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AN OPTIMAL MARKETING AND ENGINEERING DESIGN MODEL FOR PRODUCT DEVELOPMENT USING ANALYTICAL TARGET CASCADING

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ABSTRACT

Marketing and engineering design decisions are typically treated as separate tasks both in the academic literature and in industrial practice, and their interdisciplinary interactions are not well-defined. In this article, analytical target cascading (ATC), a hierarchical optimization methodology, is used to frame a formal optimization model that links marketing and engineering design decision-making models by defining and coordinating interactions between the two. For complex products, engineering constraints typically restrict the ability to achieve some desirable combinations of product characteristic targets, and the ATC process acts to guide marketing in setting achievable targets while designing feasible products that meet those targets. The model is demonstrated with a case study on the design of household scales.

KEYWORDS

Analytical target cascading, marketing, optimal product planning, design optimization, discrete choice models, logit, conjoint analysis

1. INTRODUCTION

Marketing and engineering contributions to product development are typically treated separately both in industry and in the academic literature. Research on product development decision-making in the marketing community has historically differed from research in the engineering design community in scope, perspective, product representation, and metrics of performance and success. An overview of these differences is provided in Table 1, excerpted from a comprehensive literature review of product development decision research by Krishnan and Ulrich (2001). Separating these disciplines helps in the organization and management of information but can also cause communication difficulties and disjoint decision-making resulting in inferior product decisions. Krishnan and Ulrich note this as a weakness, particularly for complex or technology-driven products. However, the two communities do

	Marketing	**Engineering Design**
Perspective on Product	A product is a bundle of attributes	A product is a complex assembly of interacting components
Typical Performance Metrics	"Fit with market", market share, consumer utility, profit	"Form and function", technical performance, innovativeness, cost
Dominant Representa-tional Paradigm	Customer utility as a function of product attributes	Geometric models, parametric models of technical performance
Example Decision Variables	Product attribute levels, price	Product size, shape, configuration, function, dimensions
Critical Success Factors	Product positioning and pricing, collecting and meeting customer needs	Creative concept and configuration, performance optimization

Table 1 Comparison of Marketing and Engineering Design Perspectives

have different foci and areas of expertise, and attempting to integrate them completely may be disadvantageous. This article offers a method to formally link decisions by the two communities while maintaining their disciplinary identity; the resulting model employs the formalism of Analytical Target Cascading (ATC) (Kim, 2001). An expanded version of this paper (Michalek et al., 2004) provides further depth from a marketing perspective and demonstrates that coordinating marketing and engineering decision models using ATC results in solutions superior to those obtained through disjoint decision-making.

1.1. Marketing Product Planning Models

Kaul and Rao (1995) provide an integrative review of product positioning and design models in the marketing literature. They differentiate between product positioning models, which involve decisions about abstract perceptual attributes, and product design models, which involve choosing optimal levels for a set of physical, measurable product characteristics. In this article we work only with measurable product characteristics; however, a comprehensive framework similar to the one proposed by Kaul and Rao could be used to include perceptual attributes, product positioning, and consumer heterogeneity. In this article, conjoint-based "product design" models from the marketing literature will be referred to as *product planning models*.

Optimal product planning in the marketing literature is typically posed as selection of optimal price and product characteristic levels that achieve maximum profit or market share. For complex products, where engineering constraints may prevent some combinations of product characteristic levels from being technically attainable, it is difficult to define explicitly which combinations of characteristics are feasible. For such products, planning decisions made without engineering input may yield inferior or infeasible solutions.

1.2. Engineering Product Design Models

The engineering design optimization literature focuses on methods for choosing values of design variables that maximize product performance objectives. Papalambros and Wilde (2000) provide an introduction to engineering design optimization modeling techniques, strategies and examples. When multiple conflicting optimization objectives exist, the solution is a Pareto set of optimal products, and the choice of a single product from that set requires explicit expression of preferences among objectives. Such preferences are notoriously difficult to define in practice. Some methods use interactive, iterative searches to elicit preferences, relying on intuition in navigating the Pareto surface and choosing an appropriate design (Diaz, 1987). Recent efforts in the design literature take the approach of resolving tradeoffs among technical objectives by proposing models of the producer's financial objective (Hazelrigg, 1988; Li and Azarm, 2000; Gupta and Samuel, 2001; Wassenaar and Chen, 2001). Gu et al. (2002) build on this work using the collaborative optimization framework to coordinate decision models in the engineering and business disciplines. Here we propose a related methodology, but we coordinate product planning and engineering design models using the ATC methodology, which has proven convergence characteristics for arbitrarily large hierarchies (Michelena et al., 2002; Michalek and Papalambros, 2004), and we draw upon techniques from the marketing literature to develop explicit mathematical models of demand based on data.

2. METHODOLOGY

Using the ATC framework, discussed in detail below, the joint product development problem is decomposed formally into a product planning subproblem and an engineering design subproblem. The product planning subproblem involves choosing the desired target product characteristics and price that will maximize the producer's expected profit, where profit depends on demand. The engineering design subproblem involves choosing a feasible design that will achieve the target product characteristics as closely as possible. Using the ATC process, the two subproblems are solved iteratively until a consistent optimal product design is achieved.

