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Linking Marketing and Engineering Product Design Decisions via Analytical Target Cascading*

Jeremy J. Michalek, Fred M. Feinberg, and Panos Y. Papalambros

Firms design products that appeal to consumers and are feasible to produce. The resulting marketing and engineering design goals are driven by consumer preferences and engineering capabilities, two issues that conveniently are addressed in isolation from one another. This convenient isolation, however, typically will not result in optimal product decisions when the two problems are interrelated. A method new to the marketing community, analytical target cascading (ATC), is adopted here to explore such interrelationships and to formalize the process of coordinating marketing and engineering design problems in a way that is proven to yield the joint optimal solution. The ATC model is built atop well-established marketing methodologies, such as conjoint, discrete choice modeling and demand forecasting. The method is demonstrated in the design of dial-readout household scales, using real conjoint choice data and a parametric engineering product design model. Results indicate that the most profitable achievable product can fall short of predictions based on marketing alone but well ahead of what engineering may produce based on original marketing target specifications. A number of extensions can be accomplished readily using techniques from the extant marketing and design optimization literature.

Introduction

Product development, as a costly and time-consuming prelude to the introduction of new products, has been the object of intense study by practitioners and academics in both marketing and engineering design. The academic literature proposes a number of models to help guide product planners in assessing consumer needs or "value systems," as well as to capitalize on synergies in the production process itself. As such, the entire process typically is broken down into a number of stages that, for parsimoniousness and reasons of disciplinary boundaries, are addressed separately in product optimization. For example, in marketing one may ask—given a set of known characteristics and levels and, presumably, an expedient method for delivering them in one product at an attractive price point—which combination would most appeal to consumers or which combination would be most profitable. Engineering design faces the converse problem of delivering an optimal, feasible product given a set of desired performance targets, features, and costs. That is, each discipline works under constraints and guidelines set by the other.

In marketing conjoint studies, for example, product characteristic *levels* are chosen to be in line with engineering guidelines and so, in a sense, are

Address correspondence to: Fred M. Feinberg, University of Michigan Business School, 701 Tappan St., Ann Arbor, MI 48109. Email: feinf@umich.edu.

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conditional upon them.[1] If engineering cannot deliver a specific product characteristic or some particular value of it, consumers are not asked for their reactions to it. So, what we learn about consumer preferences, and thereby about the set of products produced, is contingent on knowing in advance which targets are technically infeasible or unrealistic. Similarly, engineering design models aim to maximize or to achieve target levels of performance characteristics, subject to physical and production constraints, without knowing if consumers would want and would pay for them.

A turnkey system formalizing product optimization through coordinated communication between established marketing and engineering design models has not emerged for a number of reasons. First and foremost are reasons of historical development and disciplinary boundaries: research on product development in marketing long has differed from that in engineering design in terms of product representation and choice of performance and success metrics (Krishnan and Ulrich, 2001). For example, in marketing a product often is modeled as a "bundle of attributes" (e.g., McAlister, 1982) over which consumers have preferences represented by utilities, so that firms can manipulate the former to maximize the latter. In engineering design, by contrast, products may be described as complex assemblies of interacting components for which parametric models are built to represent design decisions such as shape, size, and configuration, which then are manipulated to maximize performance objectives. Measurements of "success" also differ between the two disciplines, with marketing assessing degree of market fit, consumer satisfaction, overall share, and ultimately profit and with engineering design concerning technical performance, innovativeness, and cost effectiveness. The two disciplines even point to different critical success factors external to the design process itself: marketers stress the importance of positioning, advertising messages, choosing the right price tier, and understanding "consumer needs" using data, while engineers generally use intuition when dealing with customer needs, emphasizing the creativeness and functionality of the product concept and working toward technical objectives such as reliability, durability, environmental impact, energy use, heat generation, manufacturability, and cost reduction, among others. In short, the two communities do not disagree so much on the product development process as have different languages and notions of drivers of success.

Second, marketing and engineering design models differ in terms of domains and control variables, and so their corresponding models of the product development process do not speak easily to one another. For example, in marketing, a chief goal simply is figuring out what consumers want, addressed through such methods as focus groups, test markets, surveys, and measurement models like conjoint. Consumer

BIOGRAPHICAL SKETCHES

Jeremy J. Michalek is doctoral candidate in the Department of Mechanical Engineering at the University of Michigan. He received his B.S. in mechanical engineering at Carnegie Mellon (1999), where he researched shape grammars for product design, and his M.S. in mechanical engineering at the University of Michigan (2001), where he developed interactive optimization methods for architectural layout. His current research focuses on the design of product lines for user populations with heterogeneous preferences, and he has developed models to study engineering design decision-making as it relates to economics and public policy. He also pursues sustainability and social justice as the education chair for Engineers Without Borders. He is a graduate student instructor mentor, a Michigan Teaching Fellow, and a Rackham Interdisciplinary Fellow.

Dr. Fred M. Feinberg is Mary Kay and Michael R. Hallman Fellow and associate professor at the University of Michigan Business School. He received degrees in mathematics and philosophy from MIT (1983), did graduate work in mathematics at Cornell, and completed his Ph.D. at the MIT Sloan School of Management (1989), where he worked in applications of dynamic programming and stochastic modeling. His current research focuses primarily on modeling sequential; discrete choices under uncertainty, particularly so applied to problems in brand choice, endogeneity; and the estimation of nonlinear response, typically from a Bayesian perspective. He is on the editorial boards of *Marketing Science, Marketing Letters*, and *ROMS* and is senior editor for marketing at *Production and Operations Management*.

Dr. Panos Y. Papalambros is Donald C. Graham Professor of Engineering and professor of mechanical engineering at the University of Michigan. He attended Stanford University and earned his M.S. (1976) and Ph.D. (1979) in mechanical engineering. At Michigan since 1979, he served as department chair and was the founding director of several laboratories and centers: the Design Laboratory, the Ford Durability Simulation Center, the Automotive Research Center, and the first General Motors Collaborative Research Laboratory worldwide (1998–2002). His research interests include design methods and systems design optimization, with applications to product design and development, automotive systems, and architecture. He established the Optimal Design Laboratory in 1980. With D. J. Wilde, he coauthored the textbook *Principles of Optimal Design: Modeling and Computation*, has published over 150 articles, and has served on numerous editorial boards. A fellow of ASME and SAE, he is the recipient of the ASME Design Automation Award (1998) and the Machine Design Award (1999).

