops in performance of the designs.

3. Shape Optimization of a Hydroformed Lower Compartment Rail

3.1 Problem Definition

A hydroformed lower compartment rail was designed for the offset load-case using HEEDS as the optimization software. Each potential design created by HEEDS was evaluated using explicit finite element software. The objective of the optimization problem was to maximize the crush-zone energy in the front of the rail (the crush zone shown in Figure 1) for the offset crash scenario with inequality constraints on the peak rigid wall force and mass.

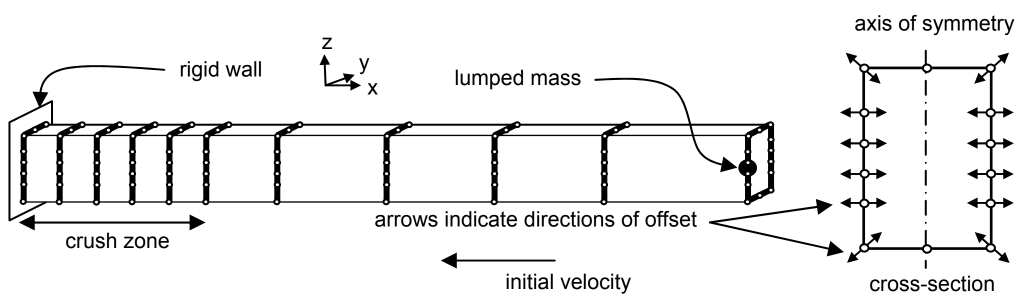

Figure 1. Geometry of Baseline Rail with Control Cross-Section Positions.

3.2 Problem Setup

An analysis model of the rail was developed for the offset crash scenario to serve as a template for the creation of potential designs. For this analysis, a lumped mass equal to approximately one-half the mass of the vehicle was placed at the rear of the rail and offset 60 mm in the negative Y direction from the rail axis to simulate the offset crash scenario (see Figure 1). The rail structure and mass were given an initial velocity and crushed into a rigid stationary wall. The crush-zone energy, peak rigid wall force, and mass were computed. HEEDS was then used to automate the creation and evaluation of each potential design to perform design optimization. Two different design runs of the same problem were performed to demonstrate the increase in the efficiency of the search process using hierarchical decomposition.

The first run was performed using a single agent that searched in a design space based on 67 design variables (66 control point shape variables and 1 thickness variable). Evolutionary search methods in combination with local search techniques were used to intelligently explore the design space. The agent sought to maximize the internal energy absorbed in the front region of the rail during the first 14 milliseconds of the crush. Inequality constraints were imposed on the total mass of the rail and on the maximum normal force on the rigid wall.

Figure 1 shows the basic geometry of the rail, as well as the location of the 11 control cross-sections located along the length of the rail. The arrows on the cross-section indicate the directions in which the control points (controlling b-splines) were offset to create new shapes during the optimization process. All cross-sections had the same initial rectangular geometry, but were independently varied to create new rail shapes. The main design variables were the control points on the cross-sections along the length of the rail and, due to symmetry conditions that were built in, each cross-section only contained 6 control points. The rail was created using a ruled surface and automatic mesh generator within HEEDS. Since a new mesh was created every time the rail shape was changed, the problems of mesh distortion were minimized.

A second run was conducted using hierarchical decomposition as depicted in the topological structure shown in Figure 2. A total of three autonomous agents were used for this second run. Designs were shared periodically in a structured manner from agent-to-agent according to the arrows in Figure 2. Agent 0 shared designs with Agent 1, and Agent 1 shared designs with Agent 2. Each agent was executed as a separate computer process on a loosely coupled network of personal computers. The agents independently sought sets of good designs for each single technical objective and constraint set, using design variables at different levels of resolution. The designs from the agents working at coarser levels were fed into the agents working on a more refined search space to expedite the search process in those agents. This allowed for economical emergence of solutions at a more refined level of discretization that satisfy all constraints and are driven by all technical objectives.

All three agents searched within a design space composed of 67 design variables. However, the level of discretization of the design variables differed for each agent. Agent 0 had the smallest number of possible values that each design variable could be assigned, and therefore had a coarse representation of the problem. In the other extreme, Agent 2 had the most refined representation because the design variables had the largest number of possible values.