2.1. Analytical Target Cascading

Analytical target cascading is an optimization methodology for systems design that works by decomposing a complex system into a hierarchy of interrelated subsystems (Kim 2001). ATC requires a mathematical model for each subsystem that computes the subsystem response as a function of the decisions at that subsystem. The subsystem models are organized into elements of a hierarchy, as in the example shown in Figure 1, where the top level represents the overall system and each lower level

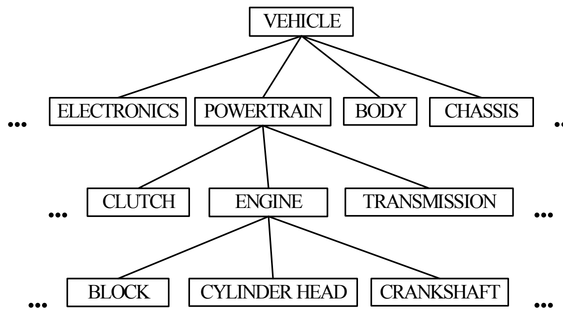

Figure 1 Example ATC hierarchy for a vehicle design

represents a subsystem of its parent element. Papalambros (2001) provides an overview of the ATC literature, and Michalek and Papalambros (2004) provide details of the generalized ATC formulation.

In the ATC process, top-level system design targets are propagated down to subsystems, which are then optimized to match the targets as closely as possible. The resulting responses are then rebalanced at higher levels by iteratively adjusting targets and designs throughout the hierarchy to achieve consistency. Michelena et al. (2002) and Michalek and Papalambros (2004) proved under assumptions of convexity that by using certain classes of coordination strategies to coordinate elements in the ATC hierarchy, the ATC formulation will converge, within a user-specified tolerance, to the same solution as if all variables in the entire system were optimized simultaneously (or, "all-at-once"). Using ATC can be advantageous because it organizes and separates models and information by focus or discipline, providing communication only where necessary. Some problems that are computationally difficult or impossible to solve all-at-once can be solved using ATC, and in some cases ATC can result in improved computational efficiency because the formulation of each individual element typically has fewer degrees of freedom and fewer constraints than the all-at-once formulation.

In the formulation and example presented in this article, there are only two elements: the marketing product planning subproblem *M* and the engineering design subproblem *E*, which is the child of *M*. However, for complex systems ATC allows the flexibility to model the engineering subproblem as a hierarchy of subsystems and components rather than with a single element. For examples of complex systems engineering design using ATC, see Kim et al. (2002), and Kim et al. (2003).

2.2. The Marketing Product Planning Subproblem

In the product planning subproblem, a simple model of profit Π is calculated as revenue minus cost, such that

$$\Pi = q\left(p - c_V\right) - c_I \tag{1}$$

where q is the quantity of the product produced and sold (product demand), p is the selling price, c_V is the variable cost per product, and c_I is the investment cost. This model is simplified and ignores such finance-related concerns as the time value of money, fixed costs, risk and uncertainty; however, this simple model will suffice to demonstrate broad trends and provide insight into the general forces at work. The price p is treated as a decision made by the firm, and for simplification in this article c_V and c_I are considered constant across all possible product designs. Product demand q depends on the price p and characteristics $\mathbf{z}$ of the product, and discrete choice analysis and conjoint analysis are used to model and predict q as a function of $\mathbf{z}$ and p. It is assumed in this article that the producer is a monopolist; however, game theory could be used to model oligopoly competition following Michalek, Skerlos and Papalambros (2003).

Discrete Choice Analysis

A set of statistical methods largely unfamiliar to engineering audiences has been developed, first in logistics and urban planning and then in economics, to predict choices made in uncertain environments (Louviere et al., 2000; Train, 2003). The chief theoretical edifice is that of *random utility models*. In such models, 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 (or household-specific) 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 in turn be combined with an error term in order to determine choice probabilities for each alternative (and the probability that none of the alternatives is chosen, often called the "outside good").

Formally, there is a set J of 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 ξ_0 and attraction value v_0 normalized to zero ($v_0 = 0$). The probability P_j that we observe a choice of alternative j is the probability that alternative j has the highest utility:

$$P_j = \Pr\left[v_j + \xi_j \geq v_{j'} + \xi_{j'}, \forall j' \in \mathrm{J} \right] \tag{2}$$

Computational efficiency depends critically on the distribution assumed for the ξ random error terms in Eq.(2). Errors can take several forms, and it generally requires extremely large samples for assumptions about distributional error to have any substantive impact; consequently, researchers often work with error specifications allowing the most tractability. For example, if errors are assumed to be normally distributed, then the form of P_j is called the *multinomial probit model*, which does not admit of closed-form expressions for choice probabilities in terms of underlying attractions. However, if ξ terms are assumed to be Type II extreme-value (or Gumbel) distributed (i.e., $\Pr[\xi < x] = \exp[-\exp(-x)]$), then it can be shown that

