Proceedings of ESDA 2002
6th Biennial Conference on Engineering Systems Design and Analysis
July 8 -11, 2002, Istanbul, Turkey

ESDA2002/INVITED

AN ENTERPRIZE CONTEXT FOR DESIGN OPTIMIZATION

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ABSTRACT

Traditional design optimization has focused on studying the tradeoffs among desirable engineering characteristics of an artifact. The value of such design decisions can increase dramatically if they can be viewed in the context of the entire enterprize whose role is to design, produce and sell the artifact. Asset allocation models can be extended to include the design of the relevant assets, and design targets can be set and propagated consistent with the hierarchy and overall goals of the enterprize. Simple examples from the automotive sector illustrate the concepts.

INTRODUCTION

Designing has been long viewed as a process most suitable to human action based on experience and creative talent. During the last twenty years this view has changed rather dramatically, primarily due to the ever increasing availability of inexpensive computation and sophisticated, robust analysis tools. A fascinating view of what has been accomplished in this direction can be found in the recent publication edited by Antonsson and Cagan (2001). Much of what is described there deals with design as an act of creation and so illustrates how design concepts can be truly created using computational tools.

The generally accepted traditional design process assumes generation of the design concept by the human designer. In the present discussion we will assume for simplicity that a concept has already been created either by humans or machines or both. The next step is then to embody the concept into a more substantiated form that would typically allow it to be expressed in terms of some quantitative parameters. A design embodiment is described by a vector of design variables. Design alternatives can be explored by changing the values assigned to these variables. For any given set of values (i.e., for any given design instantiation) the behavior of the design can be analyzed using methods available from engineering science, such as thermal, structural or dynamic analysis. A decision is then made about selecting the best alternative.

Design optimization adopts this paradigm of design as a decision making process and formulates a mathematical representation of design decisions. The typical mathematical statement is of the form

$$\begin{aligned} &\text{maximize design performance metrics} \\ &\text{with respect to design variables} \\ &\text{subject to design constraints} \end{aligned} \tag{1}$$

or symbolically, in a standardized form,

$$\begin{aligned} &\text{maximize } \mathbf{f}(\mathbf{x}) \\ &\text{with respect to } \mathbf{x} \\ &\text{subject to } \mathbf{h}(\mathbf{x}) = \mathbf{0},\ \mathbf{g}(\mathbf{x}) \leq \mathbf{0}, \end{aligned} \tag{2}$$

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where the functions **f**, **h**, **g** represent the evaluations of the performance metrics and constraints, respectively, for a given set of values of the variable vector **x** (Papalambros and Wilde 2000). This formalism has been very successful in supporting the generation of good designs and is used widely in industry with a variety of modern software tools (see, e.g., Papalambros 2002a).

One may quickly notice that, in our statement of success above, the term "good designs" was used rather than "optimal designs." Indeed, in the midst of the excitement about using such new tools, a frequently forgotten limitation is that the optimal solution obtained by a successful design optimization exercise is only optimal with respect to the mathematical model describing the design decisions at hand. There is a vast number of decisions that must be made for which we have a poor or no mathematical model, and so these decisions are not included in what we call an "optimal" solution obtained from the model above.

In modern society the act of designing an artifact is undertaken primarily for the creation of a product, whether that is a simple toy or a complex automobile. Design is, at least initially, driven by a desire to satisfy a human need; but its transformation into a product requires decisions related to the producing enterprize and the market in which it will become available. Thus economic, marketing, production and other business decisions come into play, in addition to the core technical engineering decisions about the design's functionality.

To date, design optimization as a discipline has dealt primarily with the engineering functionality of designs. There are good reasons for this. First, creating a high quality, high fidelity model of engineering functionality is not easy, even for some simple problems and more so for complex ones. Second, the mathematical challenges for solving the resulting optimization problems are ever present and demanding. Third, the generation of product models that include non-engineering decisions is not usually within easy reach of the design engineers, and requires knowledge in new fields, not traditionally studied in engineering, or collaboration with experts in these other fields—a process that requires time and patience.

The first set of issues above relates to good engineering analysis and is an on-going disciplinary endeavor from which design, and design optimization, will continuously benefit. The second set of issues is both a theoretical and a practical one and is studied in optimization theory and practice (see, e.g., Papalambros and Wilde, 2000; Papalambros 2002b). In the present article we will explore the third set of issues, namely, how design optimization can be examined in the context of the essentially multidisciplinary nature of product development—the context of the enterprize.

In a simplified view of product development the enterprize is defined as a set of activities that commence with a high level definition of the product specifications and conclude with detailed design of all the components (and production processes) of the product. The high level definition of product specifications is often referred to as target setting, and we can view this as a more narrow case of management by objectives (Schmidt and Finnegan 1992). These targets are set based on user needs, as perceived by the enterprize, and on business considerations using some appropriate metric. Modeling user needs and their relations to the product specifications requires typically the discovery of some utility functions (see, e.g., Hazzelrigg 1998, Li and Azarm 2000, Marston and Mistree 1998). A product is rarely designed for a single individual, and so utility functions have to be created for groups of users whose preference structures must be assessed in a statistical manner. The user grouping itself is a major concern as it relates to market segmentation and marketing strategies. Investment considerations can be quantified using recent developments in investment science (see, e.g., Luenberger 1997). The challenge is to understand how to link engineering decisions with investment decisions, both being product design decisions.

Once design targets are set at the top level, the next step is to see how these targets can be actually met by the embodiment of the product. Except for the simplest products, the designed artifact will consist of several systems, subsystems, and components, which we will collectively refer to as elements. More complex artifacts will be created from many building elements arranged in multilevel hierarchies of systems, subsystems and components. Each of these elements is a design problem by itself and requires individual element targets be set so that the element can work with all other elements and together meet the design targets set at the top level.

