

Development of Synthesis Level Design Model in Automobile Application Suitable for MDO using CO Approach

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ABSTRACT

The design of a complex system such as an automobile consists of the design of many highly complex subsystems. To address this level of complexity, traditionally the designers use a sequential and spiral design process with the goal of achieving a final feasible design that meets all of the competing and, sometimes, conflicting subsystem requirements. This process is highly influenced by designer's subjectivity and may lead to a suboptimal system design. Furthermore, the influence of subsystems on the overall design is reduced as the design progresses sequentially along the design spiral.

This paper explores the development and applicability of an alternative Multidisciplinary Design Optimization (MDO) method, utilizing decomposition based optimization schemes. A simplified Synthesis Design Model (SDM) is developed that expresses the marketability of a standard midsize sedan on the U.S market based on fuel efficiency, curb weight and market price. The model decomposes the overall system into these coupled subsystems in a manner suitable for advanced optimization methods such as Collaborative Optimization (CO). Several preliminary Design Space Exploration (DSE) and multi-objective optimization studies are conducted and reported.

The results of this preliminary work show that early stage synthesis design of automobiles can be substantially enhanced by using advanced MDO and CO theories together with appropriate software. The fidelity of the optimized design produced by this method depends on the complexity and fidelity of the models used to define the overall system and subsystems. Development of more comprehensive decomposed SDM models are required for practical application of this approach to new and innovative designs. These models should preferably be developed in collaboration with manufacturers in order to include relevant new and often classified data.

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1. INTRODUCTION

The automotive industry today is struggling with a number of complex and often conflicting requirements in design of new vehicles. Automotive designers need to compress vehicle design cycle time, lower the weight and cost of the vehicle and at the same time improve product performance, comfort, safety, quality, and reliability. To satisfy these requirements, the industry is increasingly relying on the use of more formal and structured approaches to design, analyze and optimize the system. The automotive design process, particularly in the early stage synthesis design phase, can substantially benefit from application of modern design/evaluation tools and advance multidisciplinary design and optimization (MDO) approaches.

Design of systems such as cars, ships and aircraft is a highly complex and challenging endeavor. It typically involves numerous stakeholders, a wide range of competing goals and countless interrelated design problems. As a result, it is often undertaken by

large design teams using an iterative top-down process known as the "design spiral" [1]. The design spiral starts with an existing system design or a set of requirements and then addresses key subsystem design challenges such as engines, structure, cost, safety, etc. in a set sequence, using information from the previous activities in the sequence to perform current or subsequent activities. The spiral revisits each activity numerous times, in sequence, seeking to refine the design and to make increasingly detailed design decisions based on the structure provided by previously made decisions. This process makes possible the coordination of multiple subsystem design activities, albeit in a cumbersome and labor-intensive fashion. Though it has been proven to work, this process is extremely time-intensive and is unable to systematically find optimal design solutions. These weaknesses have led the engineering design community to look for other design tools and methodologies, such as MDO [2], which are capable of finding optimal design solutions in a more efficient manner.

The development of a strategy for utilizing modern design/evaluation tools requires structuring them for a given phase in the design process. If hierarchy in the design process is not considered, then structuring of the tools in relation to design process phases cannot be coherently established. For example, designers are unable to apply high-fidelity computational structural codes to evaluate crash worthiness in an early stage of the design phase, as the necessary input data is not available. Even when adequate input data is available, the application of such high-fidelity solvers may be impractical due to excessive computational time. This challenge needs to be balanced with the need or desirability of incorporating such important design features at early design phases of a car.

1.1. Design Optimization

Design optimization is a widely used tool that is capable of managing the complexity of design problems involving many alternatives. It has been used successfully in engineering design efforts for many years and provides designers with a means for finding solutions based on a set of predetermined design criteria by varying available degrees of freedom in a systematic fashion. The basic concept of design optimization comes from the field of calculus, where the concept of finding the maxima or minima of a function by taking the gradient of the function and setting it equal to zero was first introduced. Figure 1 below depicts the basic concept of design optimization, which involves finding the values for the inputs to an analysis model that minimize an output, or objective, of the analysis model. Optimization tools do not depend on the nature of the analysis model, with some exceptions such as optimization of topology or certain structural optimizations.