$$P_j = \frac{e^{v_j}}{1 + \sum_{j' \in \mathrm{J}} e^{v_{j'}}} \tag{3}$$

when the utility of the outside good v_0 is normalized to zero (see Train 2003 chapter 3 for proof). This form is called the *multinomial logit model* (MNL). The MNL model allows a convenient closed-form solution for choice probabilities P_j that is especially attractive in terms of optimization. Using (3), choice probabilities for any subset of products can be calculated easily. Even if all products are offered by a single entity (i.e., a monopolist), the presence of the outside good ensures that demand for a set of unattractive products will be low, with probability of not choosing a product given by:

$$P_j = \frac{1}{1 + \sum_{j' \in \mathrm{J}} e^{v_{j'}}} \tag{4}$$

It is assumed that v can be measured as a function of observable quantities such as product characteristics, price, consumer characteristics, etc. In this paper we consider only product characteristics and price. Any number of rules for mapping price p and product characteristic values $\mathbf{z}$ onto attraction values v are possible. In practice, product characteristics and price are discretized, and the mapping is assumed a linear function of discrete price and product characteristic *levels*. The attraction v_j for product j is then written as

$$v_j = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{kl} Z_{jkl}\,, \tag{5}$$

where Z_{jkl} is a binary dummy variable such that $Z_{jkl} = 1$ indicates alternative j possesses characteristic/price k at level l, and β_{kl} is the "part-worth" coefficient of characteristic/price k at level l. Here price p is discretized and included in Z as the last term (k=K). One advantage of using discrete levels is that it does not presume linearity with respect to the continuous variables. For example, we cannot assume that a \$5 price increase has the same effect for a \$10 product as it does for a \$25 product.

Given a set of observed choice data, values can be found for the β parameters such that the likelihood of the model predicting the observed data is maximized. A great deal of research in marketing is devoted to recovering model parameters through latent classes, finite mixtures or using Hierarchical Bayes methods (Andrews, Ainslie, and Currim, 2002); however, here we simply use the standard maximum likelihood formulation. The log of the sample likelihood for a particular individual on a particular choice occasion n is:

$$\sum_{j \in \mathrm{J}_n} \Phi_n(j) \ln \left[\frac{\exp\left(\sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{kl} Z_{jkl} \right)}{1 + \sum_{j' \in \mathrm{J}_n} \exp\left(\sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{kl} Z_{j'kl} \right)} \right] \tag{6}$$

where $\Phi_n(j) = 1$ if the observed choice on choice occasion n is alternative j and $\Phi_n(j) = 0$ otherwise. Here J_n is the set of alternatives on choice occasion n. Eq.(6) is maximized with respect to the β terms after summing across all individuals and choice occasions. In this way, the part-worths β_{kl} are obtained for each level l of each attribute k.

In all random utility models, such as the logit used here, one must careful about *model identification*: for example, adding a constant term to all attraction values shifts them upward to the same extent and does not change choice probabilities predicted by the logit model. Thus, in using Eq.(5), there are an infinite number of solutions for optimal beta values that predict equivalent choice probabilities and therefore have identical likelihood values. Standard practice is to impose an *identification constraint* on the system of coefficients, which unambiguously chooses just one among all possible 'optimal' solutions. Such constraints typically set a linear combination of the coefficients to zero. For clarity, we select from the infinity of equivalent solutions the one solution where the mean beta value $\Sigma_l \beta_{kl}/L_k$ is the same for all k. By adding this constraint, the model has $1 + \Sigma_k(L_k - 1)$ degrees of freedom, and the solution is uniquely defined.

The part-worths retrieved with maximum likelihood estimation correspond to discrete values of the product characteristics and price. For example, we may have a certain part-worth for a price of $10 and another for a price of $15. To optimize over continuous values of price (as well as characteristics simultaneously), it is necessary to estimate utility for intermediate values, such as $12. There are several possible methods allowing interpolation between these discrete part-worth values for each characteristic and price, ordinarily a type of spline function. We avoid linear splines due to their indifferentiability at knots (the estimated values) and instead use higher-order polynomial splines, either quadratic or cubic, depending on which provides a closer fit. Finally, the attraction can be written as a function of the continuous variable product characteristics values **z** and price p using a spline function Ψ_k of the part-worths β_{kl} for each characteristic/price k. If price is represented as k=K, the attraction v is written as

$$v_j = \Psi(\mathbf{z}, p) = \sum_{k=1}^{K-1} \Psi_k\left(\left\langle \mathbf{z}_j \right\rangle_k\right) + \Psi_K(p), \quad (7)$$

where the angle bracket notation $<\mathbf{z}_j>_k$ denotes the k^{th} element of the vector $\mathbf{z}_j$. The model specification is completed by invoking a known market potential s so that demand q_j is related to choice probabilities as

$$q_j = sP_j = s\frac{e^{v_j}}{1 + \sum_{j' \in \mathrm{J}} e^{v_{j'}}}. \quad (8)$$

Market potentials can be given exogenously at the outset or estimated through a variety of techniques based on historical data or test markets (Lilien, Kotler and Moorthy, 1992).

Conjoint Analysis

Maximum likelihood estimation can be used to fit beta parameters to any set of observed choice data; however, collinearities in the characteristics and price of the choice sets can make accurate parameter estimation difficult and can cause problems generalizing to new choice sets (Louviere et al., 2000). Conjoint analysis (CA) has been widely used to develop efficient, orthogonal and balanced survey designs (experimental designs) to determine which product characteristics are important to consumers, and appropriate levels for each characteristic. There is vast literature on conjoint analysis and appropriate experimental designs, and we direct the reader to any of the classic or recent articles, notably Louviere’s (1988) expository article and Kuhfeld’s (2003) exhaustive account.