[1] In the marketing literature, particularly in conjoint measurement, it is common to refer to product characteristics as *attributes*. Here we retain Kaul and Rao's (1995) distinction between product attributes—abstract, perceived aspects—and product characteristics, which are physical, measurable aspects. We use the term *characteristics* consistently.

preferences are taken as primitives, and one optimizes over levels of product characteristics, looking for "sweet spots" in the product characteristic space. Engineering design, by contrast, seeks to meet specific performance goals, conditional on existing production processes and the realities of physics and geometry. In short, both optimization variables and the nature of constraints are very different. Formal models attempting to combine them therefore would have to span an unusually broad domain.

Among the main problems identified by Krishnan and Ulrich (2001) is effective communication between marketing and engineering design. Even with full information and broadly validated modeling frameworks, miscommunication can lead to suboptimal product designs, a problem particularly pronounced for high-technology products where the marketing and engineering design domains are separated widely. Such claims have broad antecedents in prior empirical and theoretical research. Gupta et al. (1986) studied the interface between marketing and research and development (R&D) in American hi-tech firms and found that other factors (besides standard market uncertainty and firm strategy explanations) exert strong effects, most notably organizational design and "sociocultural" differences between marketing managers and their R&D counterparts. This hardly is confined to U.S. firms: Song and Parry (1992) confirmed these findings for over 200 analogous firms in Japan, while also cataloguing subtle points of difference between the two nations' development cultures. Souder (1988), in analyzing a vast database of product development projects, found a variety of consistent problem types between marketing and R&D managers and thus formulated a model to improve integration between the two. Griffin and Hauser (1992) further considered the multiple interfaces among marketing, engineering, and manufacturing, comparing the effects of quality function deployment (QFD) to more traditional project development approaches. They consistently underscored the critical role and nature of information flow and how QFD uniquely allows enhanced "horizontal" flow through the development team.

In this article, a new approach is presented to link marketing and engineering product design decision-making formally. In doing so, it is not the intent of this article to merge the two but to make use of their respective strengths and to capitalize on models that are especially well suited to joint optimization. From marketing, methods are adopted from discrete choice analysis, as applied to efficient conjoint designs; both have deep theoretical roots and have been validated in hundreds of disparate empirical studies throughout the world (Cattin and Wittink, 1982; Wittink and Cattin, 1989; Wittink et al., 1994). From engineering design, a recent set of methods is adopted joined under the formalism of *Analytical Target Cascading* (Kim, 2001), a hierarchical methodology for optimizing complex systems by coordinating solutions to decomposed subsystems. The present article shows how these preexisting methods can work seamlessly in tandem to converge on optimal product designs, avoiding the time-consuming, error-prone, and costly iterations that often characterize complex product development processes.

Several key ideas pervade this study's approach. The first is a departure from assumptions made in certain marketing models, which often hold that design problems are primarily ones of capital: with sufficient funds, any desired combination of product characteristics can be achieved. Although marketers are aware that, strictly speaking, some such combinations are quite difficult to attain (Urban and Hauser, 1993) it is fairly common in conjoint studies, for example, to allow product characteristics to be paired according to the needs of the experimenter (e.g., Haaijer, 1999). Such a premise is enacted less commonly by engineers, who deal more directly with feasibility constraints: designs that cannot exist under present technology or that are physically impossible with any technology. The methodology presented is particularly suited to support the study of complex durables where feasibility constraints prohibit some combinations of characteristics from being achievable at any cost. This article considers such constraints in an empirical application, where some product characteristic combinations literally are impossible to achieve—not just difficult or costly.

The second idea is the often-underestimated complexity of interrelations among engineering constraints, even for simple artifacts such as the bathroom scale studied later in this article. When this complexity is mapped further onto the product characteristics space, simple strategies, like restricting product characteristic levels to feasible combinations in a conjoint study, have little value and will not lead to optimal solutions. The simple case study of this article is an empirical demonstration of such a situation and illustrates the need for caution when studying design domains of higher complexity.

The final idea is the key role of iteration: marketing and engineering design decisions must be updated iteratively, preserving the individuality of each discipline but converging to the optimum for the product and not for the discipline. If marketing sets targets without iterative interaction with engineering design, results can be substantially inferior when compared to an iterative convergent approach, such as the proposed analytical target cascading (ATC) method. This is especially intriguing, given that the ATC marketing model used to measure consumer preferences still can call upon the wealth of methods developed for conjoint measurement, methods that offer optimal product designs from a marketing viewpoint—so long as they are checked against their technical realization.

In the next sections a short review of the relevant literature in marketing and engineering design is provided; analytical target cascading is introduced as a formal linking mechanism between marketing and engineering design; and its use on a simple durable product—a bathroom scale—is demonstrated.

Marketing and Engineering in Product Design

This article reviews extant approaches in the core disciplines of marketing and engineering design with an eye toward how they might be yoked together for the purposes of optimal product planning.

Marketing Product Planning Models

Kaul and Rao (1995) provided an integrative review of product positioning and design models in the marketing literature. They differentiated 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. This article works only with measurable product characteristics; however, a comprehensive framework similar to the one proposed by Kaul and Rao (1995) could be used to include perceptual attributes, product positioning, and consumer heterogeneity. In this article, conjoint-based product design models from a marketing perspective will be referred to as *product planning models*.

Optimal product planning in the marketing literature typically is 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. Even if these combinations can be defined and can be eliminated from a conjoint study, the optimal solution using the conjoint data still may contain infeasible combinations of product characteristics. For such products, planning decisions made without engineering input may yield inferior solutions.

Engineering 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) provided 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 trade-offs among technical objectives by proposing models of the producer's financial objective (Georgiopoulos, 2003; Georgiopoulos et al., 2004; Gupta and Samuel, 2001; Hazelrigg, 1988; Li and Azarm, 2000; Wassenaar and Chen, 2003). Gu et al. (2002) build on this work using the collaborative optimization framework to coordinate decision models in the engineering and business disciplines. This article proposes a related methodology, but product planning and engineering design models are coordinated using the ATC methodology, which has proven convergence characteristics for arbitrarily large hierarchies (Michelena et al., 2003; Michalek and Papalambros, 2004a), and techniques from the marketing literature are drawn upon to develop explicit mathematical models of demand based on data.

Prior Approaches to Integrating Engineering into the Marketing Product Design Literature

Over the last decade, the marketing literature increasingly has turned to questions of integration with engineering design and production, usually noting the difficulty of doing so. Early discussions of problems integrating information from various sources in the product development process include Griffin (1997) and Wind and Mahajan (1997). Griffin (1997) was among the first to highlight the use of cross-functional teams to shorten—and purportedly to optimize—the product development process, a process especially lengthy for innovative and for highly complex products. Wind and Mahajan (1997) went so far as to issue a warning about the "inadequacy" of modeling techniques in marketing to encompass the entire new product development (NPD) process, particularly as design incorporates information from multiple sources. Certain externalities can come into play as well; for example, Moorman and Slotegraaf (1999) highlighted how information in the external environment can stimulate firms to deploy their technology and marketing capabilities so as to influence the level and speed of relevant product development activities. They concluded that the most valuable characteristic of firm capabilities may be their ability to serve as "flexible strategic options." How they might accomplish this, in practical terms, is still largely an open question.

