Saving Energy Through Design Optimization

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White Paper

The pessimist says "The glass is half empty." The optimist says "The glass is half full." The Optimization Expert says "The glass is over designed."

ABSTRACT

Numerical optimization is a little understood and even lesser used design tool which can have a significant effect on our efforts to reduce energy consumption, improve environmental quality and provide safer, more comfortable vehicles. Optimization is a numerical search method that can be applied to almost any engineering discipline where we perform computer analyses, whether structures, fluid dynamics or almost anything else. Though seldom taught in engineering colleges, these design methods and tools have been developed over the past forty years to a high level of maturity.

The purpose of this paper is twofold. First, we will discuss the basic concept of design optimization. It will be seen that optimization can be coupled with almost any computer analysis and even experimental tests to change the important inputs to improve one or more outputs, with limits on other outputs.

The second purpose will be to demonstrate that optimization works. Examples will be given to demonstrate that the mass of existing parts can be reduced by several percent with no loss in strength, design quality can be improved with minimal increase in mass and hybrid vehicle economy can be improved while reducing pollutants. An additional bonus of optimization is the engineering insight it provides to any design problem.

It is concluded that, whether we apply it to existing designs or to future hybrid or fuel cell vehicles, optimization technology can be used with minimal added cost or effort to significantly reduce energy consumption.

INTRODUCTION

In 1923, Henry Ford said "Saving even a few pounds of a vehicle's weight means it could go faster and consume less fuel. Reducing weight involves reducing materials, which, in turn, means reducing cost as well." (1)

In the U.S. today, we use about seven million barrels (385 million gallons) of gasoline daily. If we can reduce this consumption by only one percent, at a cost of $1.50/gallon, we can save nearly six million dollars daily! This is a savings directly to the consumer. This benefit does not even account for the savings in natural resources, reduced pollution, etc.

Figure 1 shows the relationship between vehicle mass and fuel economy for present vehicles from sub-compact through large SUVs. While there is scatter, largely due to differences in vehicle performance, the general trend is clear. If we reduce mass by one percent, we improve economy by about two percent. Of course, there is a big difference between the capabilities of small and large vehicles. If we consider the effect of mass alone, we can expect a one percent mass reduction to produce about 0.7 percent improvement in economy (2).

With present technology and materials, we clearly cannot reduce the mass of a large SUV by 50 percent. However, it is certainly reasonable to strive for a one or two percent reduction in mass. The question is, "How do we achieve this." The answer is "Design Optimization." But we need not stop at mass reduction. Why not improve efficiency of the engine, whether conventional or other. Why not reduce aerodynamic drag, reduce energy consumption of the heating and air conditioning system or the rolling resistance of tires? The answer is the same; design optimization.

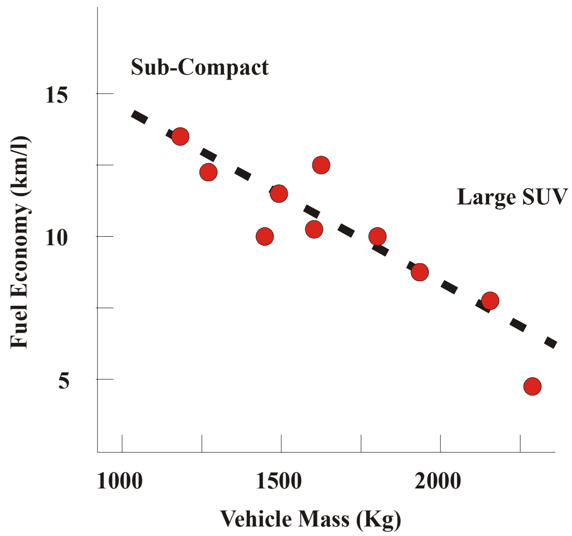

Figure 1. Fuel Economy Versus Vehicle Mass

WHAT IS DESIGN OPTIMIZATION?