Conjoint studies present subjects with a series of products or product descriptions, which they evaluate. Products can be presented in various ways, but characteristic levels are always made clear, either in list form, pictorially, or both. Subjects can indicate their preferences among products by ranking (i.e., putting in an ordered list), rating (for example, on a 1-10 scale) or choosing their favorite from a set. Each method has certain advantages; however, choice-based conjoint is considered most natural, since this is what real consumers do. Consequently, we follow that approach here, offering successive sets of products and asking which is most preferred in each, or whether none is acceptable (the “no choice” option). To avoid the combinatorial explosion required if all possible pairings of attribute values are used, an efficient design is generated. Efficient designs specially tailored to conjoint studies are supported in a number of software packages, such as Sawtooth, SPSS and SAS. In our case study (discussed later), with six attributes of 5 levels each, there are 5^6 = 15,625 possible products, yet a highly efficient conjoint design requires only 50 choice sets of size of 3.

2.3. The Engineering Design Subproblem

In the engineering subproblem, design characteristics $\mathbf{z}$ are calculated as a function of the design variables $\mathbf{x}$ using the response function $\mathbf{r}(\mathbf{x})$, where $\mathbf{x}$ is constrained to feasible values by constraint functions $\mathbf{g}(\mathbf{x})$ and $\mathbf{h}(\mathbf{x})$. General procedures for developing response functions $\mathbf{r}(\mathbf{x})$, and constraint functions $\mathbf{g}(\mathbf{x})$, and $\mathbf{h}(\mathbf{x})$ to define a design space are well established in the design optimization literature (Papalambros and Wilde, 2000); however, modeling specifics are entirely product dependent. The objective function of the engineering subproblem is to minimize deviation between the product characteristics achieved by the design $\mathbf{z}_E$ and the targets set by marketing $\mathbf{z}_M$. Using ATC notation introduced in Michalek and Papalambros (2004), this objective function is written as

$$\left\| \mathbf{w} \circ \left(\mathbf{z}_M - \mathbf{z}_E \right) \right\|_2^2, \tag{9}$$

where $\| \, \|_2^2$ denotes the square of the l_2 norm, $\mathbf{w}$ is a weighting coefficient vector, and $\circ$ indicates term-by-term multiplication. For complex products, engineering constraints typically restrict the ability to meet some combinations of product characteristic targets, and the ATC process acts to guide marketing in setting achievable targets while designing feasible products that meet those targets.

2.4. Complete ATC Formulation

Figure 2 shows the complete ATC formulation of the product development problem for a single-product-producing monopolist (there is only one product, so the index j is dropped for simplicity). In the product planning subproblem, price p and product characteristic targets $\mathbf{z}_M$ are chosen to maximize profit Π, where Π is calculated as revenue minus cost as in Eq.(1), and demand q is calculated using the logit model in Eq. (8) and Eq.(7), subject to the constraint that the targets $\mathbf{z}_M$ cannot deviate from the characteristics achieved by engineering $\mathbf{z}_E$ by more than ε, and ε is minimized. In the engineering design subproblem, design variables $\mathbf{x}$ are chosen to minimize the deviation between characteristics achieved by the design $\mathbf{z}_E$ and targets set by marketing $\mathbf{z}_M$ subject to engineering constraints $\mathbf{g}(\mathbf{x})$ and $\mathbf{h}(\mathbf{x})$. These two subproblems are solved iteratively until the system converges. The weighting update method (Michalek and Papalambros, 2004) is used to find weighting coefficient values $\mathbf{w}$ that

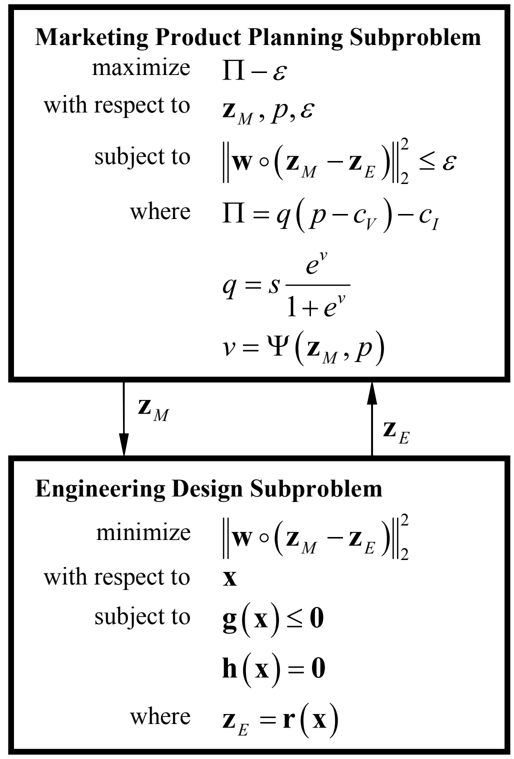

Figure 2 ATC Formulation of the Product Planning and Engineering Design Product Development Problem

produce a solution satisfying user-specified tolerances for inconsistency between marketing and engineering for each term in $\mathbf{z}$. This method is important for cases where the top level subproblem does not have an attainable target.