Part of the "integration problem" is certainly one of terminology and conceptualization. Garcia and Calantone (2002), for example, detailed the often contradictory ways in which notions of innovation are used in the NPD literature, particularly in marketing and engineering design. They emphasized the importance of maintaining both marketing and technological perspectives when discussing innovations and the relative lack of empirical work directed toward "really new" innovations and offer a set of measures to help classify innovations across the domains of practitioners and academics.

Researchers in marketing often have pointed to engineering design and production as the key contributors to product success or failure. Sethi et al. (2001) stressed that multiple studies have found that the primary determinant of new product success is innovativeness: the extent to which a new product provides meaningfully unique benefits rather than the ability to satisfy preexisting wants of the type uncovered in a typical conjoint study. Srinivasan et al. (1997), in addressing the concept selection stage of a new product development process, emphasized the importance of utilizing both product characteristic-based customer preference and product cost models, and they offered empirical evidence for the need to push beyond such models to more complete "customer-ready" prototypes. Halman et al. (2003) additionally considered the advantages of a platform-based approach to product development, showing how economies of scale enhance both marketing and physical production. Although they are interested primarily in product lines (as opposed to individual products), they underscored the paucity of literature linking marketing with engineering practice in product management.

Hauser (2001), by contrast, emphasized the sheer complexity of the development process, in terms of coordination of resources and agents with multiple criteria for success (for example, speed to market, customer satisfaction, and product quality). He applied agency theory to formulate a set of metrics and a weighting method to help firms balance and optimize such complex development processes, with variables spanning concerns from both marketing and engineering design. This article's goal is similar—the desire here is to coordinate models of the two camps and to create an explicit method for joint optimization across them.

A great majority of research on new product success has focused on product characteristics and the product development process, rather than interactive and ancillary factors. In their study of product launch support, Hultink et al. (2000) examined data on many hundreds of product introductions and identified divergent product success criteria for what they distinguish as "consumer goods" and "industrial goods." For example, the former seem to benefit from strategies that defend market positions, while the latter benefit from those that leverage technological innovations to penetrate new markets. Furthermore, the optimal marketing "mix"—the relative emphasis on consumer-oriented variables like promotion, display and advertising, and more nuts-and-bolts technological dimensions—differs systematically between the two product types, so it is unsurprising to see them receiving different degrees of emphasis in the marketing and engineering design communities. However, Kahn (2002) found that marketing assumes primary responsibility for making market forecasts across both types of goods, with a considerably shorter horizon for "consumer goods."

Pullman et al. (2002) presented one of the few studies on the relative effectiveness of marketing-based and engineering-based approaches to optimal product design; specifically, they considered conjoint analysis (a marketing-based method, and one used in the present study) and QFD (a more engineering-oriented approach). They found that the two approaches converged on many of the most important features but that the engineering approach was better able to highlight those characteristics that had both positive and negative aspects. Further, and in the present authors' view most importantly, they found that the marketing approach better identified *current* consumer preferences, while the engineering approach better identified *core* consumer needs. A major conclusion of their study is that the two approaches should be pursued in tandem. Still, no formal system combining them presently is available to the design community. While the present article does not directly address tools such as QFD, which offer help to designers in the absence of mathematical product models, it does present a formal methodology to coordinate results of conjoint analysis with product models when such models can be called upon.

Finally, Leenders and Wierenga (2002) offered a major review of extant approaches to the interplay and integration of marketing and engineering design with a particular emphasis on relative effectiveness. They found that one of the most effective methods simply is locating marketing and product development team members closer together to facilitate the interchange of information and, presumably, to encourage a form of joint optimization. They cautioned, however, that while encouraging this sort of information exchange indeed does enhance new product performance, it nevertheless carries substantial costs, mainly in the great deal of complexity intrinsic in formalizing such relationships. Although it does not address industrial design (aesthetics) or manufacturing (physical production) formally, the present study serves to initiate development of the very formalization between marketing and engineering design that prior authors have underscored as problematic.

Although the NPD literature is too vast to summarize here competently, other authors have done so in articles devoted to the subject. Brown and Eisenhardt (1995), in a broadly integrative survey, presented a snapshot of the burgeoning product development literature, distinguishing three major themes: development as rational planning, as a web of communication, and as "disciplined" problem-solving. Based on these broad distinctions, they fashion a model of critical success factors in product development, paying unusual attention to the distinct roles of various actors—senior management, project leaders, suppliers, purchasers—and the vital interplay afforded by communication among them at various stages of the development process. Meta-analyses of the product performance literature are provided by Montoya-Weiss and Calantone (1994) and by Henard and Szymanski (2001); both synthesized decades of prior research in the area with an eye toward generalizations, though the former did report a large number of points of divergence, despite commonalities in methodological approach in the surveyed literatures. Henard and Szymanski (2001) focused specifically on the key determinants of relative product success. Of two dozen such factors identified by prior authors, they found that the most broadly critical ones include product advantage, market potential, the ability to match customer needs, and preexisting firm proficiencies. Interestingly, the role of communication between various firm entities is largely that of mediator, in that many of the critical success factors can be affected directly by it.

For our purposes, among the key conclusion of all these prior lines of research is this: fostering effective, ongoing communication between marketing and engineering design (among other entities) is a critical factor in the eventual success of a product development project. The methodology presented next is suited uniquely to accomplishing exactly that goal in a rigorous, mathematical design system.

Methodology

This article introduces a joint system for product development that calls upon methodologies from both engineering design and marketing. It is anticipated that the marketing audience will be familiar with the "marketing-related" methods, namely conjoint analysis and discrete choice modeling; however, descriptions and references to these methodologies are provided for the engineering community later in this section. Conversely, ATC, despite a good deal of recent application in the engineering design community, is all but unknown to the marketing community. As such, this article serves the expository purpose of placing ATC in context, explaining what it does, and presenting it formally with an eye toward encouraging the marketing community to apply it and to integrate more closely with engineering design. Many of these ideas are placed directly in an engineering design optimization context by Michalek et al. (2004a), who similarly encouraged the engineering design community toward greater integration.

Marketing Product Planning Subproblem

maximize	**Profit**, and
minimize	**Deviation** from engineering design
with respect to	Price and product characteristic targets,
where	Profit depends on price, demand, and cost, and Demand is predicted using discrete choice analysis and conjoint data.

Product characteristic targets ↓ ↑ Engineering design responses

Engineering Design Subproblem

minimize	**Deviation** from product characteristic targets set by marketing
with respect to	Design decisions
subject to	Engineering constraints
where	Product characteristics depend on the design decisions.

