A SOCIAL AND ENTERPRISE PERSPECTIVE TO DESIGN OPTIMIZATION

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ABSTRACT

Design optimization has largely remained an engineering endeavor. Yet many product decisions are made based on business criteria derived from economic, investment, and marketing considerations. These decisions are presented to the engineers who must then optimize the design within the given criteria and constraints. We propose the hypothesis that in a significant number of situations engineering optimization can be integrated with the social and business environment where decisions are made and thus reach substantially better decisions for the designing enterprise and society. Since the foundation of this work is decision models, a key challenge remains the construction of models of proper fidelity for the integrated enterprise-wide decisions. Engineers who are willing to invest in such modeling knowledge are likely to have strong positive impact on the technological decisions made by enterprises and society.

1. INTRODUCTION

Design optimization in engineering is a mature field, extensively used in all major technology sectors, including aerospace, automotive, electronics, marine, and construction. An optimization problem can be written in a canonical form (here in the so-called negative null form) as follows

$$\begin{align*}
\min f(x) \\
\text{subject to:} \\
h(x) &= 0 \\
g(x) &\leq 0,
\end{align*}$$

where $f$ is the objective function to be minimized, $h$ and $g$ are vectors representing the functions in the equality and inequality constraints, respectively, and $x$ is the vector of variables that we have to find values for in order to solve the problem of Eq. (1). In product design the objective is a criterion of product performance that should be optimized, the constraints are design requirements that must be satisfied, and the variables are the design quantities that we have the ability to assign values to, as we seek the best design [Papalambros and Wilde 2000].

Product development in the high technology sectors is often dominated by the complexity of the technology, and so engineering design optimization is a significant contributor to the decision making process associated with product development and launch. In the consumer goods sector, engineering design is often secondary to production cost considerations, marketing, and distribution. In countries with advanced economies consumer goods are increasingly imported from countries with more favorable economics of production, at least from the viewpoint of the enterprises that market the imported goods under their own brand. Although the design of these products was initially handed to the foreign producer for “built to print” operations, the actual engineering design is now increasingly performed in the producing country. There is much controversy, political and otherwise, about the latter situation, in both the producing and the consuming countries, particularly as the classification of high technology and consumer goods becomes increasingly blurred. Indeed, there is little room for design optimization of consumer products, except as it might pertain to marketing and investment decisions.

It would seem that product optimization would be dominated by engineering design optimization for complex, high technology products, and by financial/marketing optimization for consumer goods, something that the engineers typically leave to the “planning” groups within the producing enterprise. However, in both cases this dominance in decision making often evolves into isolation during product development that leads to inferior products from both the user and producer perspectives. Even in the case of complex products, the design optimization performed by the engineers is based on design targets given to them by management; how well can these targets be achieved is often not fully understood until the later stages of product development, and can be a source of costly delays or reduced product quality.
Moreover, design decisions impact users in the aggregate, as represented by society that may include also non-users. The interests of society at large are in principle represented by the government, which through legislative policy can have significant impact on the design decisions made by the producers. Interestingly, government intervention is usually seeing as design constraints imposed through regulations and codes. However, government regulation can be viewed as part of the objective function in the design optimization problem, driving decisions towards both social and enterprise goals.

This article puts forth the view that the design of any artifact should be approached in a holistic manner, where all decisions regarding a produced artifact are in essence design decisions from diverse perspectives. In particular, this holistic decision making is not just a general philosophical principle, which many have advocated over the past decades, but it can be approached quantitatively using the design optimization framework. Such quantification requires (i) appropriate mathematical models that represent each perspective and (ii) a model framework for coordinating the interactions among these perspectives. In the article we review recent efforts in addressing these two issues, discussing them in general terms and providing references for more comprehensive descriptions.

2. QUANTITATIVE PRODUCT DESIGN

A framework for analytical product design based on an optimization model is shown in Figure 1. The main block contains the activities by the producing organization, in general one of many such organizations that may compete in a given market. Blocks in grey represent analysis activities that use mathematical models (or simulations) to compute responses for given inputs. A producer must operate in an environment that includes competitors and possible government regulations. Decisions made by these entities interact with the decisions made by the producer.

Each producer \( k \) decides on a set \( J_k \) of designs to produce; decisions include engineering entities, prices, and production volumes for each design. Each product may have several design topologies \( M_j \) and associated design variables \( x \), which determine product characteristics \( z \), calculated using an engineering analysis model. Design variables, production volume \( v \), and regulation penalties \( c^k \) also determine producer cost \( c_k \) calculated by the cost analysis model. Competitor designs \( J-J_k \) are assumed static for simplicity, and consumers make purchasing choices among all designs \( J \) (producer and competitor products) based on product characteristics and prices \( p \). The purchasing choices that the consumers make determine demand for each design \( q \), calculated by the demand model, and resulting profits \( \Pi \) are calculated in terms of \( p \), \( q \), and \( c \). The optimization model represents each producer's attempt to maximize profit by making the best design, pricing, and production decisions. Consumers are assumed to purchase products that maximize their benefit (utility) based on each individual’s preferences, and this must be represented in the demand analysis model. Government regulation may affect cost and thus influence the design by contributing to the objective function. Regulations may also provide constraints directly into the engineering model (not shown in the figure).

![Figure 1. A framework for analytical product design](image-url)
produce less volume than there is demand for (instead, the price can be increased), and so \( v_j = q_j \).

The producer profit model is then

\[
\max \Pi_x = \left( \sum q_j p_j \right) - c_x
\]

(2)

with respect to \( \{M_j, x_j, p_j \} \forall j \in J \),

subject to engineering constraints

3. PRODUCT DEMAND MODELS

The need for integration between marketing and engineering decisions is well documented, as is the need to overcome the obstacles to disciplinary differences that actually exist in practice, see Table 1 [Krishnan and Ulrich 2001, Michalek et al. 2003].