3. CASE STUDY

The demonstration case study involves dial-readout household scales. This particular durable consumer product was chosen because scales have high penetration, are not highly differentiated, are inexpensive, and have clearly identifiable components and consumer benefits.

3.1. Marketing Product Planning Subproblem

Five product characteristics were adopted because of their design relevance and the ability to define metrics to measure them. These factors, shown in Table 2, are also advertised or visible in online scale e-commerce. Other factors, such as brand name and warranty, were not included in the study in order to focus on factors affected by the design of the

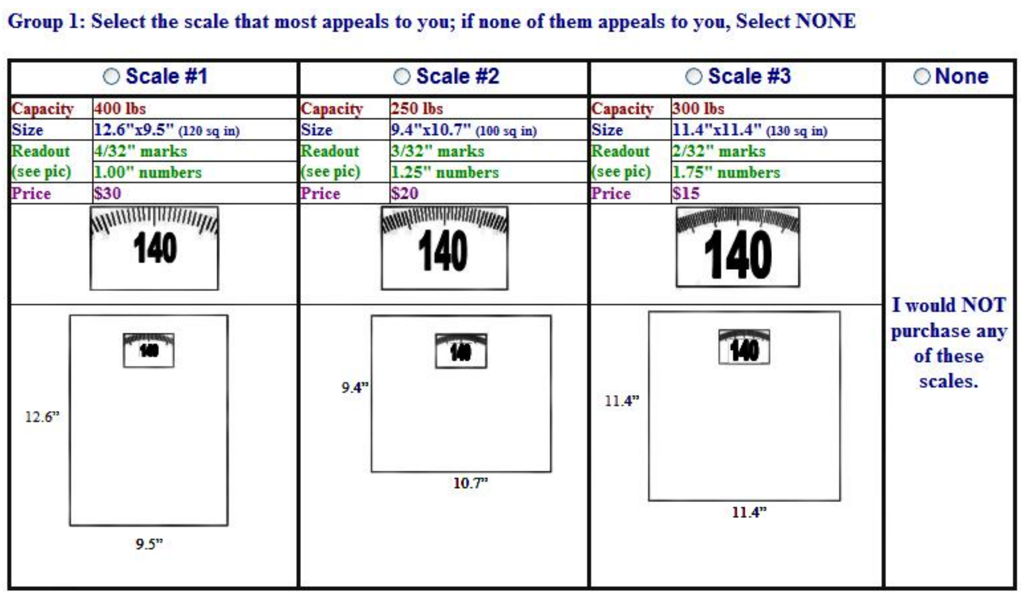

Figure 3 Screen shot of the online scale conjoint survey

product. Factors that are difficult to measure or difficult for consumers to assess before use, such as "easy to clean," were ignored.

An efficient choice-based conjoint analysis survey was used to collect data on consumer preferences. The survey was implemented online to simulate aspects of online purchase decision-making. The survey can be found at http://www.umich.edu/~lstojan, and a screen capture is provided in Figure 3. The survey includes fifty questions, each of which asks the respondent to choose among three scales or select the "no choice" option. The scales are described by numerical values, a drawing, and a close-up of the dial. The survey includes some scales with physically infeasible characteristic combinations because responses to these questions serve to infer trade-offs in consumer preferences. Five levels were chosen for each product characteristic in the conjoint analysis as shown in Table 2. The levels were chosen to span the range of values of products in the market, based on a sample of 32 different scales sold on the internet, to ensure realism and to capture anticipated trade-offs.

Data were collected from 184 respondents, who were solicited from online newsgroups and from engineering and marketing students at the University of Michigan. Respondent data from the survey was used to estimate the model's β parameters using Eq.(6) summed over all respondents and all survey questions and a modified Newton-Raphson search algorithm (Greene, 2003). The resulting β values are provided in Table 2. Six cubic splines Ψ_k were fit to these β values (one for each characteristic and one for price), and the logit model was used to calculate demand q for the monopolist using Eq.(7) and Eq.(7).

Based on discussions with a scale manufacturer, a variable cost c_V of \$3 per unit and an investment cost c_I of \$1 million was assumed for this example. The

Weight Capacity (z_1)		**Interval Mark Gap** (z_4)	
200 lbs.	-0.534	2/32 in.	-0.366
250 lbs.	0.129	3/32 in.	-0.164
300 lbs.	0.228	4/32 in.	0.215
350 lbs.	0.104	5/32 in.	0.194
400 lbs.	0.052	6/32 in.	0.100
Platform Aspect Ratio (z_2)		**Size of Number** (z_5)	
0.75	-0.058	0.75 in.	-0.744
0.88	0.253	1.00 in.	-0.198
1.00	0.278	1.25 in.	0.235
1.14	-0.025	1.50 in.	0.291
1.33	-0.467	1.75 in.	0.396
Platform Area (z_3)		**Price** (p)	
100 in.^{2}	0.015	\$10	0.719
110 in.^{2}	-0.098	\$15	0.482
120 in.^{2}	0.049	\$20	0.054
130 in.^{2}	0.047	\$25	-0.368
140 in.^{2}	-0.033	\$30	-0.908

Table 2 Logit coefficient part-worth β values

market size s was assumed to be five million people, the approximate yearly market for dial scales in the United States.