This simple expectation can be very daunting in the design of complex artifacts comprising hundreds or thousands of elements and element designers. The process of allocating design targets within a product hierarchy is referred to as target cascading (Kim et al. 2000, Kim 2001). Once targets have been set at the top and cascaded throughout the product element hierarchy, design decisions can be made in an independent, concurrent fashion, as long as they maintain the agreed upon values for the targets that link everything together.

The product development process defined above is illustrated in Figure 1. At the enterprize level the target setting process takes place using selected key technical and economic design considerations. The outcome is a set of top-level targets the artifact must satisfy. Some design targets at other levels of the hierarchy may also be defined at that point. Next, the target cascading process is undertaken. Its outcome is a set of design targets for all the elements that comprise the artifact; these target values are determined both for design criteria associated with each element as well for the quantities linking two or more elements. Since the targets initially passed to the elements may not allow feasible designs to be achieved, it would be usually necessary to iterate within the target cascading process until all the elements are optimized so that their corresponding targets are met as closely as individual element feasibility allows them to be.

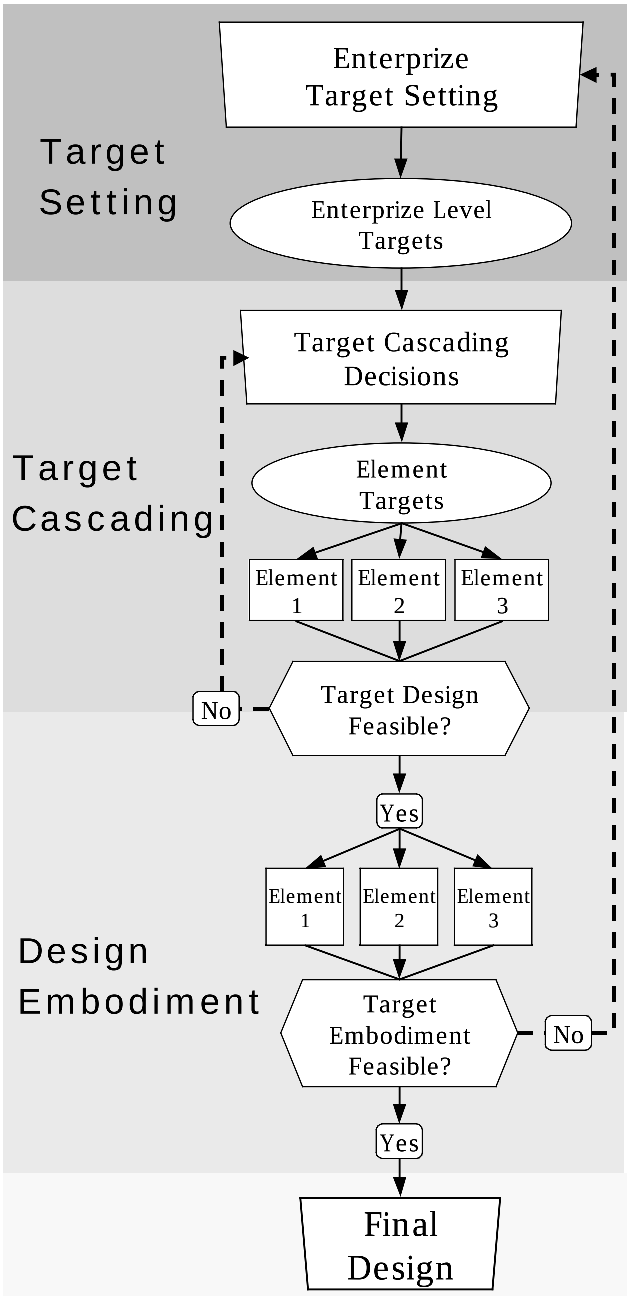

Figure 1. Design decision flow in the enterprize-wide product development process.

At that stage, all target and link values are fixed and the target cascading process is completed. Each element has an initial partial set of specifications that, if met, guarantees that the element will work well with the other elements and that the overall artifact design targets will be met as closely as possible. The element design must be now embodied, namely, several more design decisions must be made to complete the design details necessary for full specification of the element. These decisions are localized to the element and can be executed concurrently. This potential concurrency is an important attraction of the target cascading philosophy in that it rigorously decomposes the design tasks and shortens the design cycle time. The outcome of the embodiment process is a set of completed element designs, which collectively give us the final design. However, even at that embodiment stage it is possible to discover that local requirements cannot be met as desired. Then it would be necessary to reexamine the targets set at the enterprize level and the assumptions on which they were based. A new global iteration may be necessary in order to match enterprize decisions with actual technical capabilities.

Clearly, the earlier we can explore the need for such global iterations the more efficient the process will be. If a virtual prototyping capability can be assumed with some appropriate (but not very high) degree of fidelity, then the design decisions described above can be made using the mathematical models that support the virtual prototype. The corresponding key processes in the figure will become what we term analytical target setting and analytical target cascading.

In the remainder of this article we will look at these two processes, analytical target setting and analytical target cascading, and examine how they can be quantified mathematically and placed within the framework of design optimization. Analytical target setting uses a business model that looks at products as investment decisions, so that assets are allocated for products while product attributes are also decided upon at the same time, meeting engineering constraints and a financial objective. A product portfolio strategy results, along with the top level targets that the product embodiment must accomplish. Analytical target cascading formulates the target cascading problem as a multilevel, hierarchical optimization problem and solves it using a rigorous coordination method. Such coordination guarantees that the optimality of the overall system will not be sacrificed by distributed decision making.

ANALYTICAL TARGET SETTING

Target setting is approached as a generalized resource allocation problem. Traditional resource allocation determines the percentage of available assets to invest in different products. In our generalization we add the simultaneous determination of selected design properties of the products corresponding to these assets. The values determined for these properties will become the top level targets to be cascaded through the artifact's system hierarchy. The approach described here follows Georgiopoulos et al. (2002), where more details can be found.