The problem was further decomposed by considering different periods of crush time for each agent (6 ms for agent 0, 10ms for agent 1and 14 ms for agent 2). Due to this topology setup, Agent 0 quickly (due to smaller crush time as well as a coarser design space) determined good designs within its coarse design space. The designs found in agent 0 had good crush initiators near the front of the rail and were resistant to buckling in the rear of the rail. Agent 0 then shared the information from its search process with Agent 1 (which is simultaneously searching for designs in a more refined design space), pointing it to the regions in the design space with potential for good designs. This results in a significant speedup of the search process as compared to the agent searching only at the highest level of the problem representation.

Though not employed in the current example, many other techniques exist to decompose design problems within HEEDS. For example, HEEDS also allows the number of design variables to be different in each agent, often a very effective method of problem decomposition.

Crush Time	Agent Topology	Design Variable Discretization
t=6 ms	0	Coarse
t=10 ms	1	Medium
t=14 ms	2	Refined

Figure 2. Topological Structure Used for the 3-Agent Run.

3.3 Discussion of Results

Many high-performance designs were found during the runs, since HEEDS evolved a set of designs over a number of cycles. Figure 3 depicts the undeformed geometry of the best overall design found by HEEDS for the offset load case. The design crushes progressively in an “accordion” fashion, primarily due to the structure’s shape. These progressive short-column buckling modes of crush are inherently robust against off-axis dynamic load cases. Energy is absorbed primarily through plastic deformation of the material during the progressive deformation. These accordion-like deformation modes help to maximize the plastic material deformation and folding contact during crash scenarios.

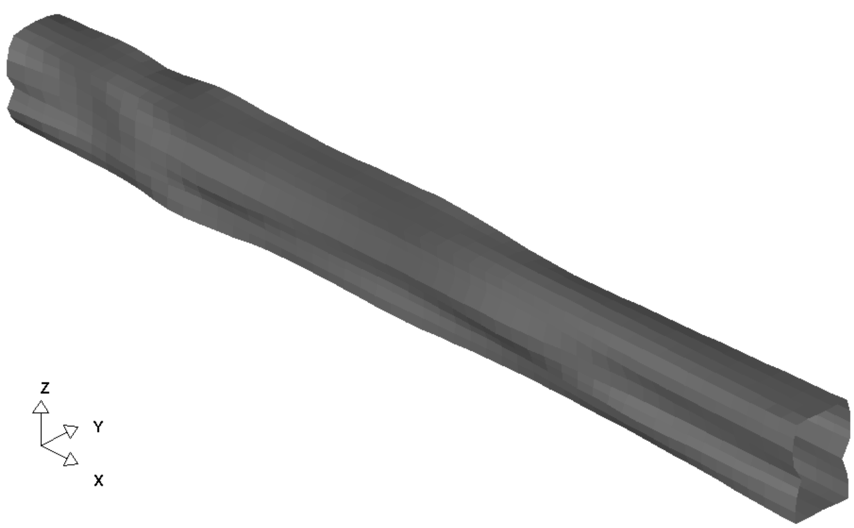

Figure 3. Geometric Shape of Best Rail Design Found.

Figure 4 shows the variation of the objective with respect to the number of design evaluations performed during the search process. The results of the search from the single agent run are compared with the results from the multi-agent run (using decomposition). The results of the three-agent run are plotted for the agent searching over the same design space as the single agent. Figure 4 illustrates the savings in terms of the number of evaluations required to find good designs when hierarchical decomposition is used in a problem. In the multi-agent run, searching at low levels of resolution identifies high-performance solutions very quickly. These solutions are then injected into agents searching at higher resolution for solution refinement. On the other hand, in the single agent run the agent has to search the entire design space alone, and thus requires a greater number of iterations to identify good designs. Both design runs were executed for the same number of cycles and appear to have converged. The multi-agent run found solutions that absorbed significantly more energy than did the best solution found by the single agent run. This illustrates the ability of a multi-agent approach to search the design space more broadly, continuously identifying fruitful regions for search.