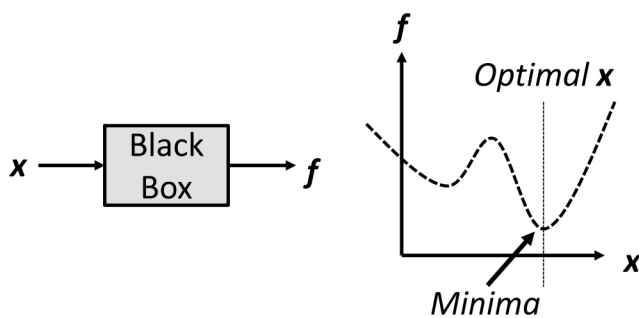


Figure 1. Design Optimization

Formally speaking, the design optimization process involves finding the values for a vector of design variables, $\mathbf{x}$, that minimize a function, f , (or vector of functions, $\mathbf{f}$), such that a set of design constraints, $\mathbf{g}$, are not violated, where in many cases the objective and constraint functions also depend on a vector of fixed parameters, $\mathbf{p}$. This relationship is provided below.

$$\begin{aligned} \min \quad & f_i(\mathbf{x}, \mathbf{p}) \quad i = 1 \dots I \\ \text{s.t.} \quad & g_j(\mathbf{x}, \mathbf{p}) \leq 0 \quad j = 1 \dots J \end{aligned} \quad (1)$$

Once the design problem is posed in the proper format of an optimization, as provided above, there are many different tools that can be used to solve the optimization problem and determine the values for the vector of design variables, $\mathbf{x}$, that define the optimally performing design. Examples of these tools include gradient based

optimizers, such as sequential quadratic programming [3], or meta-heuristic based solvers, such as genetic algorithms (GA) [4] or particle swarm optimization (PSO) [5]. If the optimization problem has multiple objectives (e.g. $\mathbf{f}$ is a vector), then the problem is said to be a multi-objective design optimization problem and must be solved with a multi-objective strategy such as the constraint- ϵ approach or with a population-based strategy such as multi-objective genetic algorithms (MOGA) [6].

1.2. Design Models

The real challenge in using design optimization lies not only in specifying the variables which define the design of the system to be optimized, but also in determining and quantifying the system objectives and constraint functions (i.e. f_i and g_j), or in other words, what lies within the black box (as shown in a simplified fashion in Figure 2.) For example, an objective function might be the vehicle weight, based on dimensions and material composition of the car, while a constraint function might be a maximum passenger volume. Determining these functions is often the real work of design and is not a trivial process. These functions can be as simple as algebraic or closed form equations, or as complex as a set of coupled analysis models involving finite element analysis (FEA) or various other computational tools. The development and coordination of the complete set of equations, data and analysis models that are required to properly analyze and design something as complex as an automobile are extremely demanding and drive much of the challenges associated with finding optimal car designs.

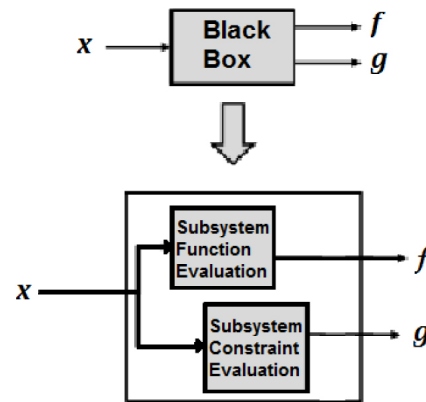


Figure 2. Complexity of Design Models

Coordinating the necessary suite of design and analysis models is typically accomplished through some type of Process Integration and Design Optimization (PIDO) software such as PHX ModelCenter™ [7].

1.3. Surrogate Approximation

Another challenge presented by the use of design optimization to solve design problems is that it can be computationally intensive. Virtually all optimization solvers function through iterative evaluation of the design and analysis models that define the system's objective and constraint functions. If these design models are relatively simple, then the required iterative evaluation is relatively fast and the optimizer can converge on an optimal design solution quickly. However, if the design models used are computationally intensive, then computational effort

and time becomes a limiting factor. For example, if a structural analysis model involves a FEA code that requires one hour of run time, and if an optimization effort requires 100 iterations of the FEA code to converge, over 100 hours of computational time would be required to find an optimal solution. This problem is further exacerbated by high dimensionality, as the number of iterative evaluations required by an optimizer is strongly correlated to the number of design variables considered. Clearly, a problem of high dimensions, requiring computationally intensive analysis models would lead to great challenges for design optimization.

This computational effort challenge has given rise to the concept of “surrogate approximation.” This strategy involves replacing computationally intensive analysis codes with more computationally efficient surrogates within optimization algorithms whenever possible. Surrogate models allow advanced physics-based methods such as FEA to be used at much earlier stages of design, and facilitate optimization and Design of Experiments (DOE) procedures.

The nature of the surrogate chosen depends on the nature of the computationally expensive design model and the needs of the specific design optimization problem, but designers have numerous options from which to choose.