3.2. Engineering Design Subproblem

The engineering design model was developed through reverse engineering: three scales were disassembled, and the components and functionality were studied, as shown in Figure 4. We chose to restrict our focus to dial-readout scales to keep the demonstration simple; however, the model could be expanded to include digital scales.

The model of the dial-readout scale is based on the topology of scales found in the market: levers *A* provide mechanical advantage and transfer the force of the user's weight from the cover *B* onto a coil spring *C* which resists displacement proportionally to the applied force. Another lever *D* is used to transfer the vertical motion of the spring to the horizontal motion of a gear rack *E*. The pinion gear *F* translates linear motion of the rack to rotational motion of the dial *G*. This basic topology is common among the products observed, but dimensions vary, and the ratio of dial-turn per applied force depends on the dimensions of the levers, the rack and pinion, and the spring properties. This design topology was parameterized and modeled using fourteen design variables, eight feasibility constraints, and five response functions that calculate product characteristics as a function of the design variables.

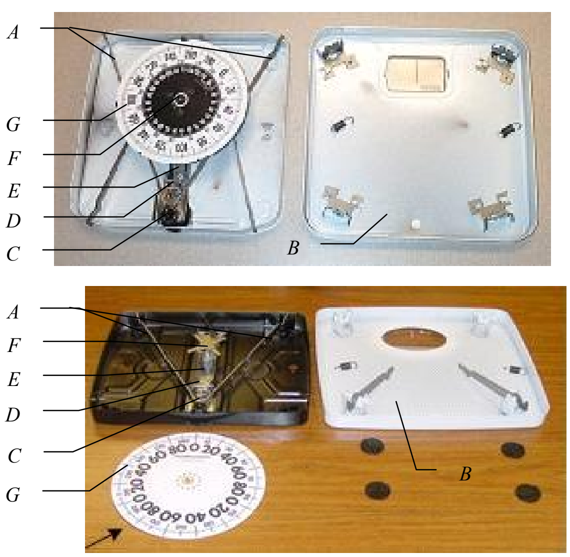

Figure 4 Disassembled dial readout scale

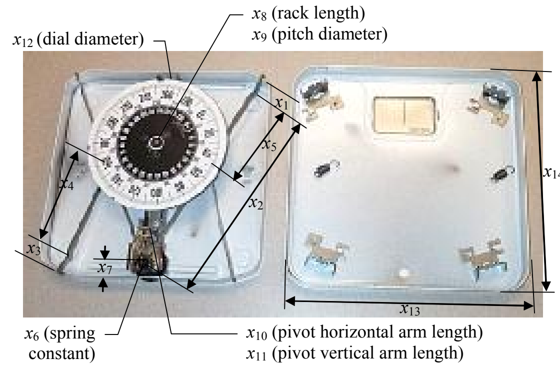

Figure 5 Design variables for the scale

Figure 5 shows the design variables used for the scale. Other dimensions were considered fixed parameters, and the dial number size and tick mark gap were calculated based on scale dimensions. The response and constraint functions were derived using geometric and mechanical relationships. We omit these derivations here for brevity and focus; however, the entire engineering model is provided in the Appendix.

3.3. Results

The engineering design and marketing subproblems were solved iteratively until convergence. At the solution, shown in Table 3, the optimal scale design is bounded by active engineering constraints that ensure the dial, the spring plate, and the levers are small enough to fit inside the scale. None of the variable bounds were active at the solution, and the optimal scale characteristics are within the range of scales found in the online market. This design represents the joint optimal solution obtained through coordinated communication between marketing and engineering models, and it is superior to the solution obtained by considering disjoint marketing and engineering decision models sequentially, as discussed in an expanded version of this paper (Michalek et al., 2004).

Mkt. Variables		Engineering Design Variables			
p	$26.41	x_1	0.71 in.	x_8	5.00 in.
z_1	254 lbs.	x_2	11.10 in.	x_9	0.31 in.
z_2	0.997	x_3	0.72 in.	x_{10}	0.52 in.
z_3	134 in^2	x_4	4.46 in.	x_{11}	1.59 in.
z_4	0.116 in.	x_5	4.20 in.	x_{12}	9.36 in.
z_5	1.33 in.	x_6	23.41 lb./in.	x_{13}	11.56 in.
		x_7	0.50 in.	x_{14}	11.60 in.

Table 3 Optimal scale design

4. CONCLUSIONS

This article presented and demonstrated a methodology for defining a formal link between marketing product planning and engineering design decision-making. The ATC framework is especially suitable in allowing disciplinary separation while retaining rigorous linking and coordination.

For the marketing community, this method will help in working with complex products where some combinations of desired characteristics are technologically impractical or physically impossible. The infeasible set is typically a function of the technical decisions of the product and is difficult to express as a function of the target characteristic levels without exhaustive enumeration. Using this method allows constraints to be derived in terms of design decisions and then linked through the model to product characteristics.