A design optimization problem is formulated where the objective is the net present value created for the enterprize. Utility theory has been proposed as a way of linking engineering and business decisions, e.g., in Hazzelrigg (1998). The approach advocated here broadens the scope of traditional utility and seeks to model design decisions not simply as an isolated maximization (say, of profit or return on investment) but in comparison to the value of the decision-making firm within society, perhaps as expressed by the stock market. This approach is akin to the arbitrage theory used in capital budgeting (Carr et al. 2002). The general form of the optimization problem is

$$\begin{aligned} \text{maximize } & \textit{(expected net present value)} \\ \text{with respect to } & \textit{(engineering variables,} \\ & \textit{investment variables,} \\ \text{subject to } & \textit{(engineering constraints,} \\ & \textit{enterprize constraints).} \end{aligned} \tag{3}$$

The enterprize-wide decision model includes revenues and expenditures resulting from asset allocation and the engineering performance of these assets. The enterprize constraints can be production constraints, such as production capacity.

Target setting for a product portfolio problem

The use of the general model above can be understood better with a specific example. Looking at arbitrage decisions involves more complicated financial mathematics models, such as real options theory (see, e.g., Trigeorgis 1998), beyond the present summary exposition. Therefore here we will use only a more traditional financial objective, monthly profit, to illustrate the financial-engineering linking in setting design targets.

Consider an automotive manufacturer that markets vehicles in the premium-compact (PC) and full-size sport utility vehicle (SUV) segments. It operates in a mature environment with given complementary assets, such as distribution channels and service networks. Other simplifying assumptions for building the business model are made, for example, that the firm's output decision does not affect the product's price and that there is no competitive interaction. In principle these assumptions can be relaxed but the complexity of the models will increase substantially. The manufacturer plans to produce new engines and drivetrains for both the PC and SUV segments. There is a production capacity constraint with a maximum number of C units monthly production capacity for engines and drivetrains.

The enterprize decision problem is how to allocate capacity between the two segments and what should be the performance specifications for engines and drivetrains within each segment so that the firm's value is maximized. Figure 2 illustrates the decisions that the firm is facing.

The enterprize decision model

The following terms and symbols are used in the descriptions used in the models below.

CAFE	Corporate Average Fuel Economy
PC	premium compact vehicle
SUV	sport utility vehicle
C	units of capacity currently installed
fe	fuel economy
$\mathbf{g}(\mathbf{x})$	engineering constraint set
i	vehicle index
L	vehicle's segment CAFE limit
M	vehicle's profit margin
P	vehicle's price.
t_{0-60}	time 0 to 60 acceleration
$\mathbf{x}$	engineering design variables
$\mathbf{w}$	product portfolio weights

The mathematical representation of the target setting decision model is given in Eq.(4).

$$\begin{aligned} \text{minimize } & -\sum_{i=1}^{2} w_i \Pi_i \\ \text{with respect to } & \{\mathbf{w}, \mathbf{x}\} \\ \text{subject to } & w_i \cdot C - \mathbb{E}[Sales_i] \leq 0 \\ & \textstyle\sum_{i=1}^{2} \mathrm{Cost}_{\mathrm{CAFE_i}} \leq 0 \\ & \textstyle\sum_{i=1}^{2} w_i = 1 \\ & \mathbf{g}(\mathbf{x})_{\mathrm{PC}} \leq 0 \\ & \mathbf{g}(\mathbf{x})_{\mathrm{SUV}} \leq 0 \end{aligned} \tag{4}$$

The model combines an investment decision model and an engineering decision model. We will look at these two models in turn.

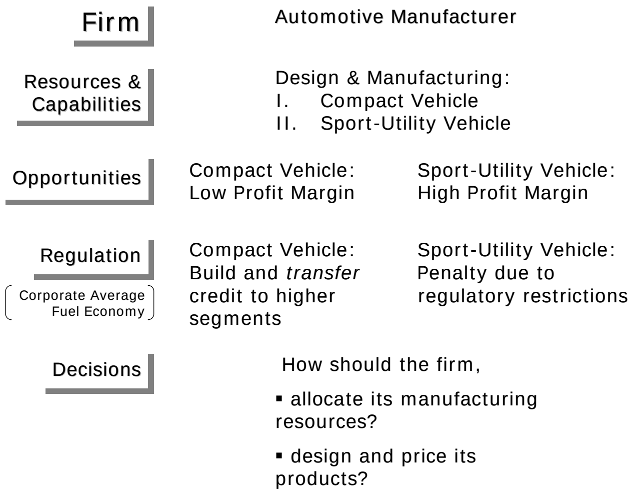

Figure 2. Design decisions for vehicle portfolio example.

Modeling investment decisions

The objective function is an investment decision expressed as the monthly profit for each product.

$$\Pi_i = (\text{Price}_i \times \text{Profit Margin}_i \times \text{Sales}_i) - \text{Cost}_{\text{CAFE}_i} \quad (5)$$

As noted already, an actual portfolio valuation could be performed using monthly cash flows over a specified period of sales using capital asset pricing or options models. A much more extensive computation will be required to capture the essential stochastic nature of the decision environment.