Figure 1. ATC Formulation of the Product Planning and Engineering Design Product Development Subproblems

The ATC framework, which is discussed in detail later in this section, allows a joint planning and engineering design problem to be decomposed formally into a (marketing) product planning subproblem and an engineering design subproblem. Each of these separately has been the object of intense study, and among the felicities of ATC is the ability to call on methods for optimizing each of these subproblems in order to attack the much more difficult joint problem and to prove that obtained solutions are identical. The product planning subproblem is well known to marketers, as it involves choosing product characteristics and price (e.g., as warranted by a conjoint or similar model) that will maximize some firm-level objective function. Here, a simple model of expected firm profit is used, contingent on an estimated discrete choice model, such as logit or probit. The ATC formalism allows flexibility in this regard, and profit is just one among any number of possible firm-level objectives. The engineering design subproblem is quite different and involves choosing a *feasible* design that achieves known target product characteristics as closely as possible.

Using ATC, the subproblems are solved iteratively until the joint system converges upon a consistent optimal product design. Michelena et al. (2003) and Michalek and Papalambros (2004a) showed that ATC converges, within user-defined tolerances, to the solution of the joint system for a wide class of problems, variable types, and for any number of subsystems in a hierarchy. Although the model is presented formally later, the main ideas are depicted in Figure 1.

The marketing product planning subproblem requires that profit be maximized with respect to product characteristics and price but also stipulates minimal deviation from an achievable engineering design; it is in this last requirement that the formulation differs from the one typical in marketing applications. The engineering design subproblem is in some sense the dual: it sets design decisions to minimize deviations from the product characteristics requested by marketers but must respect engineering constraints, which often are exogenous in the sense of being dictated by, for example, geometry and physics. The two problems ''speak'' to one another in a very natural sense. In real organizations, it is typical for one group, either marketing or engineering design, to deliver an initial set of specifications, which the other attempts to meet, thus starting off an actual iterative process between the two. This article uses models to perform iterations and to reach a desirable, feasible, and consistent solution. It does not address potential savings in reducing the ''physical'' iteration between groups of people, but it is believed that these will be considerable if the models required for ATC are available.

Next, ATC is considered in greater detail, with specific attention paid to its interrelations with prior and potential future research in marketing.

Analytical Target Cascading

At its core, analytical target cascading is a methodology for systems optimization. It works by viewing a complex system as a decomposable hierarchy of interrelated subsystems, each of which can be analyzed and optimized separately and then coordinated (Kim, 2001). In order to apply ATC, one must have a mathematical model for each of the subsystems—which in general can be numerous, although this article refers to only one engineering design subsystem—so that one can compute subsystem response as a function of decisions made for that subsystem. Given the various mathematical models for the subsystems, the modeler organizes them into a *hierarchy*, as in the computer example shown in Figure 2; note that the top level represents the overall system and that each lower level represents a subsystem of its parent element. The process would be similar for even small durables, although the number of subsystems and their potential interactions would be smaller. For example, in the

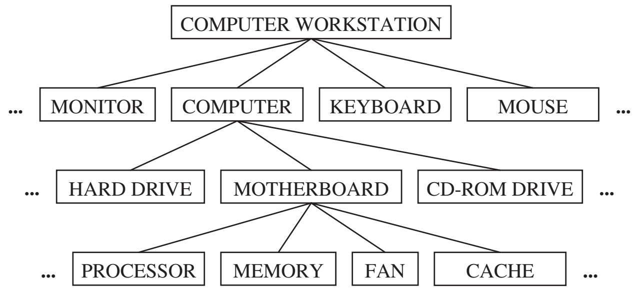

Figure 2. Hypothetical ATC Hierarchy for a Computer Workstation

dial-readout scales studied here, the hierarchy consists only of one marketing subsystem (parent) and one engineering design subsystem (child); however, in general both the marketing and engineering models could consist of a hierarchy of any number of submodels. Papalambros (2001) provided an overview of the ATC literature, and Michalek and Papalambros (2004b) provided details of the generalized ATC formulation. ATC has been applied to automotive systems (Kim et al., 2002, 2003a, 2003b) including the design of product families (Kokkolaras et al., 2002), as well as to design of building systems (Choudhary et al., 2003).

In the ATC process, top-level system design targets are propagated down to subsystems, which then are optimized to match the targets as closely as possible. The resulting responses are rebalanced at higher levels by iteratively adjusting targets and designs throughout the hierarchy to achieve consistency, the latter process called a coordination strategy. Michelena et al. (2003) proved that, using certain classes of coordination strategies, the ATC formulation will converge to the same solution as the undecomposed (or "all-at-once") problem, within a user-specified tolerance (Michalek and Papalambros, 2004a).

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.

As mentioned earlier, the formulation and example presented in this article contains a hierarchy of only two elements: the marketing product planning subproblem M and the engineering design subproblem E, which is the child (sublevel) of M. However, for complex systems ATC allows the flexibility to model the engineering design subproblem as a hierarchy of subsystems and components rather than with a single element. It is possible to conceive of a formulation where marketing tasks are also modeled as a hierarchy such that the product planning subsystem interacts with engineering design while other subsystems represent other aspects of the marketing mix such as promotion, packaging, pricing, and positioning.

In the following subsections, the engineering design model and product planning model used in this article are described in detail. Table 1 provides an overview of the notation.

ATC Engineering Design Subproblem

In the engineering design subproblem, design characteristics $\mathbf{z}$ are calculated as functions of the design variables $\mathbf{x}$ using the response functions $\mathbf{r(x)}$, where the variables $\mathbf{x}$ are constrained to feasible values by constraint functions $\mathbf{g(x)}$ and $\mathbf{h(x)}$. General procedures for defining design variables $\mathbf{x}$, response functions $\mathbf{r(x)}$, and constraint functions $\mathbf{g(x)}$, and $\mathbf{h(x)}$ to define a product design space are well

Table 1. Summary of Notation Used for Formal ATC Setup

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

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 (2004b), this objective function is written as

$$\|\mathbf{w} \circ (\mathbf{z}_M - \mathbf{z}_E)\|_2^2, \tag{1}$$

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, such that $[a_1\, a_2 \ldots a_n] \circ [b_1\, b_2 \ldots b_n] = [ab_1\, ab_2 \ldots ab_n]$. 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.