Optimization is intrinsically tied to our desire to excel, whether we are an athlete, artist or engineer. We all adjust some parameters, perhaps our time, to minimize or maximize one or more results such as income, leisure time or job satisfaction. We do this subject to limitations or constraints, such as physical ability, time available, legal restrictions or moral codes of conduct. Thus, whatever our field of endeavor, we constantly strive to solve a constrained optimization problem.

In engineering, we create products. To do this, we normally use computer analysis to judge the quality of our designs. We use computational fluid dynamics codes to calculate energy requirements and flow patterns in a ducting system. We use finite element analysis to calculate stresses, deflections, vibration frequencies, etc. of a structure. In almost all disciplines, we use computational, and sometimes experimental, tools to judge the quality of our proposed designs. If not satisfactory, we modify the design and perform repeated analyses in an effort to improve the product, or at least meet the design requirements.

This traditional approach of analyze and revise normally involves only changing a few variables (often only one) at a time and does not account very well for the interaction among the variables.

Now imagine we can change large numbers of design parameters simultaneously in order to improve the design while satisfying all design requirements, at the same time accounting for the interactions among the parameters. This is exactly what numerical optimization does.

Our computer analysis program has a set of inputs that we may consider to be contained in a vector **X**. Based on this input, the analysis provides outputs. One or more of these outputs can be called an objective function which we wish to minimize or maximize. Other outputs may be required to be within some bounds. These we call constraints. Both the objective(s) and constraints are functions of the input or design variables contained in **X**.

Numerical optimization solves the general problem (3): Find the values of the design variables contained in **X** that will;

Minimize $F(\mathbf{X})$ (1)

Subject to:

$$g_j(\mathbf{X}) \le 0 \qquad j = 1, m \tag{2}$$

$$X_i^L \le X_i \le X_i^U \qquad i = 1, n \tag{3}$$

The function, F(**X**) is referred to as the objective or merit function and is dependent on the values of the design variables, **X**, which themselves include member dimensions or shape variables of a structure as examples. The limits on the design variables, given in Equation 3, are referred to as side constraints and are used simply to limit the region of search for the optimum. For example, it would not make sense to allow the thickness of a structural element to take on a negative value. Thus, the lower bounds are set to a reasonable minimum gage size. If we wish to maximize F(**X**), for example, maximize fuel economy, we simply minimize the negative of F(**X**).

The $g_j(\mathbf{X})$ are referred to as constraints, and they provide bounds on various response quantities. A common constraint is the limits imposed on stresses at various points within a structure. Then if $\bar{\sigma}$ is the upper bound allowed on stress, the constraint function would be written, in normalized form, as

$$\frac{\sigma_{ijk}}{\bar{\sigma}} - 1 \le 0 \tag{4}$$

i = element,
j = stress component,
k = load condition

Additionally, we could include equality constraints of the form

$$h_k(\mathbf{X}) = 0 \qquad k = 1, L \tag{5}$$

Normally, equality constraints can be included in the original problem definition as two equal and opposite inequality constraints.

Now consider how we might solve this general optimization problem. One approach would be to pick many combinations of the design variables and call our analysis program to evaluate each, picking the one with the best objective function which also satisfies all constraints. This would be a classical random search approach or perhaps the modern version known as genetic search (4).

Another approach would be to perturb each design variable and evaluate the objective and constraint functions. This would determine the sensitivity (gradient) of the design with respect to the variables. With this information, we can mathematically (numerically) determine how to change the design variables to improve the objective while satisfying the constraints. There are a multitude of such “gradient based” methods and considerable software available today (3).

These methods closely model what we do in design already. Normally, we begin with a candidate design and ask “How can we change the design to improve it?” Thus, we modify our design as;

$$\mathbf{X}^{\mathrm{New}} = \mathbf{X}^{\mathrm{Old}} + \delta\mathbf{X} \tag{6}$$

Optimization does much the same thing, but in two steps. First, we ask what direction to move in and then we ask how far to move. That is,

$$\mathbf{X}^{\mathrm{New}} = \mathbf{X}^{\mathrm{Old}} + \alpha\mathbf{S} \tag{7}$$

where **S** is the search direction and α is the number of steps we move in this direction (partial steps are allowed).