In the model of Eq. (4) the design variables are $\mathbf{x}_{PC}$, w_{PC}, $\mathbf{x}_{SUV}$ and w_{SUV} representing engine sizes and final drive ratios (cf. $\mathbf{x}$), and portions of the total monthly capacity to be allocated (cf. $\mathbf{w} = \{w_i : i = 1,2 \text{ for PC, SUV respectively}\}$) for each vehicle segment/product. Since,

$$\sum_{i=1}^{2} \frac{\text{Production}_i}{\text{Capacity}} = 1. \quad (6)$$

then

$$w_{PC} + w_{SUV} = 1 \quad (7)$$

The price of the product can be expressed as a functional relationship of the vehicle attributes aggregated (i.e., customer-perceived) value. Modeling this relationship is a complex process. For simplicity here we assume that the only vehicle attribute that influences the customer's purchasing decision is vehicle acceleration and that the vehicle price is proportional to the value of the 0-60 mph acceleration time

$$\text{Price} = (\text{Base Price}) \times (\text{Attribute Value}). \quad (8)$$

To assess the customer-perceived value of vehicle acceleration the value curve method for attribute value assessment is used (Donndelinger and Cook 1997). Each performance attribute is assumed to have three specification points, the ideal point where value for the attribute is at its highest level, the baseline point where value is at its nominal value (that is, one), and the critical point where the product becomes valueless independent of the level of other attributes. A heuristic expression can be used to approximate the interpolating value between the critical and ideal point. This function has been validated for a midsize vehicle customer (Cook 1997; McConville and Cook 1996) and is used here. Its meaning is that if a design achieves 1.1 value the firm will price the vehicle 10% higher.

The profit margin is 1% and 35% for the PC and SUV segments, respectively.

The size of the engine determines the fuel economy of each product and is used to calculate the corporate average fuel-economy (CAFE), the legislated environmental metric that profoundly influences US manufacturers' decision making. For light trucks (including vans and sport utility vehicles) the 1993 CAFE standard was 20.3 mpg. Failure to comply with the limit, L_i, results in a civil penalty of \$5 for each 0.1 mpg the manufacturer's fleet falls below the standard, multiplied by the number of vehicles it produces. Thus the penalty (or credit) due to CAFE is

$$\text{Cost}_{\text{CAFE}_i} = \left[5 \times \frac{L_i - fe_i}{0.1}\right] \times \text{Sales}_i. \quad (9)$$

Expected sales are expressed as a product of two sources of uncertainty, namely, product demand and market share

$$\mathbb{E}[\text{Sales}_i] = \mathbb{E}[\text{Product Demand}_i \times \text{Market Share}_i]. \quad (10)$$

The production for each vehicle should not exceed the total amount that the firm can expect to sell, which adds the constraint

$$\text{Production}_i \leq \mathbb{E}[\text{Sales}_i]. \quad (11)$$

To estimate expected sales we can use a random walk simulation using historical sales data. Each random walk includes 84 points that represent, in months, two years of product development and five years of product life-cycle. The maximum expected sales over the life-cycle of the product is then used as the upper bound of Eq. (11).

The CAFE penalty should be non-positive, because products that result in civil penalties will damage the firm's corporate image and affect revenues indirectly.

$$\sum_{i=1}^{2} \mathbb{E}[\text{Cost}_{\text{CAFE}_i}] \leq 0 \quad (12)$$

The expectation on CAFE cost is derived from the expectation on future sales.

Based on the above, Eq.(5) is written as

$$\Pi_i = \text{P}_i \cdot \text{M}_i \cdot w_i \cdot C - \left[5 \tfrac{L_i - fe_i}{0.1}\right] w_i \cdot C \quad (13)$$

and used in the enterprize model Eq. (4).

Modeling engineering decisions

Engineering decisions are included implicitly in the objective function of Eq. (4) and explicitly as bounds on vehicle performance attributes in the constraints. The implicit objective is the minimization of 0-60 acceleration time, as long as it increases the customer perceived value and hence the price, according to the value curve model above. The constraints

$$\begin{aligned} \mathbf{g}(\mathbf{x})_{\mathrm{PC}} &\le 0 \\ \mathbf{g}(\mathbf{x})_{\mathrm{SUV}} &\le 0 \end{aligned} \tag{14}$$

are the following

$$\begin{aligned} \text{fuel economy} &\ge b_1 \\ t_{0-60} &\le b_2 \\ t_{0-80} &\le b_3 \\ t_{40-60} &\le b_4 \\ \text{5-sec distance} &\ge b_5 \\ \text{max acceleration} &\ge b_6 \\ \text{max speed} &\ge b_7 \\ \text{max grade at 55mph} &\ge b_8 \end{aligned} \tag{15}$$

where the b's are upper and lower bound parameters. Values for the b's used in this example are given in Table 1. The computation of all the constraint functions is done using the Advanced Vehicle Simulator (ADVISOR) program (Wipke and Cuddy 1996), a quite sophisticated modeling tool. The actual evaluation of these functions is not trivial and presents a research topic unto itself.

Obtaining the top level targets

The model in Eq.(4) is solved using appropriate numerical optimization tools. In the present study the direct rectangles (DIRECT) algorithm due to Jones et al. (1993) was combined with a sequential quadratic programming (SQP) algorithm. This allows a global/local search combination with a good balance between robustness and lowered computational costs. The model involves six variables (four design and two portfolio variables) and 19 constraints (three from the investment requirements and eight each for the PC and SUV segments of the engineering requirements). Solutions were obtained for two vehicle production capacities, 100,000 and 48,500; the latter happens to be the maximum expected monthly sales of SUVs. The results are shown in Table 2. For C = 100,000 the computed solution matches intuition: produce as many high profit SUVs as the market will bear (48,500). When the capacity equals the market limit, the solution is less obvious. One may produce only SUVs, making them meet the CAFE standard so as not to violate Eq.(12). Yet, forcing the

Table 1. Bound parameter values for the two vehicle products

Constraint Boundary	PC	SUV
b_1 (mpg)	27.3	12.8
b_2 (s)	12.5	9.8
b_3 (s)	26.3	22.8
b_4 (s)	5.9	5.0
b_5 (ft)	123.5	154.5
b_6 (ft/s^2)	13.0	15.4
b_7 (mph)	97.3	100.4
b_8 (%)	18.1	18.6