ATC Marketing Product Planning Subproblem

In the marketing planning subproblem, a fairly simple model of profit, Π, is adopted, which in the standard way is taken to be revenue minus cost, or

$$\Pi = q(p - c_V) - c_I. \tag{2}$$

Here, 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. It would be possible to augment this model further in any number of ways popular in the extant literature—for example, a discount function to capture the time value of money, a separate term to account for fixed costs or salvage value, or a concave loss-like function for risk and uncertainty. Nevertheless, Eq. (2) captures the main forces at work and can be modified readily. Among the firm's decision variables are pricing and product characteristics. For simplicity here the variable and investment costs c_V and c_I are considered constant across all possible product designs; however, they also could be written as functions of the engineering design decisions. Note that overall demand q depends on price p as well as on product characteristics $\mathbf{z}$.

To establish a plausible demand function q as a function of the decision variables $\mathbf{z}$ and p a straightforward version of choice-based conjoint using the standard logit model is called upon; see, for example, Louviere and Woodworth (1983) for an early application of a similar model. Only the design of a single product is considered here, and so the types of heterogeneity corrections allowed by more recent latent class and hierarchical Bayes approaches are less relevant here than they would be in the case of a product *line*, thus simplifying implementation considerably. Andrews et al. (2002b) provided a full discussion of these issues specifically in the context of conjoint. Finally, demand is formulated with the producer operating as a monopolist or at least in a market where the firm's decision variables do not result in predictable systematic variation in the actions of other firms (i.e., in a so-called "zero conjectural variations" setting). It is possible to adopt a game theoretic setting to account for potential oligopoly, and a version of such a setup applied in a similar production-based context can be found in Michalek et al. (2004b).

Demand model. A vast body of work in discrete choice analysis has enabled the modeling of choices made in uncertain environments (Train, 2003). As is typical in marketing applications, this article turns to a random utility formulation to link observed covariates—here, price and product characteristics—to observed individual-level choices. Formally, there is a set $\mathcal{J}$ of product alternatives numbered 1, 2, ..., J with deterministic components $\{v_1, v_2, \ldots, v_J\}$ and associated errors $\{\xi_1, \xi_2, \ldots, \xi_J\}$. To account for the possibility of no alternative being acceptable, there is also 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 a choice of alternative j is observed is equal to the probability that alternative j has the highest utility:

$$P_j = \Pr\left[v_j + \xi_j \geq v_{j'} + \xi_{j'}, \forall j' \in \mathcal{J}\right]. \tag{3}$$

Computational efficiency depends critically on the distribution assumed for the ξ random error terms in Eq. (3). 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., $\Pr[\xi < x] = \exp[-\exp(-x)]$), as in Guadagni and Little (1983), then it can be shown that

$$P_j = e^{v_j}\left[1 + \sum_{j' \in \mathcal{J}} e^{v_{j'}}\right]^{-1}$$
$$P_0 = \Pr[\text{No Choice}] = \left[1 + \sum_{j' \in \mathcal{J}} e^{v_{j'}}\right]^{-1}, \tag{4}$$

where the "1" in the denominator accounts for the outside good, with $v_0 = 0$ (see Train 2003, chapter 3 for proof). This form is called the *multinomial logit model* (MNL). Note that, even in a monopolist setting, the presence of an outside good ensures that the probability of "no choice" is always non-zero, and so choice probabilities for undesirable or overly expensive products will be low.

It is assumed that v can be measured as a function of observable quantities such as price, product characteristics, consumer characteristics, and so forth. This article considers only price and product characteristics. A rule is needed for mapping prices and product characteristics into the deterministic component of utility v. A good deal of recent work examines nonparametric methods for accommodating individual-level (Kalyanam and Shively, 1998; Kim et al., 2003c) or latent utility functions (Andrews et al., 2002a). These, however, are computationally intensive and are difficult to embed within an iterative optimization scheme. Instead, this article turns to a simple linear mapping of product characteristic *levels* (conjoint part-worths), using natural splines to interpolate intermediate values and noting that any fully specified, differentiable rule would work equally well. The observable component of utility 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. In Z the elements of the product characteristic vector $\mathbf{z}$ are enumerated as $k = \{1, 2, \ldots K-1\}$, and price p included as the last term, $k = K$. Each product characteristic/price k is discretized into L_k levels, $l = \{1, 2, \ldots L_k\}$. One advantage of using discrete levels is that it does not presume linearity with respect to the continuous variables. For example, it cannot be assumed that a US\$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 et al., 2002a); however, here simply the standard maximum likelihood formulation is used (Louviere et al., 2000). The log of the sample likelihood for a particular individual on a particular choice occasion n is

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

where $\Phi_{nj} = 1$ if the observed choice on choice occasion n is alternative j and $\Phi_{nj} = 0$ if j is not the observed choice. Here $\mathcal{J}_n$ is the set of alternatives available on choice occasion n. Equation is maximized with respect to the β terms after summing across all individuals and choice occasions. In this way, the part-worth coefficients β_{kl} are obtained for each level l of each product characteristic/price k.

In all random utility models, such as the logit used here, one must be careful about *model identification*; for example, adding a constant term to all attraction values v shifts them upward to the same extent and does not change choice probabilities predicted by the logit model. Thus, in using (5), there is an infinite number of solutions for optimal β 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, this article selects from the infinity of equivalent solutions the one solution where the mean coefficient value $\sum_{l=1}^{L_k}\left(\frac{\beta_{kl}}{L_k}\right)$ is the same for all k. By adding this constraint the model has $1 + \sum_{k=1}^{K}(L_k - 1)$ degrees of freedom, and the solution is uniquely defined (i.e., "identified").

The β_{kl} terms represent part-worths of discrete values but have no information about intermediate values. To optimize over continuously valued product characteristics and price, it is necessary to estimate utilities for such intermediate values. To this end, polynomial splines are used, because linear splines are not differentiable at knots (the estimated values). In the case study natural cubic splines are used, although with a greater number of characteristic levels higher-order splines would be possible. Lastly, then, the deterministic component of utility can be written as a function of the continuous-valued product characteristics values $\mathbf{z}$ and price p using the spline function Ψ_k of the discrete level part-worths β_{kl} for each characteristic/price k. If price is indexed as $k = K$, the attraction value is written as

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

where the angle bracket notation $\langle \mathbf{z}_j \rangle_k$ indicates the k^{th} element of the vector $\mathbf{z}_j$.

Thus far, only the question of relative preference among the alternatives has been taken up, as embodied by choice probability. The model specification is completed through invoking a known market potential, s. This is reasonable, given the quasi-monopolist setting, although it is acknowledged that markets with some degree of category expansion—as a function of price and product characteristics—would need to have market potential measured as a function of those quantities, after which optimization could be carried out. Given market potential s, demand q_j for product j is linearly related to choice probabilities:

$$q_j = sP_j = se^{v_j} \left[1 + \sum_{j' \in \mathcal{J}} e^{v_{j'}} \right]^{-1}. \qquad (8)$$

Such market potentials can be given exogenously at the outset or estimated through a variety of techniques based on historical data or test markets [See Lilien et al. (1992) for a full review of such methods]. It is stressed once again that the ATC methodology requires only representation of demand as a function of price and product characteristics, not necessarily one related to the form chosen for this or any particular study.