For the engineering design community, this method will help to put design decisions into the larger context of the firm and its objectives. This context can help to resolve tradeoffs among competing performance objectives in multiobjective optimization by providing information about the relative importance of each engineering objective in the context of explicit models of demand and the producer's objectives.

This article focused on the basic elements of the links between marketing and engineering design. The methodology can be extended in several ways. Models of demand heterogeneity can be introduced to design product lines. Multiple product topologies can be included for product variety, and design topologies could potentially be generated automatically (Campbell, Kotovsky and Cagan, 1998). Cost models can be integrated to the engineering subproblem such that the marketing product planning subproblem sets target production cost and the engineering design subproblem designs products that meet the cost targets. In addition, models of product families can be used to study commonality effects on product cost structure (Fellini, Kokkolaras and Papalambros, 2003), and manufacturing investment decisions, particularly considering reconfigurable and flexible equipment (Koren *et. al.*, 1999), can be included in the model. Finally, if the conjoint analysis survey can be designed optimally to avoid questions about infeasible product characteristic combinations, then the expense of the survey can be reduced and the accuracy improved.

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NOMENCLATURE

$\circ$	Term-by-term vector multiplication
c_I	Investment cost
c_V	Variable cost per product
$\mathbf{g}$	Vector function of inequality constraints
$\mathbf{h}$	Vector function of equality constraints
j	Product index
J	Number of product alternatives
k	Product characteristic index
l	Product characteristic level index
n	Choice occasion number
p	Selling price
P_j	Probability of choosing alternative j
q	Product demand
$\mathbf{r}$	Vector response function that calculates product characteristics
s	Size of the entire market
v	Deterministic component of utility
$\mathbf{w}$	Vector of weighting coefficients
$\mathbf{x}$	Vector of design variables
$\mathbf{z}_E$	Vector of product characteristics achieved by engineering
$\mathbf{z}_M$	Vector of product characteristic targets set by marketing
Z	Binary characteristic level indicator variable
β	Part-worth coefficient
ε	ATC deviation tolerance variable
Π	Profit
Ψ_k	Spline function to interpolate part-worths for characteristic/price k
Φ	Binary function indicating observed choice
ξ	Random (error) component of utility

Marketing Model

Maximize profit with respect to price and product characteristic targets

Objective Function

Name	Description	Value	Units	Scaled	Formula
f	Maximize profit while minimizing deviation from engineering design	-67900986	-	-6.790	$f=-\Pi+\varepsilon$
Π	Profit	$67,990,263	$		$\Pi=q(p-c_V)-c_I$
ε	Weighted deviation	89,277	-		$\varepsilon=\left\Vert \mathbf{w}\circ(\mathbf{z}_M-\mathbf{z}_E)\right\Vert_2^2$

Decision Variables : $\mathbf{z}_M, p$

Name	Description		Units	Scaled	Min	Max
$z1$	Weight Capacity	255	lbs	0.273	200	400
$z2$	Platform aspect ratio	0.996	-	0.422	0.75	1.333
$z3$	Platform Area	134.0	in^2	0.851	100	140
$z4$	Size of gap between 1-lb interval marks	0.1159	in	0.427	0.063	0.1875
$z5$	Size of number (length)	1.334	in	0.584	0.75	1.75
p	Price	$26.41	$	0.820	10	30

Eng. Design : $\mathbf{z}_E$

Value	Dev.	% Dev	Weight
254	-0.4	-0.183%	1.0E+05
0.997	0.001	0.089%	1.0E+05
134.0	0.0	0.045%	1.0E+05
0.1156	-0.0003	-0.211%	1.0E+05
1.334	0.000	-0.036%	1.0E+05

Intermediate Calculations

Name	Description	Value	Units		Formula
vp	Interpolated part worth of price	-0.507	-		
$v1$	Interpolated part worth of capacity	0.162	-		
$v2$	Interpolated part worth of aspect ratio	0.282	-		
$v3$	Interpolated part worth of area	0.017	-		
$v4$	Interpolated part worth of gap	0.127	-		
$v5$	Interpolated part worth of number size	0.281	-		
v	Total deterministic component of utility	0.362	-		$\Psi_\beta(\mathbf{z},p)$
S	Market Share	58.95%	-		$S=\frac{e^v}{1+e^v}$
q	Demand	2,947,574	units		$q=s\frac{e^v}{1+e^v}$

Parameters

Name	Description	Value	Units
s	Size of market	5,000,000	-
cV	Variable cost per unit	$3.00	$
cI	Investment cost	$1,000,000	$
$u0$	Utility of the outside good	0	-

Engineering Model

Minimize deviation from target product characteristic values

Objective Function

Name	Description	Value	Scaled	Formula	Last
f	Minimize normalized squared target deviation	8.9E+04	8.9E-06	$f = \left\| \mathbf{w} \circ (\mathbf{z}_M - \mathbf{z}_E) \right\|_2^2$	9.E+04