Table 2. Computed top level targets for different capacities

Variable	Solution for $C = 100,000$	Solution for $C = 48,500$
w_{PC}	0.52	0.14
w_{SUV}	0.48	0.86
engine$_{PC}$	75 kW	74 kW
final drive$_{PC}$	3.4	3.4
engine$_{SUV}$	185 kW	162 kW
final drive$_{SUV}$	4.2	4.0
monthly profit	\$5.0M	\$4.1M
fuel economy$_{PC}$	37.2 (mpg)	37.6 (mpg)
time 0 to 60$_{PC}$	12.3 (s)	12.5 (s)
time 0 to 80$_{PC}$	25.8 (s)	26.3 (s)
time 40 to 60$_{PC}$	5.7 (s)	5.8 (s)
5-sec distance$_{PC}$	132.6 (ft)	130.5 (ft)
max acceleration$_{PC}$	16.2 (ft/s^2)	16.0 (ft/s^2)
max speed$_{PC}$	110.7 (mph)	109.9 (mph)
max grade at 55mph$_{PC}$	18.4 (%)	18.1 (%)
fuel economy$_{SUV}$	17.1 (mpg)	18.7 (mpg)
time 0 to 60$_{SUV}$	8.7 (s)	9.6 (s)
time 0 to 80$_{SUV}$	19.6 (s)	23.0 (s)
time 40 to 60$_{SUV}$	4.3 (s)	4.8 (s)
5-sec distance$_{SUV}$	190.3 (ft)	177.5 (ft)
max acceleration$_{SUV}$	19.2 (ft/s^2)	19.2 (ft/s^2)
max speed$_{SUV}$	130.6 (mph)	121.1 (mph)
max grade at 55mph$_{SUV}$	26.8 (%)	22.4 (%)

SUVs to meet the CAFE standard reduces their price in Eq.(8) because they would suffer performance loss. A compromise between a smaller SUV engine (better fuel economy) and a small percentage of PC production yields a more profitable portfolio. The example illustrates how the target-setting decisions can be affected by the fixed parameters in the optimization problem.

ANALYTICAL TARGET CASCADING

In this section we outline the basic ideas involved in translating the concept of target cascading into a quantitative one. Again the description is brief and more information can be found in the cited references. First we show how a multilevel design optimization problem can be formulated and then we discuss how the results of this problem are linked to the target setting problem discussed above.

Design Optimization Formulation

Once the top level targets are set the next problem we face can be stated as follows.

$$
\begin{aligned}
&\min_{\mathbf{x}} \|\mathbf{T}-\mathbf{R}\| \\
&\text{where} \quad \mathbf{R}=r(\mathbf{x}) \\
&\text{subject to} \\
&g_i(\mathbf{x}) \le 0 \qquad i=1,\ldots,m_i \\
&h_j(\mathbf{x}) \le 0 \qquad i=1,\ldots,n_e \\
&x_k^{\min} \le x_k \le x_k^{\max} \qquad k=1,\ldots,n
\end{aligned}
\tag{16}
$$

The objective is defined as the discrepancy between the target **T** and the response **R** obtained from the analysis model $r(\mathbf{x})$; **g** and **h** are inequality and equality design constraint vectors with sizes m_i, n_e, and the design variable **x** is defined within lower and upper bounds, $\mathbf{x}^{\min}$ and $\mathbf{x}^{\max}$.

If the problem in Eq.(16) can be solved *all-at-once*, i.e., as a single optimization problem, then there is no need for target cascading. Its solution will determine all the required design decisions including all links among the elements comprising the artifact. Such a happy situation is rarely possible in practice for two reasons. First, except for very simple artifacts, the design work is done in a distributed fashion by groups of people (and corresponding modeling tools) that work independently, thus making it very difficult to aggregate a complete detailed model. Second, the mathematical optimization problem itself becomes so large and complicated that it defies our ability to solve it.

When the all-at-once approach cannot be used, target cascading becomes necessary. In the formal analytical target cascading (ATC) process we assume that the artifact can be decomposed into a hierarchy of elements (i.e., systems, subsystems or components), each of which will require determination of its own targets along with values for the variables that link them. To represent the hierarchy of the partitioned design problem, the set $\mathcal{E}_i$ is defined at each level i, in which all the elements of the level are included. For each element j in the set $\mathcal{E}_i$, the set of children $\mathcal{C}_{ij}$ is defined, which includes the elements of the set $\mathcal{E}_{i+1}$ that are children of the element. These relationships are illustrated in Figure 3: At level $i=2$ of the partitioned problem we have $\mathcal{E}_2 = \{\text{A, B}\}$, and for element "B" on that level we have $\mathcal{C}_{2\text{B}} = \{\text{C, D}\}$.

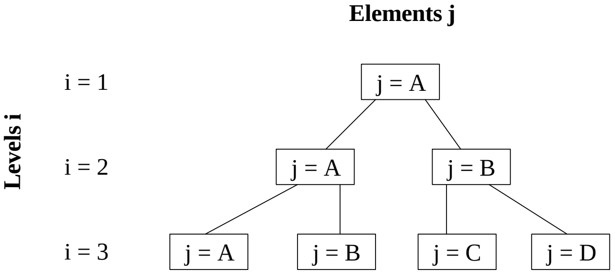

Figure 3. A hierarchical partition for analytical target cascading

The actual mathematical representation is quite involved. A two-level ATC hierarchy is shown in Figure 4 along with the information flows accounted for in the process. There are two types of responses: responses $\tilde{R}$ linked to "local" targets (e.g., at the top level), and responses R linked to "cascaded" targets, i.e., linking two successive levels in the problem hierarchy. We will comment on these types of targets further below. The design problem P_{ij} corresponding to the j-th element at the i-th level is