The difference in optimization algorithms is mainly in how we calculate the search direction, **S**, and how we do the “one-dimensional search” to determine α. The key point here is that all variables are considered simultaneously according to their effect on the objective function and all constraints. Also, since this is all automated and today’s computers are very fast, we can find an optimum design with much less time and effort than just finding an acceptable design using traditional methods.

This problem statement provides a remarkably general design approach and a multitude of methods are available today for solving this general problem. Much of the theoretical development has been in the operations research community and applications there are widespread today. In engineering, while development has been underway for over forty years, applications have lagged far behind. The time has come for that to change.

HISTORY

Numerical methods for solving the optimization problem have been under development for over fifty years. Creation of linear programming techniques by Dantzig (5), together with the advent of the digital computer, led to the application of linear programming techniques to the plastic design of beam and frame structures as described by Hyman (6).

Schmit (7) in 1960 was the first to offer a comprehensive statement of the use of mathematical programming techniques to solve the nonlinear, inequality constrained problem of designing elastic structures under a multiplicity of loading conditions. He combined numerical optimization with finite element analysis, itself an emerging technology, to solve the structural synthesis problem.

Since then, structural optimization techniques have advanced to the point that we have solid commercial software capable of finding an optimum structure in a fraction of the time needed to find only an acceptable structure by other means.

Additionally, optimization techniques have been applied to a wide range of design tasks, such as conceptual aircraft and ship design, aerodynamic shape, electronic components, hybrid automobiles and a multitude of others.

Today, optimization technology can be divided into two key categories; structural optimization and general optimization. These will be discussed separately.

<u>Structural Optimization</u> – Structural optimization is considered separately because the methods here are particularly well developed. Today, structural optimization, based on linear finite element analysis, can be routinely performed for member sizing, shape and topology optimization. Almost any calculated response can be treated as the objective function or can be constrained. Most of the time, mass is treated as the objective function to be minimized, though it is also common to maximize frequencies (stiffness). Constraints typically include limits on stresses, strains, frequencies, dynamic response, thermal response, buckling loads and aeroelastic response. A typical structural optimization problem may consist of perhaps 500 design variables with 1,000,000 constraints. Indeed, in this author’s experience, a mass minimization problem with over 135,000 design variables has been solved subject to frequency constraints.

The key to today’s efficiency in structural optimization is approximation techniques (8, 9). Here, the original problem is approximated in terms of intermediate variables and intermediate responses. These approximations are gradient based and gradients are efficiently calculated as part of the finite element analysis (10, 11). The approximate optimization problem is then solved, a new finite element analyses is performed, and the process is repeated to convergence. These approximations go far beyond simple linearization and are of such high quality that the design variables can typically be changed by up to 50% before a new analysis is needed. The result is that, for member sizing and shape optimization we require only about ten detailed finite element analyses and for topology optimization about twenty detailed analyses. This is a key issue because finite element models of the order of one million degrees of freedom are becoming commonplace and a single analysis can be quite expensive. Thus, with this efficiency, we can achieve an optimum design for a cost well below the cost of just achieving an acceptable design in the past.

General Applications – Beyond the field of finite element based structural optimization, we do not usually have gradient information readily available and so finite difference gradients are used. Also, we do not have highly refined approximation techniques for these other disciplines. Thus, we simply treat the optimization process as a “black box,” where we directly couple our analyses with the optimization program.

These limitations are only issues of efficiency. They do not effect the optimization process or the underlying algorithms. The exceptional computational resources available today make it possible to solve complex optimization problems using this black box approach. Additionally, response surface approximations, where we approximate the original problem using curve fits, work well for problems in the 10-20 variable category (12, 13). Finally, distributed or parallel computing can dramatically reduce computational times, even when the analysis is very complex and time consuming (14).

Reference 3 discusses numerous applications of this type of optimization, including airfoil, heat exchanger, conceptual aircraft and ship design as examples.

OPTIMIZATION WORKS

To indicate the benefits of optimization when applied to next generation automobiles, consider the hybrid vehicle shown in Figure 2.