Product Characteristics : $z_E(x,y)$

Name	Description	Value	Units	Formula	Min	Max
z1	Weight Capacity	254	lbs	$z_1 = \dfrac{4\pi x_6 x_9 x_{10}(x_1+x_2)(x_3+x_4)}{x_{11}\left(x_1(x_3+x_4)+x_3(x_1+x_5)\right)}$	200	400
z2	Platform aspect ratio	0.997	-	$z_2 = \dfrac{x_{14}}{x_{15}}$	0.75	1.333
z3	Platform Area	134.0	in^2	$z_3 = x_{14}x_{15}$	100	140
z4	Size of gap between 1-lb interval marks	0.1156	in	$z_4 = \pi \dfrac{x_{12}}{z_1}$	0.063	0.188
z5	Size of number (length)	1.334	in	$z_5 = \dfrac{\left(2\tan\left(\frac{\pi y_{11}}{z_1}\right)\right)\left(\frac{x_{12}}{2} - y_{10}\right)}{\left(1+\frac{2}{y_{12}}\tan\left(\frac{\pi y_{11}}{z_1}\right)\right)}$	0.75	1.75

Targets : z_M

Target	% Dev	Weight
255	-0.183%	1.0E+05
0.996	0.089%	1.0E+05
134.0	0.045%	1.0E+05
0.1159	-0.211%	1.0E+05
1.334	-0.036%	1.0E+05

Design Variables (x)

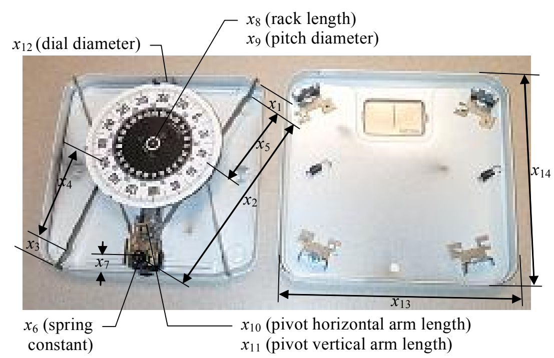
Name	Description	Value	Units	Ref. Values (from rev. eng.)	Min	Max
x1	Length from base to force on long lever	0.71	in	0.63	0.125	36
x2	Length from force to spring on long lever	11.10	in	9.25	0.125	36
x3	Length from base to force on short lever	0.72	in	0.63	0.125	24
x4	Length from force to joint on short lever	4.46	in	4.50	0.125	24
x5	Length from force to joint on long lever	4.20	in	4.19	0.125	36
x6	Spring constant	23.41	lb/in	23.44	1	200
x7	Distance from base edge to spring	0.50	in	0.50	0.5	12
x8	Length of rack	5.00	in	5.00	1	36
x9	Pitch diameter of pinion	0.31	in	0.25	0.25	24
x10	Length of pivot's horizontal arm	0.52	in	0.50	0.5	1.9
x11	Length of pivot's vertical arm	1.59	in	1.00	0.5	1.9
x12	Dial diameter	9.36	in	5.75	1	36
x13	Cover length	11.56	in	10.00	1	36
x14	Cover width	11.60	in	10.25	1	36

Constraints (g(x,y),h(x,y))

Name	Description	Value	Units	Formula
g1	Rack length must be sufficient to span between pivot and center of dial	-1.97	in	$x_8 \ge (x_{14} - 2y_1) - \left(\frac{x_{12}}{2} + y_7\right) - x_7 - y_9 - x_{10}$
g2	Long lever must attach to top of scale, so length of lever is limited by scale width (Pythagorean)	0.00	in	$(x_1+x_2)^2 \le (x_{14} - 2y_1 - x_7)^2 + \left(\frac{x_{15} - 2y_1}{2}\right)^2$
g3	Rack shorter than base when pivot is rotated 90 deg	-2.76	in	$x_7 + y_9 + x_{11} + x_8 \le x_{14} - 2y_1$
g4	Length of short lever has to be less than base length	-2.30	in	$(x_4 + x_5) \le x_{14} - 2y_1$
g5	Lever joint occurs at a position on the long lever, must not be larger than the length	-7.62	in	$x_5 \le x_1 + x_2$
g6	Dial diameter must be less than base width	-1.64	in	$x_{12} \le x_{15} - 2y_1$
g7	Dial diameter must be less than base length minus spring and plate	0.00	in	$x_{12} \le x_{14} - 2y_1 - x_7 - y_9$
g8	Long lever must be a minimum distance y13 away from centerline at base connection	-14.23	in	$(x_{14} - 2y_1 - x_7)^2 + y_{13}^2 \le (x_1 + x_2)^2$

Parameters (y)

Name	Description	Value	Units
y1	Gap between base and cover	0.30	in
y2	Minimum distance between spring and base	0.50	in
y3	Internal thickness of scale	1.90	in
y4	Minimum pinion pitch diameter	0.25	in
y5	Length of window	3.00	in
y6	Width of window	2.00	in
y7	Distance btwn top of cover and window	1.13	in
y8	Number of lbs measured per tick mark	1.00	lbs
y9	Horizontal distance between spring and pivot	1.10	in
y10	Length of tick mark + gap to number	0.31	in
y11	Number of lbs that number length spans	16.00	lbs
y12	Aspect ratio of number (length/width)	1.29	-
y13	Min. allowable dist. of lever at base to centerline	4.00	in



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