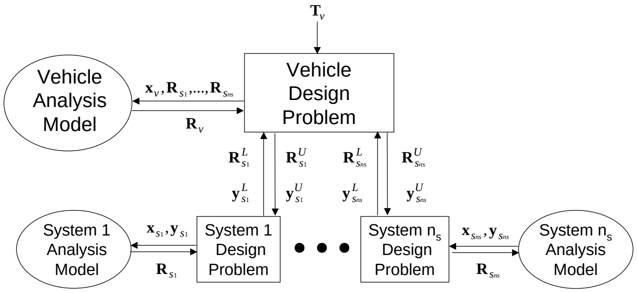

Figure 4. Information flow in a two-level target cascading hierarchy

formulated as follows:

$$
\begin{aligned}
\min_{\bar{x}_{ij}} \; & \|\tilde{R}_{ij} - T_{ij}\| + \|R_{ij} - R^U_{ij}\| + \|y_{ij} - y^U_{ij}\| \\
& \qquad + \varepsilon^R_{ij} + \varepsilon^y_{ij} \\
\text{subject to} \quad & \sum_{k \in C_{ij}} \|R_{(i+1)k} - R^L_{(i+1)k}\| \le \varepsilon^R_{ij} \\
& \sum_{k \in C_{ij}} \|y_{(i+1)k} - y^L_{(i+1)k}\| \le \varepsilon^y_{ij} \\
& g_{ij}(\hat{R}_{ij}, x_{ij}, y_{ij}) \le 0, \\
& h_{ij}(\hat{R}_{ij}, x_{ij}, y_{ij}) = 0,
\end{aligned}
\tag{17}
$$

where $\hat{R}_{ij} = \left[\tilde{R}_{ij}, R_{ij}\right]^T = r_{ij}(R_{(i+1)k_1}, \ldots, R_{(i+1)k_{c_{ij}}}, x_{ij}, y_{ij})$, $C_{ij} = \{k_1, \ldots k_{c_{ij}}\}$, and c_{ij} is the number of child elements. Note that an element's response depends on the element's design variables as well as on its children's responses.

The following notation is used in this formulation.

$\bar{x}_{ij} = \left[x_{ij}, y_{ij}, y_{(i+1)k_1}, \ldots, y_{(i+1)k_{c_{ij}}}, R_{(i+1)k_1}, \ldots, R_{(i+1)k_{c_{ij}}}, \varepsilon^R_{ij}, \varepsilon^y_{ij}\right]^T \in \mathbb{R}^{z_{ij}}$ is the vector of all optimization variables where $z_{ij} := n_{ij} + l_{ij} + 2 + \sum_{k \in C_{ij}} l_{(i+1)k} + \sum_{k \in C_{ij}} d_{(i+1)k}$,

$x_{ij} \in \mathbb{R}^{n_{ij}}$ is the vector of local design variables, that is, variables exclusively associated with the element,

$y_{ij} \in \mathbb{R}^{l_{ij}}$ is the vector of linking design variables, that is, variables associated with two or more elements that share the same parent,

$\hat{R}_{ij} \in \mathbb{R}^{\hat{d}_{ij}}$ is the vector of responses, where $\tilde{R}_{ij}$ corresponds to responses linked to local targets, while R_{ij} corresponds to responses linked with cascaded targets ($\hat{d}_{ij} := \tilde{d}_{ij} + d_{ij}$). As shown above, $\hat{R}_{ij}$ is a function of local and linking design variables and responses of child elements: $r_{ij} : \mathbb{R}^{a_{ij}} \longrightarrow \mathbb{R}^{\hat{d}_{ij}}$, where $a_{ij} = n_{ij} + l_{ij} + \sum_{k \in C_{ij}} d_{(i+1)k}$,

$\varepsilon^R_{ij} \in \mathbb{R}_+ \bigcup \{0\}$ is the tolerance optimization variable for coordinating the responses of the children of the element,

$\varepsilon^y_{ij} \in \mathbb{R}_+ \bigcup \{0\}$ is the tolerance optimization variable for coordinating the linking design variables of the children of the element,

$T_{ij} \in \mathbb{R}^{\tilde{d}_{ij}}$ is the vector of local target values,

$R^U_{ij} \in \mathbb{R}^{d_{ij}}$ is the vector of response values cascaded down to the element from its parent,

$y^U_{ij} \in \mathbb{R}^{l_{ij}}$ is the vector of linking design variable values cascaded down to the element from its parent,

$R^L_{(i+1)k} \in \mathbb{R}^{d_{(i+1)k}}$ is the vector of response values cascaded up to the element from its *k*-th child,

$y^L_{(i+1)k} \in \mathbb{R}^{l_{(i+1)k}}$ is the vector of linking design variable values cascaded up to the element from its *k*-th child,

$g_{ij} : \mathbb{R}^{b_{ij}} \longrightarrow \mathbb{R}^{v_{ij}}$ and $h_{ij} : \mathbb{R}^{b_{ij}} \longrightarrow \mathbb{R}^{w_{ij}}$ are vector functions representing inequality and equality design constraints, respectively, where $b_{ij} = \hat{d}_{ij} + n_{ij} + l_{ij}$, and

$\| \cdot \|$ is some norm; typically, some weighted norm is used for the metrics involving local targets T_{ij} in order to noble trade-off evaluation studies, while the l_2-norm is used in all other cases.

The notation is necessarily complicated because the ATC problem is itself quite complicated in its full form. Indeed, an even more complex notation is required when ATC is applied to families of products (Fellini et al. 2001). Nevertheless, one can master it starting with simple bilevel problems before proceeding with problems of more realistic complexity.