Conjoint analysis. Maximum likelihood estimation can be used to fit β 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 used widely 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 a vast literature on conjoint analysis and appropriate experimental designs, and the reader should be directed to any of the classic or recent articles, notably Louviere's (1988) expository article, the review by Green and Srinivasan (1990), or 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 always are 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. This article suggests the use of choice-based conjoint for data collection because it is more natural for respondents (who choose products rather than rating or ranking them in their daily lives). Concordant with standard practice (Kuhfeld, 2003), efficient designs are generated to collect maximum information about preferences with a minimum number of questions, offering successive sets of products and asking which is most preferred in each or whether none is acceptable (the "no choice" option).

Complete Formulation

Figure 3 depicts a schematic of the complete ATC formulation of the product development problem for a single-product-producing monopolist using the reduced variable formulation (substituting for epsilon in the original formulation) described in Michalek and Papalambros (2004b). In this formulation there is only one product, so the product index j is dropped. In the product planning subproblem, price p and product characteristic targets $\mathbf{z}_\mathrm{M}$ are chosen to maximize profit Π while minimizing the deviation between the product characteristic targets set by marketing $\mathbf{z}_\mathrm{M}$ and those achieved by the engineering design $\mathbf{z}_\mathrm{E}$ using weighting coefficients $\mathbf{w}$ to specify the tradeoff between the two objectives. Profit Π is calculated as revenue minus cost as in Eq. (2), and demand q is calculated using the logit model in Eqs. (7)–(8) with known market potential s. In the engineering design subproblem, design variables $\mathbf{x}$ are chosen to minimize the deviation between characteristics achieved by the design $\mathbf{z}_\mathrm{E}$ and targets set by marketing $\mathbf{z}_\mathrm{M}$ using Eq. (1) subject to engineering constraints $\mathbf{g}(\mathbf{x})$ and $\mathbf{h}(\mathbf{x})$. These two subproblems are solved iteratively, each using standard nonlinear programming

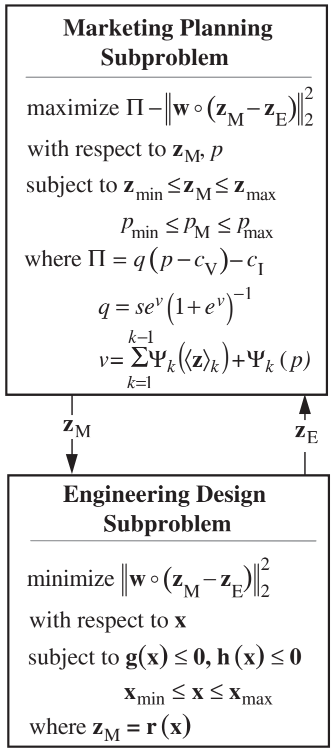

Figure 3. ATC Formulation of the Product Planning and Engineering Design Product Development Problem

techniques (Papalambros and Wilde, 2000) to solve each subproblem until the system converges. The weighting update method (Michalek and Papalambros, 2004a) then may be used to find weighting coefficient values **w** that produce a solution satisfying user-specified tolerances for inconsistency between marketing and engineering for each term in **z**. This method is important for producing consistent solutions in cases where the top-level subproblem does not have an attainable target: in this case profit is maximized rather than setting an attainable profit target.

Empirical Application: Dial-Readout Scales

The potential of the joint marketing and engineering design model is illustrated in the design of a standard household dial-readout bathroom scale. Scales possess a number of attractive features for the purposes of this article: (1) consumers are nearly uniformly familiar with them; (2) the ‘‘range’’ of bathroom scales in the marketplace is relatively small, even among inexpensive consumer durables, and as such would have to be considered moderately differentiated at most; (3) even the best scales are not very costly, so one could potentially measure price effects well; (4) the number of characteristics consumers value is not large, the number of ‘‘levels’’ (part-worths) within each characteristic is reasonable, and characteristics and levels can be known in advance through prior studies and on-line data; and (5) lack of mechanical complexity makes it possible to formulate a small, explicit set of geometric and physical constraints for the engineering design subproblem. These simplifications are convenient, but the methodology presented here can be used for most durable products, even if certain modeling aspects may vary considerably (in terms of arduousness) among products.

Marketing Planning Subproblem

Marketers first must identify which product characteristics under their control are of interest to consumers and which levels they can distinguish. A great deal of information on bathroom scales was made available to us in a proprietary report indicating which characteristics figured high in consumer preferences. Some, like color, could be interchanged or manipulated on the fly without interaction with other scale components and thus were left out of this study's experimental design. It also was considered which characteristics would be especially important to convey in an online purchase environment, the environment the current experiment was meant loosely to simulate, given that the study itself was conducted on the Web. Finally, it is important that the chosen characteristics can be quantified directly and can be conveyed easily to respondents in an unambiguous manner; thus, nebulous descriptors such as ‘‘nicely proportioned’’ were

Table 2. Product Characteristic and Price Levels

k	Description	Metric	Units	Levels				
z_1	Weight Capacity	Weight Causing a 360° Dial Turn	lbs	200	250	300	350	400
z_2	Aspect Ratio	Platform Length Divided by Width	—	6/8	7/8	8/8	8/7	8/6
z_3	Platform Area	Platform Length Times Width	in^2	100	110	120	130	140
z_4	Tick Mark Gap	Distance between 1-lb Tick Marks	in.	2/32	3/32	4/32	5/32	6/32
z_5	Number Size	Length of Readout Number	in.	0.75	1.00	1.25	1.50	1.75
p	Price	US Dollars	$	10	15	20	25	30