Optimal product planning in marketing involves selection of price and product characteristic values that maximize profit (or market share). Following Eq. (2) we have

\[
\Pi = q (p - c_y) - c_x
\]

(3)

where \( q \) is the quantity of the product produced and sold (product demand), \( p \) is the selling price, \( c_y \) is the variable cost per product, and \( c_x \) is the investment cost. The price \( p \) is treated as a decision made by the firm, and discrete choice analysis and conjoint analysis are used to model and predict demand \( q \) as a function of \( z \) and \( p \).

<table>
<thead>
<tr>
<th>Perspective on Product</th>
<th>Marketing</th>
<th>Engineering Design</th>
</tr>
</thead>
<tbody>
<tr>
<td>A product is a bundle of attributes</td>
<td>A product is a complex assembly of interacting components</td>
<td></td>
</tr>
<tr>
<td>“Fit with market”, market share, consumer utility, profit</td>
<td>“Form and function”, technical performance, innovativeness, cost</td>
<td></td>
</tr>
<tr>
<td>Customer utility as a function of product attributes</td>
<td>Geometric models, parametric models of technical performance</td>
<td></td>
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<tr>
<td>Product attribute levels, price</td>
<td>Product size, shape, configuration, function, dimensions</td>
<td></td>
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<tr>
<td>Product positioning and pricing, collecting and meeting customer needs</td>
<td>Creative concept and configuration, performance optimization</td>
<td></td>
</tr>
</tbody>
</table>

Table 1 Comparison of marketing and engineering design perspectives (Michalek et al. 2003)

In discrete choice analysis a decision-maker is presumed to derive utility from each alternative in a set of possible alternatives, to an extent partially predictable in terms of observed covariates. In marketing applications, these covariates are typically product characteristics, whose values can be used to obtain an overall "attraction" for each alternative, where attraction refers to the observable, deterministic component of utility. Because we cannot predict consumer utility perfectly, these attraction values must be combined with an error process to determine choice probabilities for each alternative. Formally, there are \( J \) product alternatives numbered 1 through \( J \) with attraction values \( \{v_1, v_2, \ldots, v_J\} \) and associated errors \( \{\xi_1, \xi_2, \ldots, \xi_J\} \) plus an "outside good," indexed as alternative 0, with error \( \xi_0 \) and attraction value \( v_0 \) normalized to zero. The probability that we observe a choice of alternative \( j \) is therefore:

\[
P_j = \Pr \left[ v_j + \xi_j \geq v_j' + \xi_j', \forall j' \neq j \right]
\]

(4)

If errors are normally distributed, then \( P_j \) follows the multinomial probit model, which has no closed-form expressions. If errors are assumed to be Gumbel-distributed then \( P_j \) follows the closed-form multinomial logit model (MNL) with \( v_0 = 0 \).

\[
P_j = \frac{e^{v_j}}{1 + \sum_{i=1}^{J} e^{v_i}}
\]

(5)

Invoking a known market potential, \( s \), the demand \( q_i \) is related to choice probabilities as:

\[
q_i = s P_i = s \frac{e^{v_i}}{1 + \sum_{j=1}^{J} e^{v_j}}
\]

(6)

Mapping product characteristic values \( z \) onto attraction values \( v \) is an important area of research in marketing. Among several methods, conjoint analysis is a widely used one. Using survey tools, respondent choices are treated as dependent variables in the MNL model, with binary attribute "level" (value) indicators \( Z \) for each alternative used as covariates. Specifically, if we have \( K \) characteristics and the \( k \)-th has \( L_k \) levels, the attraction for alternative \( j \) is:

\[
v_j = \alpha + \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{kl} Z_{jkl}
\]

(7)

where \( Z_{jkl} \) is a binary variable and the binary "part-worths" \( \beta_{kl} \) are obtained through regression.
deterministic component of utility can be written as a function of the continuous variable product characteristics values \( z \) and price \( p \) using a spline function \( \Psi_\beta \) of the part-worths \( \beta \).

\[
v_j = \Psi_\beta \left( z_j, p \right)
\]

(8)

4. TARGET CASCADING

The analytical target cascading process (ATC) can be used to link engineering and planning decisions (Kim 2001, Michelena et al. 2003), Figure 2. In the product planning subproblem, the price \( p \) and product characteristic targets \( z_M \) are chosen to maximize profit, subject to the constraint that the targets \( z_M \) cannot deviate from the characteristics \( z_E \) achieved by engineering by more than a tolerance \( \varepsilon \), and \( \varepsilon \) is minimized. In the engineering design subproblem, design variables \( x \) are chosen to minimize the deviation between characteristics achieved by the design \( z_e \) and targets set by marketing \( z_M \). The weighting coefficient vector \( w \) is added to weight each term of the \( z \) vector, where \( \circ \) indicates term-by-term multiplication. Appropriate weights allow user-specified tolerances for inconsistency between the design values for \( z \) derived from the marketing and engineering models.

5. CONCLUSION

The goal of linking traditionally separate areas of product development can be accomplished using a design optimization framework that includes models from engineering, finance and marketing. Analytical target cascading is particularly suitable in this linking because it maintains the relative independence of the disciplines. Demand models that match design requirements can be built using analytical methods from applied psychology. Social policy can be included through studying the effects of government regulation. The ideas here are based on the papers by Michalek et al [2003, 2004]. Developing design-oriented models for financial considerations can be found in Georgiopoulos [2003].

REFERENCES