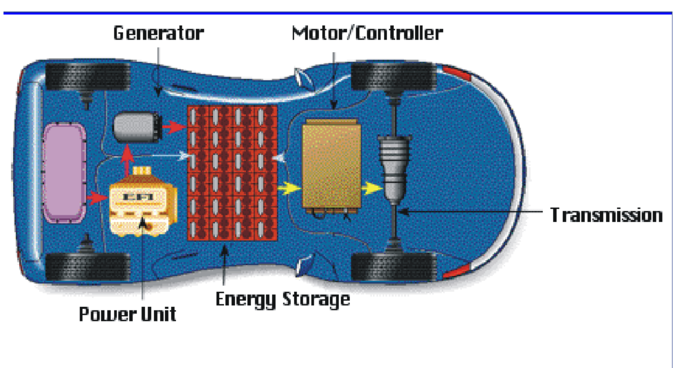

Figure 2. Hybrid Electric Vehicle

This vehicle was modeled using the ADVISOR program developed by the National Renewable Energy Laboratory (NREL) in Golden Colorado (15, 16). The ADVISOR program was coupled with the VisualDOC (17) program to perform optimization of the control system.

This is a multi-objective optimization task where we wish to maximize fuel economy, minimize hydrocarbon emissions and minimize nitrous oxide emissions. Constraints include acceleration and grade climbing requirements, and minimum battery charge as examples. The design variables are listed in Table 1.

Note that this design was for a fixed mass vehicle. If we use optimization to also reduce vehicle mass, corresponding further improvements in economy and emissions can be expected.

Table 1: Hybrid Vehicle Design Variables

Description	Units
Battery Pack’s High State of Charge	Percentage
Battery Pack’s Low State of Charge	Percentage
Electric Launch Speed (Vehicle speed below which vehicle operates as a Zero Emissions Vehicle)	Meters/Sec.
Charge Torque (Torque loading on the engine to recharge the battery pack whenever the engine is on)	Meters/Sec.
Off Torque Fraction (Fraction of the torque capability of the engine for a given speed at which the engine may shut off)	- - -
Minimum Torque Fraction (Fraction of the torque capability of the engine for a given speed at which the motor may act as a generator)	- - -

The optimization results are given in Table 2.

Table 2: Optimization Results

Objective	Percent Change
Mileage	+6.5
Hydrocarbon Emissions	-3.6
Nitrous Oxide Emissions	-11.5

While the ADVISOR code is a research program, this demonstrates the ease with which optimization could be added to company proprietary software as well, for modeling future vehicles. The gains achieved through using optimization should be similar. Most importantly, optimization allows us to compare competing concepts on a more rational basis, where each design is the best possible, rather than considering single “point” designs.

Next, consider the design of a heat sink for electronic applications. Here VisualDOC was coupled with the FLUX2D thermal analysis program from Cedrat Corporation (18). The initial design is shown in Figure 3. Heat is generated by the thyristor and dissipated by the heat sink. The objective is to minimize the material of the heat sink, and the design variables are the thickness of the base, height and width of the fins. Constraints include heat dissipated to the air, heat dissipated between the heat sink and the supporting chassis and the maximum temperature allowed in the thyristor. The initial design was chosen to have an unreasonably thick base to test the optimization. The optimum design is shown in Figure 4 and is very similar to heat sinks commonly found in electronic devices. This demonstrates the ease with which a commercial analysis program can be coupled with optimization.