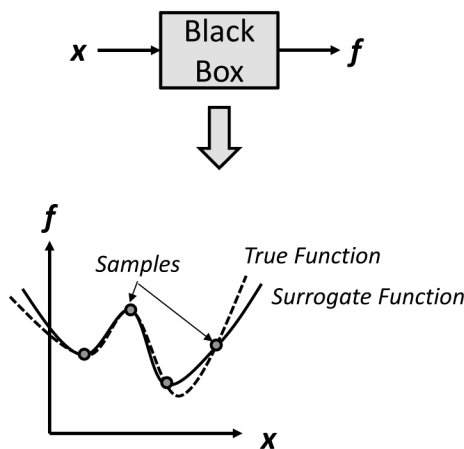


Figure 3. Surrogate of Black Box Function

Surrogates can be as simple as basic polynomial regression models, or as complex as mathematical models such as Kriging interpolations [8], or artificial neural networks [9].

1.4. Multidisciplinary Design and Optimization

MDO is a numerical design optimization technique used to find an optimal solution for an overall system which may consist of several subsystems (disciplines). In the context of automobile design, subsystems may include powertrain, chassis, electric system, etc. The foundation of MDO approach is that a multidisciplinary system is not driven only by performance of the individual disciplines but also by their interaction. The organization of systems numerical discipline-analysis models, approximation models and optimization software in line with the problem formulation is called MDO architecture. The MDO architecture defines both how the different models are coupled and how the overall optimization problem is solved [10]. The architecture can either have a monolithic approach where a single

optimization problem is solved or a distributed approach where the same problems disciplines (subsystems) are optimized separately with local subsets of variables and constraints. Constraints in the context of MDO are used to both set boundaries for the variables, inputs and outputs, and to control and enforce consistency between coupled variables, inputs and outputs during optimization.

The monolithic MDO architecture is a standard constrained nonlinear program problem, where values for the design variables that minimize or maximize the objective function must be found within the constraints of the system. The most basic monolithic MDO problem is the All-At-Once (AAO) architecture problem statement first developed by Cramer et al [11] and described in its most general form by equations (2). All problem statements are derived from the AAO which can therefore be seen as the fundamental problem statement for MDO.

$$\begin{aligned}
 &\text{Minimize} && f_0(x, y) + \sum_{i=1}^N f_i(x_0, x_i, y_i) \\
 &\text{with respect to} && x, \hat{y}, y, \bar{y} \\
 &\text{subject to} && c_0(x, y) \geq 0 \\
 &&& c_i(x_0, x_i, y_i) \geq 0 \quad \text{for } i = 1, \dots, N \\
 &&& c_i^f = \hat{y}_i - y_i = 0 \quad \text{for } i = 1, \dots, N \\
 &&& R_i(x_0, x_i, \hat{y}_{j \neq i}, \hat{y}_i, y_i) = 0 \quad \text{for } i = 1, \dots, N
 \end{aligned} \tag{2}$$

Here a vector of design variables local to subsystem i is denoted by x_i and shared variables by x_0 . The full vector of design variables is given by $x = [x_0^T, x_1^T, \dots, x_N^T]^T$. The subscripts also describe various subsystem objectives and constraints. For detailed review of AAO approach the reader is referred to [10]. The following additional monolithic MDO architectures are derived from the AAO problem formulation which are also described in [10]. The Simultaneous Optimization and Design (SAND) architecture is derived by eliminating the consistency constraints and replacing them with a single group of coupling variables. The Individual Discipline Feasible (IDF) architecture is derived by eliminating discipline-analysis constraints and applying the implicit function theorem. The Multidisciplinary Feasible (MDF) architecture is derived by eliminating both the analysis and the consistency constraints.

1.5. Collaborative Optimization

Collaborative optimization CO is an approach of a distributed MDO architecture developed in the early 90's [12]. The motivation for using a distributed architecture with a decomposed optimization problem is to exploit the structure of the problem and reduce solution time. Moreover, CO replicates the typical engineering design environment, where the design of a large system is divided in design groups working on different subsystems. To allow these groups to work more efficiently they control their own set of design variables while periodically receiving from other groups and sending to other groups updated information on their designs.

The key feature of the CO approach is that system-level optimizer selects values for all system-level variables as well as target values for all subsystem level coupling parameters. Then in the subsequent

independent subsystem optimizations, the system-level variables are held fixed and the subsystem local variables are selected to minimize each subsystem's deviation from the system-level specified target values. Each subsystem's total deviation is reported back to the system-level optimizer, where it is used to constrain the system-level optimization (either to zero deviation in all subsystems or to deviation values less than a specified maximum value). Figure 4 schematically shows the CO framework.