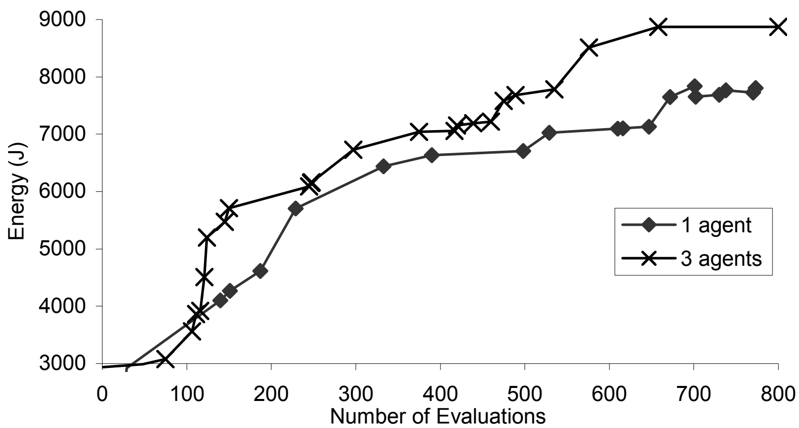

Figure 4. Trajectory of internal energy.

4. Shape Optimization of a Spot Welded Vehicle Front Rail

4.1 Problem Definition

A welded vehicle front rail was designed using HEEDS as the optimization software and LS-DYNA Explicit as the finite element solver. The rail consists of two open "L" shaped surfaces that are welded together to create a closed surface. HEEDS found the cross-sectional shape, material, and spot-weld placement in order to maximize the amount of crush-zone energy in the front of the rail for both direct and offset crash scenarios with inequality constraints on the peak rigid wall force and mass.

4.2 Problem Setup

An analysis model of the vehicle front rail was developed to serve as a template for the creation of potential designs. A lumped mass was placed at various offset positions at the rear of the rail structure to allow emulation of multiple crash scenarios, see Figure 5. The rail structure and mass were given an initial velocity and crushed into a rigid stationary wall. The crush-zone energy, peak rigid wall force, and mass of the rail were computed with LS-DYNA.

To improve upon this initial design, different parameters affecting the performance of the rail were allowed to vary. The thickness, Young's moduli, and yield strength of each of the two "L" shaped open surfaces represent six of the design variables. Twelve possible spot weld locations were identified, along with sixty variables that affect the shape of the rail. These sixty shape variables are depicted in Figure 6, which shows ten control points affecting the cross-sectional shape (for the coarse representation) at six different cross sections along the length of the rail. The design space therefore contains 72 variables and is further complicated by the need to treat the variables and load cases in a stochastic manner.

In order to more efficiently search the design space for an optimal design, the problem was hierarchically decomposed such that nine search agents could independently seek a set of good designs for each single technical objective and constraint set while working with a small number of design variables. These sub-optimal solutions were shared such that global solutions were found from the complete design space. Figure 7 depicts this topological structure. Each agent was executed on a separate computer process on a loosely coupled network of personal computers (550 MHz). Designs were shared periodically in a structured manner from agent-to-agent according to the arrows in Figure 7.

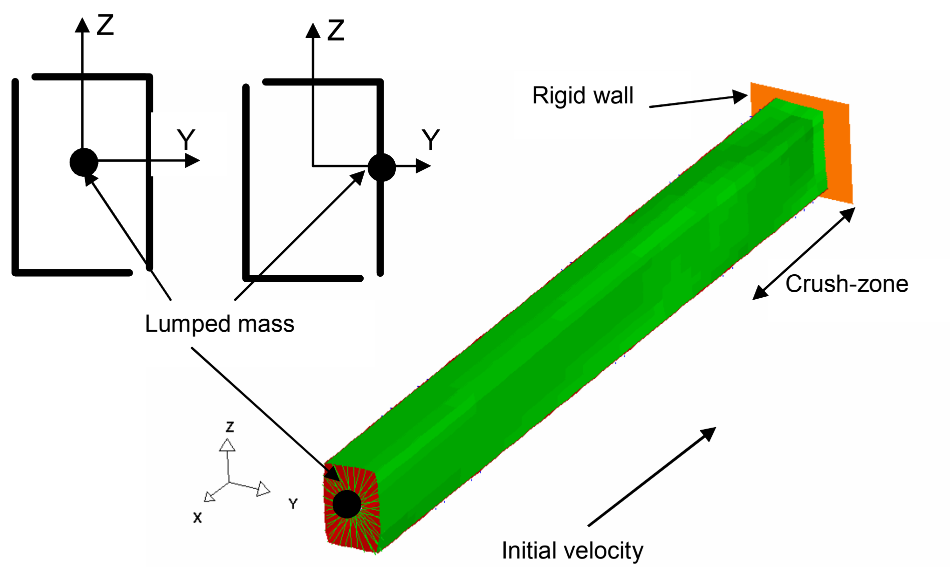

Figure 5. Geometry of Baseline Rail with Offset Mass Positions.