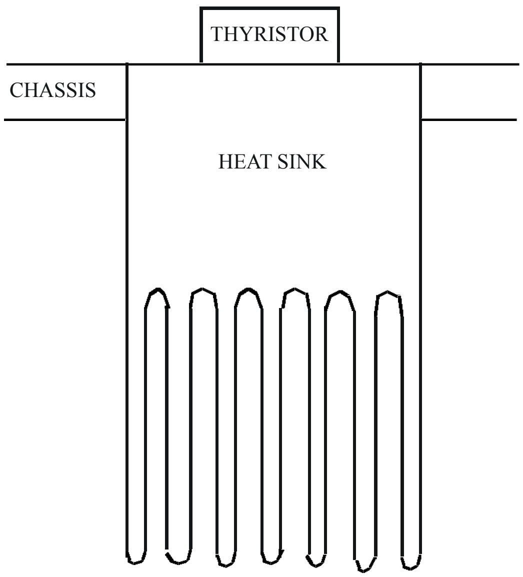

Figure 3. Initial Heat Sink Geometry

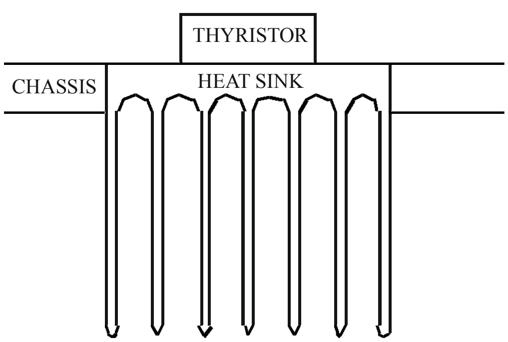

Figure 4. Optimum Heat Sink Geometry

As a final example to demonstrate coupling existing commercial analysis software with optimization, the Fluent CFD code (19) was coupled with VisualDOC. As a simple demonstration, the lift to drag ratio of an airfoil was maximized. The initial design was a NACA 0012 airfoil and the design condition was at very low speed (20 m/s). The design variables were the camber, position of maximum camber, maximum thickness and angle of attack. Response surface approximations were used to optimize the airfoil and the lift/drag ratio was increased by 160%. The optimization required fifteen Fluent analyses. The optimum airfoil is shown in Figure 5. Note that, while this is an aerospace example, similar applications exist in fan, pump and torque converter design.

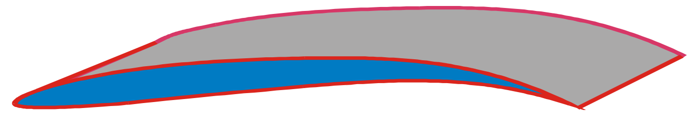

Figure 5. Optimum Airfoil

These examples serve to demonstrate that we have well established technology and software to couple a wide range of commercial analysis software with optimization. Coupling of the analysis programs used here typically required less than one week, most of which was spent by the optimization engineer to become familiar with the analysis software, with only a small portion of the time spent on the actual coupling of the programs.

Now consider some examples of structural optimization. Here, the methods are highly refined so that, even if we consider several thousand design variables. We typically achieve an optimum using about ten detailed finite element analyses if we treat member dimensions and shape as design variables, and twenty detailed analyses if we design the topology (remove chunks of material).

Figure 6 shows topology optimization of a truck front crossmember.

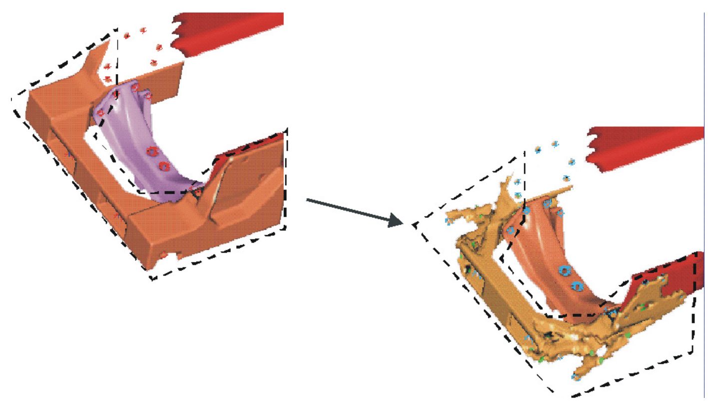

Figure 6. Topology Optimization

The structure was first modeled by filling the available design space with solid elements. Topology optimization was applied by letting the density of each element be a design variable and maximizing the stiffness of the structure. This example included over 10,900 design variables. Those elements whose density was reduced to zero were removed from the structure to provide the optimum topology shown in the right half of figure 6. Optimization required 20 detailed finite element analyses to achieve this result. This example is several years old and today smoothing techniques are used to generate a more smooth topology. After this first step, shape optimization can be applied to further refine the structure, including stress and other constraints.