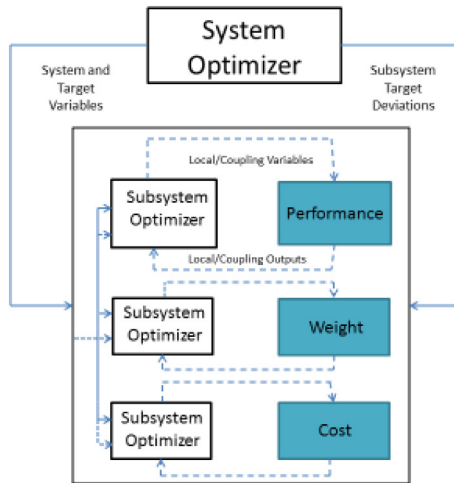


Figure 4. CO framework

This approach shortens the optimization time and results in a system that is optimized at system level as well as subsystem levels.

In the CO approach of a distributed MDO architecture, the discipline optimization subsystem problems are made independent of each other by using copies of coupling and shared design variables. This problem statement was formulated by [12] and is described in [10] as follows:

$$\begin{aligned}
 &\text{Minimize} && f_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \\
 &\text{with respect to} && x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y} \\
 &\text{subject to} && c_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \geq 0 \\
 &&& J_i^* = \|\hat{x}_{0i} - x_0\|_2^2 + \|\hat{x}_i - x_i\|_2^2 + \\
 &&& \|\hat{y}_i - y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i})\|_2^2 = 0 \quad \text{for } i = 1, \dots, N,
 \end{aligned}
 \tag{3}$$

Where the notation $\hat{x}_{0i}$ are copies of shared design variables passed to (and manipulated by) discipline i , and $\hat{x}_i$ are copies of the local design variables passed to the subsystem. Equality constraints are used to ensure that copies agree on a single value. These consistency constraints (equality constraints) denoted J_i^* as seen in (3) are using square of Euclidian norms to ensure that multidimensional variables and variable copies are equal through the iterations.

Majority of the MDO application in vehicle design, which are reported in the literature, are based on the AAO approach. Reference [13] for example uses a single-level optimization method in combination with metamodels to optimize automotive structures. In

another example, reference [14] uses a RSM-Based MDO in vehicle body design. Reference [15] presents the MDO of subframe component of a vehicle front suspension. A large body of work also is reported on the application of MDO to the automobile electronic systems and instrumentation panel. Reference [16] is an example. Examples of decomposition based optimization approach, which is the focus of this paper, are few and include reference [17] where analytical target cascading method is applied to the chassis design of a sport-utility vehicle. The overall status of MDO in the auto industry is briefly reviewed in an NSF industry panel review [18].

The present work aims to outline a bi-level distributed collaborative optimization approach for vehicle synthesis design. It is an extension of the work of one of the authors, where such MDO methods have been developed and applied to a notional set of requirements for a high speed trimaran ship [19], [20].

In the subsequent sections of this paper a simplified automobile SDM is described. This SDM is a highly idealized version of what is proposed in reference [18]. This model is then used to conduct some preliminary DSE and optimization studies. Results are described and indicate that distributed MDO methods such as CO can be applied to vehicle design in order to potentially enhance the early stage synthesis design of automobiles. Practical applications of this method to new and innovative designs however requires much more complex SDMs.

2. SYNTHESIS DESIGN MODEL

One of the key elements for successful application of distributed MDO methods such as CO is the development of an appropriately decomposed SDM. Figure 5 presents a highly idealized SDM in order to illustrate the methodology. Marketability is the measure of merit for the overall design. The system is decomposed into three subsystems. They are defined as the performance subsystem with fuel efficiency as its objective function, weight subsystem with the curb weight as its objective function and cost subsystem with market price as its objective function. The overall system measure of merit is marketability and is defined according to:

$$F = f_1 w_1 + f_2 w_2 + f_3 w_3, \tag{4}$$

where F is marketability and f_1, f_2 and f_3 are fuel efficiency, curb weight and market price respectively. Further, w_1, w_2 and w_3 are some specified weight functions.

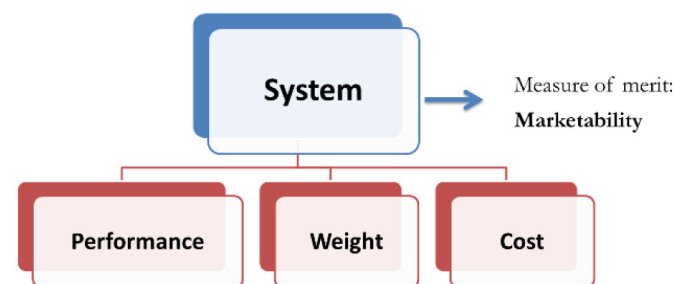


Figure 5. The overall system definition