Completing the ATC process requires solution of all the individual design optimization problems P_{ij} along with a *coordination strategy* that iterates through the hierarchy from top to bottom and back, until all targets are matched as closely as possible and all designs are feasible. Solution of the individual optimization problems is generally assumed accessible, because the models should be relatively simple and small. Models appropriate for ATC should be computationally inexpensive, possibly derived as surrogate (meta-) models from expensive simulations. Different optimization algorithms can be used for different subproblems.

The choice of coordination is often challenging. In the case of ATC it is possible to prove convergence under convexity assumptions based on the hierarchical overlapping coordination convergence theory (Michelena et al. 1999, 2002). Global convergence is an important strength of the ATC formulation. However, the rate of convergence (i.e., the number of coordination iterations needed to converge to a solution) has not been established theoretically or empirically through extensive tests. Experience to date shows that the process could be much slower than an all-at-once solution —if that were possible— and that good problem scaling is important for termination of iterations.

Linking Target Setting and Target Cascading

In general the results of the target setting process will be used to define the targets at the top level of the hierarchy, but this is not always the case. Targets can be also set at other levels, and this capability is accommodated in the ATC formulation above.

To illustrate the point, recall the enterprize portfolio problem for premium-compact vs. sports-utility vehicles used above. The design targets will be the values for engine size and final drive ratio, as well as the values for accelaration performance metrics and fuel economy. In the ATC hierarchy for vehicle design, it is possible to place performance and fuel economy targets at the top level, while the engine size and final drive ratio will be targets at two systems, engine and drivetrain, respectively, at a level below the top level. This ability to place targets set from enterprize design considerations throughout the ATC hierarchy is an important practical issue. In real product development processes rarely do the engineers face just top level requirement setting.

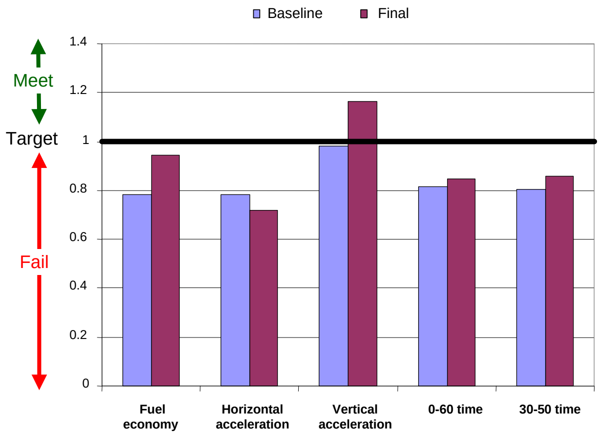

Figure 5. Target cascading results in a sports utility vehicle study (Kim et al. 2002)

Business and other considerations dictate a priori decisions, such as the use of a certain component or subsystem because of production plant or supplier constraints. In a sense, the analytical target setting idea can be used not only globally, as illustrated in the portfolio example, but also locally at each element of the ATC hierarchy.

The output of the target cascading process will provide information as illustrated in Figures 5 and 6. The problem relates to a sports-utility vehicle with several top level targets, including performance, fuel economy, and handling; details of this target cascading application can be found in Kim, et al. (2001). In Figure 5 the results of target cascading are shown in comparison with a baseline design available prior to the cascading process. The targets are all normalized so we can see how close we are to the set targets; targets close to the unit value are met, above the unit are exceeded, and below the unit targets have failed to be met. If during an outer iteration of Figure 1 we need to reset some targets, the process will yield different results. For example, the targets can be reset to zero, as an extreme case meaning that all performance metrics are to be improved as much as possible. The results are shown in Figure 6.

In comparing how well the targets that have been set can be met after the target cascading process is complete, we must realize that the ATC problem as posed in Eq. (17) is actually a multiobjective problem using a scalar substitute function that is linear with equal weights. This implies that all targets are treated as equally important. Clearly, the decision maker can have preferences that emphasize meeting one target more than another, which means that the ATC problem can be solved with (different) weights assigned to the matching norms used in the objectives of Eq. (17). This weighting can happen at the top level or at any of the other levels/elements in the hierarchy.

Being able to select separate weights a priori for all these multiobjective problems is highly unlikely. The more likely scenario is to apply the ATC process with equal weights and, after one round of determining targets that can be cascaded to obtain a technically feasible design, to initiate a negotiation process in oder to determine relative weights among competing, poorly met targets. In addition, constraint bounds may be also relaxed to allow targets to be met more closely. Relaxing constraints typically implies additional costs for improved technology (e.g., production equipment, materials, plant capacity). The bounds themselves are treated as fixed parameters during optimization, so a sensitivity analysis or a broader parametric study (cf. Papalambros and Wilde 2000) can be performed to understand the effect of parameter changes on optimality.

Performing Pareto optimality studies, parametric studies, and repeated target setting-target cascading cycles can be very expensive, particularly if the models utilize simulations, as in the above vehicle examples. Nevertheless, the point is that these studies *can* be performed and results obtained of quality commensurable to the quality of the engineering and management science models employed to describe the situation. In a product development process involving possibly several years and billions of dollars of investment, such an exercise may be very worthwhile.