Figure 7 shows a heavy truck where the front suspension mount is to be designed. The objective was to minimize mass, subject to the requirement that the maximum stress not exceeded the maximum stress in the existing design. As shown in Figure 8, the mass was reduced by 30% with no reduction in strength. The optimum design was achieved using ten detailed finite element analyses.

Figure 7. Truck Suspension Support

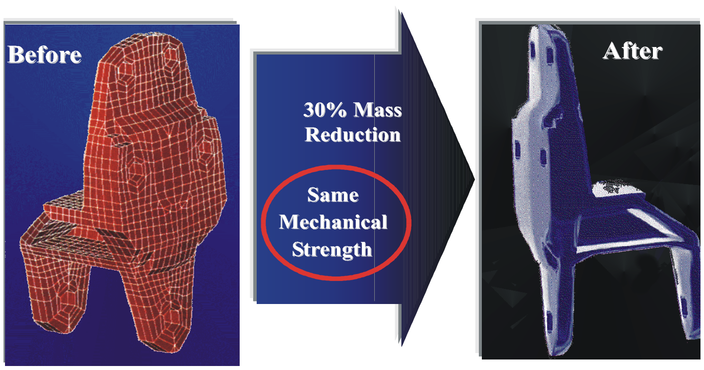

Figure 8. Truck Suspension Support Results

Figure 9 shows an air suspension system, where we wish to design the spring. The initial design exceed the stress limit by 65%. With optimization, the spring was resized by reducing the maximum stress by 65% with only a 3.5% increase in mass.

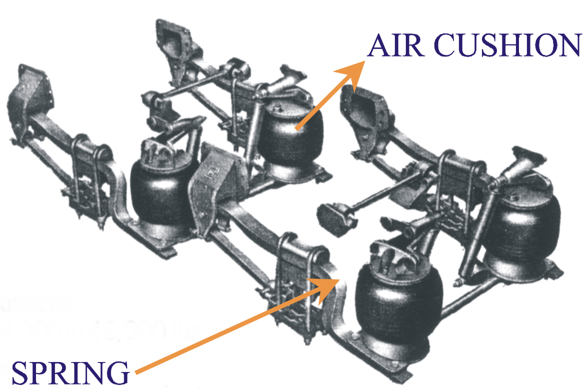

Figure 9. Spring Design

Figure 10 shows a car seat where we wish to minimize the mass with limits on stress and deflections. The design variables were the material thicknesses of the recliner and the spring support constant. With optimization, the mass was reduced by 45% while satisfying all constraints.

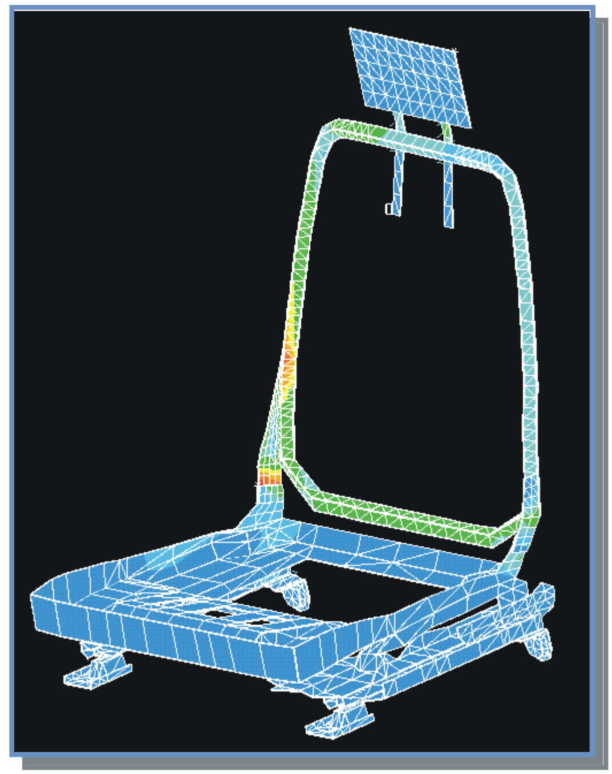

Figure 10. Car Seat Model

Next, consider the gas tank shown in Figure 11.