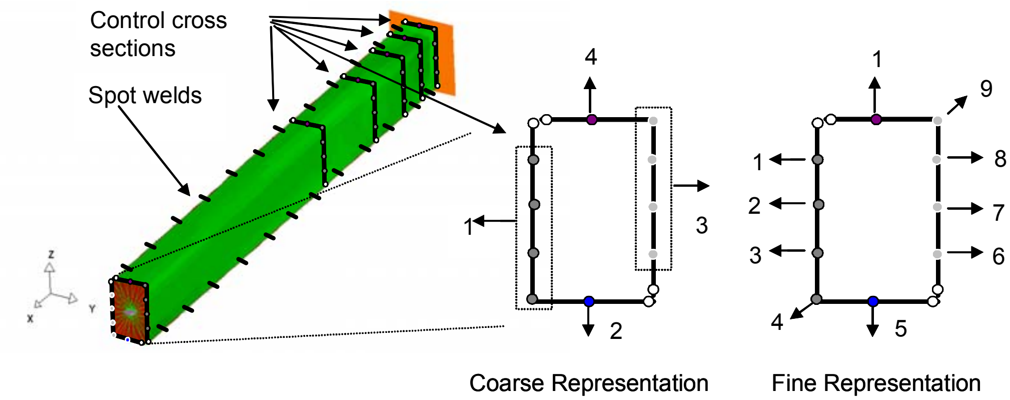

Figure 6. Control Cross-Section Positions.

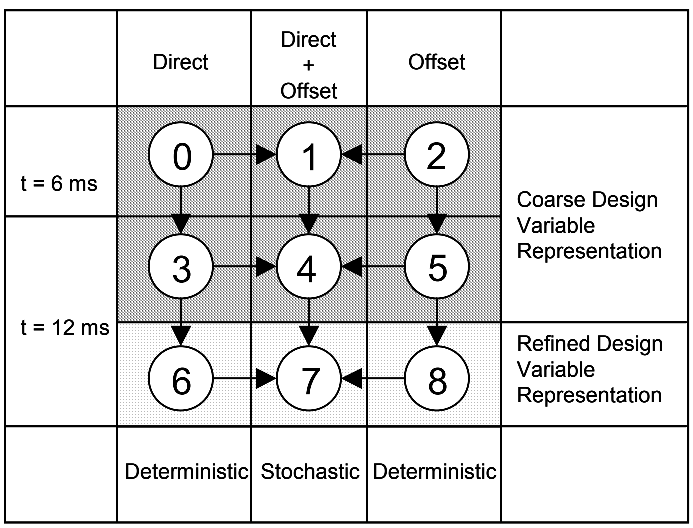

Figure 7. Topological Structure Used for the 9-Agent Run.

The difference between the refined and coarse representations of the problem lies in the number of design variables used to depict the cross-sectional shape along the length of the rail. While the refined representation of the problem allows each of the cross-sectional control points to vary independently, the coarse representation groups the control points using master-slave conditions such that only four design variables control the shape of the cross-section. Figure 6 shows the master-slave groupings used for both the coarse and refined representations.

Although each of the nine agents seek to maximize the amount of crush-zone energy in the front of the rail for crash scenarios with inequality constraints on both the peak rigid wall force and the mass, Agents 0 through 2 only consider a small period of crush time (6 ms) while agent 4 through 9 consider a larger period of time (12 ms). The agents are grouped such that agents 0, 3, and 6 only consider the direct load case crash scenario (lumped mass is placed directly behind the rail) with deterministic design variables. Agents 2, 5, and 8 only consider 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.

4.3 Discussion of Results

Many high-performance designs were found during the run since HEEDS evolves a set of designs over a period of cycles. 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 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.

5. Summary

HEEDS was applied to two crashworthiness problems 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 these examples, HEEDS used 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, allowing economical emergence of solutions with a larger number of design variables that satisfy all constraints and are driven by all technical objectives. In addition, stochasticity of the loads and design variables was taken into account so that the structure would be somewhat insensitive to these variations.

6. References

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