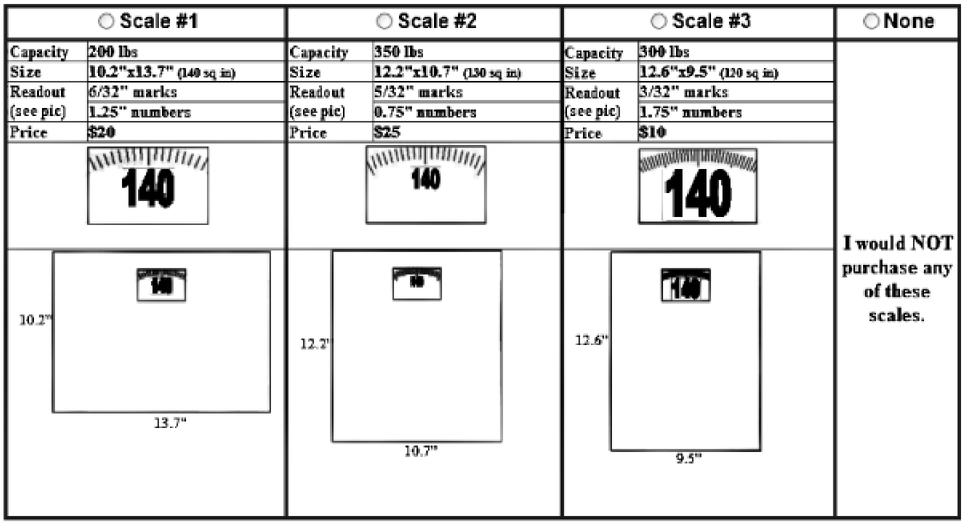

Figure 4. Online Conjoint Scale Choice Task

eschewed in favor of actual proportions. Five product characteristics—weight capacity, aspect ratio, platform area, tick mark gap, and number size—plus price were adopted because of their relevance to consumers and designers as well as their prevalence in online purchase descriptions and pictures. These appear, along with the levels for each, in Table 2. Each characteristic was discretized into five levels, which allowed adequate spline interpolation (see the Appendix). These 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 realistic anticipated trade-offs. Characteristics such as brand name were avoided deliberately because of great differential familiarity and lack of a direct tie-in with the design of the underlying product.

An efficient choice-based conjoint design (50 sets of three-products, plus “no choice”) was used and implemented on the Internet. Respondents were solicited through announcements on numerous Internet newsgroups as well as through two classes at the University of Michigan: one in marketing research, the other in engineering design. All respondents,[2] 184 in total, were offered incentives in the form of sweepstakes for gift certificates in various amounts. A great deal of effort was put into having the choice task correspond to the sort found at online shopping sites. To that end, scales were presented in terms of their underlying product characteristic information in list format and pictorially, including a close-up of the dial to facilitate comparison across the last two characteristics; a screen capture is provided in Figure 4.

As dictated by the conjoint design, options involving physically or geometrically infeasible product characteristic level combinations were included, because responses were used to measure consumer value systems (part-worth utilities) and trade-offs, not to be restricted to feasible designs in the engineering design subproblem. Not requiring such a feasible set to be delineated explicitly in advance is among the main strengths of the ATC approach, as is shown later.

Model parameters were estimated, as described earlier, using maximum likelihood and a Newton-type algorithm.[3] The resulting β values are listed in Table 3; these values have been scaled so that the mean in each set of characteristics is the same. The average β value for each characteristic is -0.004,

[2] Demographic data also were solicited from respondents. This study’s sample was 58% male. For men, mean height, weight, and age were 70.7 inches, 177 pounds, and 28.2, respectively; corresponding values for women were 64.6 inches, 129 pounds, and 26.5, respectively. Respondents also were asked three questions relevant to scale purchase behavior: (1) Do you need vision correction to see clearly at a distance of 6 feet? (2) Have you tried (deliberately) to lose at least 10 pounds in the last year? and (3) Have you purchased a scale in the past two years? Female and male affirmative proportions were {0.49, 0.40, 0.22} and {0.48, 0.36, 0.22}, respectively and were not statistically distinguishable. No significant systematic relationships were noted between these variables and preference patterns in the conjoint task.

[3] Estimation for the conjoint model was based on maximum likelihood using standard gradient search methods; all starting values converged to identical optima. At the optimum, the log-likelihood, LL = -10983. This model can be compared to a series of nested alternatives: to a seven-parameter model, which sets equal levels within characteristics but allows the characteristics themselves to vary (LL = -12066); to a one-parameter model, which estimates only the “no choice” option’s relative attractiveness (LL = -12716); and to a ‘zero parameter’ model, which assigns equal probability to all choices (LL = -12753). Each can be rejected very strongly against the preceding one.

Table 3. Part-Worth Coefficient (β) Values

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

corresponding to the relative attractiveness of scales with respect to the "no choice" option, which for identification purposes has $v_0 = 0$ identically. These values show reasonable trends: respondents monotonically prefer larger numbers and lower cost but have interior preferences for weight capacity, platform area, shape (aspect ratio), and interval mark gap. One might argue that more weight capacity is always better, so body weight data was collected on participants. The heaviest was 280 pounds, so none in fact would have required either of the two highest capacity levels (therefore the mild utility decline may be attributable to wanting to avoid excess capacity or even not wishing to appear as if it were needed). Natural cubic spline functions Ψ_β, provided in the Appendix, were fit to these β values for each characteristic and for price. Based on discussions with a major scale manufacturer, (exogenous) values for cost $c_V = \$3$ per unit and for initial investment $c_I = \$1$ million were assumed, as well as for market size s, which was set to 5 million, the approximate yearly market for dial scales in the United States. Using this last figure and the estimated splines, demand q was computed using Eqs. (7)–(8).

Engineering Design Subproblem

Reverse engineering was used to create the engineering design submodel. Three scales of different construction were purchased and were disassembled; this allowed a determination of the relevant functional components and their dependencies and interrelations. These are shown in Figure 5a (Michalek et al., 2004), and the resultant design variables for the engineering design submodel are depicted in Figure 5b.

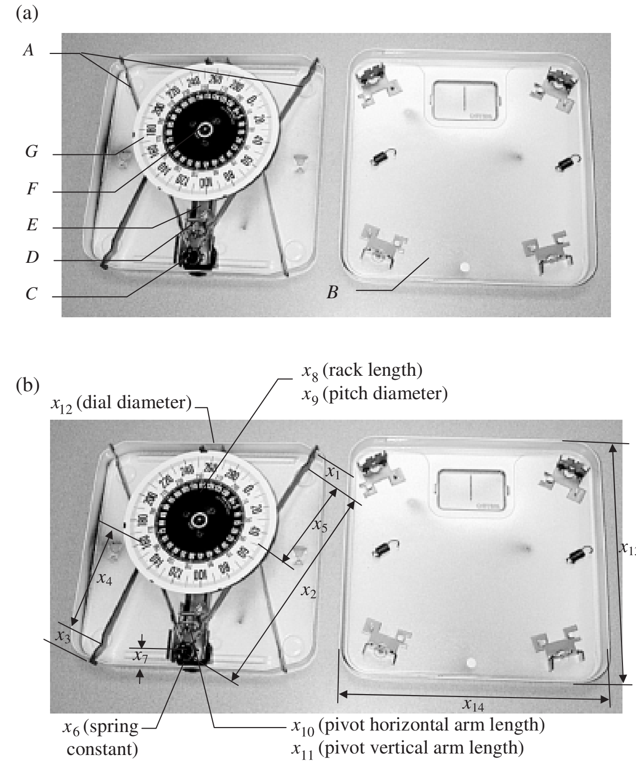

Figure 5. Disassembled Scale Showing (a) Components and (b) Design Variables

Analysis of the three different scales indicated they operated on essentially identical principles. In Figure 5a, levers *A* create mechanical advantage and translate the force of the user's weight from the cover *B* to coil spring *C*, which is displaced proportionally to the applied force; a pivot lever *D* transfers the vertical motion of the spring to the horizontal motion of gear rack *E*, after which pinion gear *F* translates the rack's linear motion to rotation of the dial *G*. Although this basic topology is common to the three scales examined, dimensions vary; for example, the ratio of dial-turn per applied force depends on the dimensions of the levers, the rack and pinion, and the spring properties. Because the topology is common, it is possible to represent a parametric space of design alternatives using a set of design variables. Figure 5b shows the set of 14 design variables chosen for this study, all of which are real-valued, positive, and continuous in nature. Other dimensions were considered to be fixed parameters **y** with values based on the observed scales, as shown in Table 4.