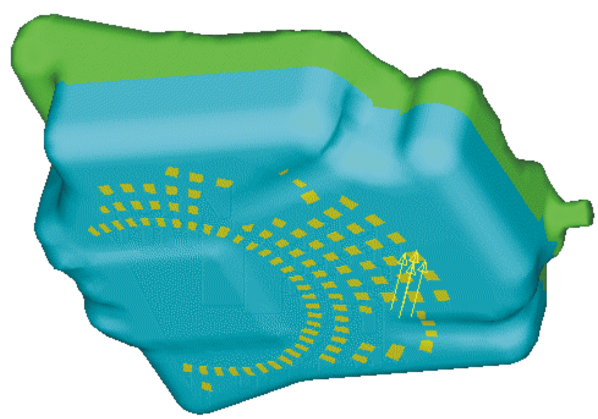

Figure 11. Gas tank

The design requirements included both stress and stiffness. Also, the interior volume of the tank could not be less than a prescribed value. Visteon corporation optimized this tank using 99 variables defining the shape of the “beads” on the bottom of the tank (20).

Finally, consider the automobile dash cross beam shown in Figure 12.

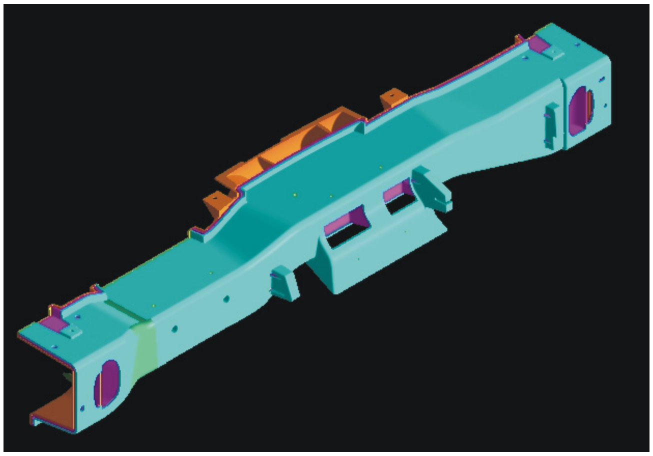

Figure 12. Dash Cross-Beam

This is made of three principal components as shown in Figure 13.

Figure 13. Dash Cross-Beam Components

Optimization was performed by Delphi Automotive Systems (21). First, topology optimization (such as used in Figure 6) was performed for four loading cases to identify several regions for improvement. Then, element sizing optimization was performed to minimize mass, subject to stress, deflection and manufacturability limits. Optimization in conjunction with material and process changes was able to reduce the mass by 33% and material cost by 39%.

These problems were solved using the GENESIS structural optimization software (22). While these examples are typical of structural optimization, they represent only a small fraction of design tasks being solved today. In each case, except for the topology optimization example of Figure 6, the initial design used for optimization was an existing design, created by conventional design methods.

Also, much larger problems are feasible where thousands of design variables and millions of constraints can be included. Recently, a mass minimization automotive body design problem was solved subject to increasing the fundamental frequency by 10%. The finite element model was 800,000 degrees of freedom and 105,000 member sizing variables were considered. An optimum design was achieved using 14 detailed finite element analyses and required only 0.3% increase in body mass.

CONCLUSIONS

Numerical optimization methods for design have been described here and demonstrated with a variety of applications. It has been shown that this design tool provides a powerful means of designing present and future automobiles. In almost all cases where this author and his associates have applied optimization to design, the existing design has been improved by five percent or more. Furthermore, optimum designs are found in a fraction of the time needed to improve the design by traditional "cut and try" methods.

Finally, optimization is in no way limited to the examples presented here. These design tools can be used throughout the energy industry, whether for automobiles or power plants or windmills and beyond. The key to their use is that we must change the way we do design. The changes are not big, only necessary.

CONTACT

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