CONCLUSION

Target cascading and target setting were originally conceived as ”business” processes. We have seen here that they can be formalized as quantitative design optimization processes. In doing so we are able to expand the context in which engineering design decisions are made to include the broader viewpoint of the

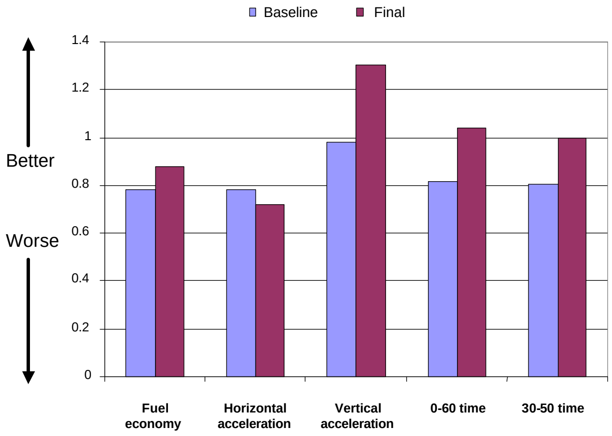

Figure 6. Modified target results–sports utility vehicle study (Kim et al. 2002)

enterprize within which designing takes place. The execution of such quantification is a substantial undertaking, whose biggest challenge is the procurement of appropriate analysis models that can compute the values and engineering responses associated with each design alternative. The engineering analysis models are becoming increasingly available through the proliferation of computer-aided engineering tools. Financial models have been and continue to be created but their accessibility to the design engineering community is still limited. Proper analogies between financial and product development concepts must be inferred, along with mastery of the relevant mathematics. All this indicates an opportunity for innovation and for an expanded rigorous approach to artifact design and product development.

ACKNOWLEDGMENT

This work was partially supported by the US Army TACOM through the Automotive Research Center at the University of Michigan and the Dual Use Science and Technology Program, and by General Motors and Ford Motor Corporations. This support is gratefully acknowledged. The views presented here are only those of the author. Thanks are due to J. D. Powers & Associates for providing historical data in the original investment analysis study. The author also thanks A. B. Cooper, P. Georgiopoulos, M. Kokkolaras, and A. Perez-Duarte for assistance in preparing the manuscript.

REFERENCES

Antonsson, E. K., and J. Cagan, *Formal Engineering Design Synthesis*, Cambridge University Press, Cambridge, UK, 2001.

Carr, P., Geman, H., and , D. B. Madan, “Pricing and Hedging in Incomplete Markets,” *J. of Financial Economics*, 2002, to appear.

Cook, H.E., *Product Management: Value, Quality, Cost, Price, Profits, and Organization*, Chapman & Hall, 1997.

Donndelinger, J. and H.E. Cook, “Methods for Analyzing the Value of Automobiles,” *SAE Intern. Congress*, Detroit, MI, SAE Paper 970762, 1997.

Georgiopoulos, P., Fellini, R., Sasena, M., and P.Y. Papalambros, ”Optimal Design Decisions in Product Portfolio Valuation,” *28th Design Auto. Conf.*, Paper No. 34097, Montreal, Quebec, Canada, October 2002.

Hazelrigg, G.A., “A Framework for Decision Based Engineering Design,” *J. of Mechanical Design*, vol. 120, pp. 653-658, 1998.

Jones, D.R. and Perttunen, C.D. and B.E. Stuckman, “Lipschitzian optimization without the Lipschitz constant”, *J. of Optimization Theory and Application*, 79(1):157–181, 1993.

Kim, H.M., *Target Cascading in Optimal System Design*, Doctoral Dissertation, University of Michigan, 2001.

Kim, H.M., Michelena, N., Papalambros, P.Y., and T. Jiang, ”Target cascading in optimal system design,” *26th Design Auto. Conf.*, Paper No. 14265, Baltimore, MD, September 2000.

Kim, H.M., Rideout, D.G., N., Papalambros, P.Y., and J.L. Stein, ”Analytical target cascading in automotive vehicle design,” *27th Design Auto. Conf.*, Paper No.21079 , Pittsburg, PA, September 2001.

Fellini, R., Kim, H.M., Kokkolaras, M., Michelena, N., and P.Y. Papalambros, ”Target Cascading for Design of Product Families,” *Proc. of 4th Congress on Structural and Multidisciplinary Optimization*, Dalian, China, June 4-8, 2001.

Li, X. and S. Azarm, “Product Design Selection under Uncertainty and with Competitive Advantage”, *ASME 2000 DETC’00*, Baltimore, MD, DETC2000/DAC-14234, 2000.

Luenberger, D.G., *Investement Science*, Oxford University Press, Oxford, UK, 1997

Marston, M. and F. Mistree, “An Implementation of Expected Utility Theory in Decision Based Design”, *ASME 1998 DETC’98*, Atlanta, GA, DETC1998/DTM-5670, 1998.

McConville, G.P., and H.E. Cook, “Estimating the Value Trade-Off Between Automobile Performance and Fuel Economy,” *SAE Intern. Congress*, Detroit, MI, SAE Paper 960004, 1996.

Michelena, N.F., Papalambros, P.Y., Park, H.A., and D. Kulkarni, “Hierarchical overlapping coordination for large-scale optimization by decomposition,”*AIAA Journal*, 37:890–896, July 1999.

Michelena, N., Park, H., and P.Y. Papalambros, ”Convergence Properties of Analytical Target Cascading,” *Proc. of 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, AIAA-2002-5506, Atlanta, GA, September 4-6, 2002.

Papalambros, P.Y., (2002a), guest editor, “Special issue on commercial (design optimization) software,” *Structural and Multidisciplinary Optimization*, 23(2), March 2002.

Papalambros, P.Y., (2002b),“The optimization paradigm in engineering design: promises and challenges,” *Computer-Aided Design*, 2002, to appear.

Papalambros, P.Y., and D.J. Wilde, *Principles of Optimal Design: Modeling and Computation*, Cambridge University Press, New York, 2000.

Schmidt, W.H., and J.P. Finnegan, *The Race Without a Finish Line: America’s Quest for Total Quality*, Jossey-Bass Press, San Francisco, 1992.

Trigeorgis L., *Real Options, Managerial Flexibility and Strategy in Resource Allocation*, MIT Press, Cambridge, MA, 1998.

Wipke K. and M. Cuddy, *Using an Advanced Vehicle Simulator (ADVISOR) to Guide Hybrid Vehicle Propulsion System Development*, NREL, S/EV96, 1996.