Constraint functions. Eight mathematical constraint functions **g(x)** were developed based on geometric and mechanical relationships to ensure that the design

Table 4. Engineering Design Model Parameters

Name	Description	Value	Units
y_1	Gap between Base and Cover	0.30	in
y_2	Minimum Distance between Spring and Base	0.50	in
y_3	Internal Thickness of Scale	1.90	in
y_4	Minimum Pinion Pitch Diameter	0.25	in
y_5	Length of Window	3.00	in
y_6	Width of Window	2.00	in
y_7	Distance between Top of Cover and Window	1.13	in
y_8	Number of lbs Measured per Tick Mark	1.00	lbs
y_9	Horizontal Distance between Spring and Pivot	1.10	in
y_{10}	Length of Tick Mark + Gap to Number	0.31	in
y_{11}	Number of lbs that Number Length Spans	16.00	lbs
y_{12}	Aspect Ratio of Number (Length/Width)	1.29	—
y_{13}	Minimum Allowable Distance of Lever at Base to Centerline	4.00	in

variable vector $\mathbf{x}$ represents a meaningful, feasible design. First, the dial (G) diameter x_{12} must be small enough to fit inside the base widthwise, where the base width is measured as the cover width x_{14} minus the gap y_1 between the cover and the base on both sides:

$$x_{12} \leq x_{14} - 2y_1. \tag{9}$$

The dial G also must fit lengthwise inside the scale base $(x_{13} - 2y_1)$ with sufficient room for the spring plate $(x_7 + y_9)$:

$$x_{12} \leq x_{13} - 2y_1 - x_7 - y_9. \tag{10}$$

The length of the short levers $(x_4 + x_5)$ must be small enough to fit inside the base lengthwise $(x_{13} - 2y_1)$:

$$(x_4 + x_5) \leq x_{13} - 2y_1. \tag{11}$$

The position along the long lever of the short lever joint x_5 must be within the bounds of the long lever length x_2:

$$x_5 \leq x_2. \tag{12}$$

In the fully extended position, the end of the rack E $(x_7 + y_9 + x_{11} + x_8)$ must fit inside the scale body lengthwise $(x_{13} - 2y_1)$:

$$x_7 + y_9 + x_{11} + x_8 \leq x_{13} - 2y_1. \tag{13}$$

However, the length x_8 of the rack E must be long enough to span the space between the pivot lever D and the pinion F:

$$x_8 \geq (x_{13} - 2y_1) - \left(\frac{x_{12}}{2} + y_7\right) - x_7 - y_9 - x_{10}. \tag{14}$$

The two long levers connect to the top edge of the base rather than the side. Therefore, the lever length $(x_1 + x_2)$ is limited by the width dimension of the scale body $(x_{14} - 2y_1)$. Using the Pythagorean Theorem,

$$(x_1 + x_2)^2 \leq (x_{13} - 2y_1 - x_7)^2 + \left(\frac{x_{14} - 2y_1}{2}\right)^2. \tag{15}$$

However, for stability the long levers must be long enough $(x_1 + x_2)$ to attach to the top edge of the base at a minimum distance y_{13} from the centerline. Again, using the Pythagorean Theorem,

$$(x_1 + x_2)^2 \geq (x_{13} - 2y_1 - x_7)^2 + y_{13}^2. \tag{16}$$

In addition, simple bounds are provided to ensure that all variables are positive. Given that all x are positive, any real-valued vector $\mathbf{x}$ that satisfies Eqs. (10)–(16) represents a valid, feasible design.

Response functions. Next, the response functions $\mathbf{r}(\mathbf{x})$ that calculate product characteristics $\mathbf{z}$ in terms of the design variables $\mathbf{x}$ are defined. Assuming the scale is made up of rigid bodies (except for the spring) and using standard static force and moment balancing (Hibbeler, 1993), the weight capacity z_1 can be derived as a function of the position of the cover force on the long (x_1) and short (x_3) levers, the length of the long $(x_1 + x_2)$ and short $(x_3 + x_4)$ levers, the position of the joint x_5, the dimensions of the pivot (x_{10} and x_{11}), the pitch diameter of the pinion x_9, and the spring constant x_6:

$$z_1 = \frac{4\pi x_6 x_9 x_{10}(x_1 + x_2)(x_3 + x_4)}{x_{11}(x_1(x_3 + x_4) + x_3(x_1 + x_5))}. \tag{17}$$

The aspect ratio is the length of the cover divided by its width:

$$z_2 = \frac{x_{13}}{x_{14}}. \tag{18}$$

The area of the scale cover is its length times its width:

$$z_3 = x_{13}x_{14}. \tag{19}$$

The arc length of the gap between 1–lb interval tick marks is proportional to the dial diameter x_{12} and inversely proportional to the weight capacity z_1 [see Eq. (17)]:

$$z_4 = \pi\frac{x_{12}}{z_1}. \tag{20}$$

Finally, the number length, a measure of overall printed number size, is calculated in terms of the dial diameter x_{12} and weight capacity z_1 using trigonometry based on the fixed span of numbers along the tick marks y_{10} (the printed number is assumed to span a fixed number of tick marks), the positioning of the numbers on the dial y_{11}, and the aspect ratio (length/

width) of the rectangular space allocated for the number y_{12}:

$$z_5 = \frac{\left(2\tan\left(\frac{\pi y_{11}}{z_1}\right)\right)\left(\frac{x_{12}}{2} - y_{10}\right)}{\left(1 + \frac{2}{y_{12}}\tan\left(\frac{\pi y_{11}}{z_1}\right)\right)}. \tag{21}$$

Equations (17)–(21) form the vector function $\mathbf{r}(\mathbf{x})$, which maps design variables $\mathbf{x}$ onto product characteristics $\mathbf{z}$ so that product characteristics can be calculated for any design. The design variables $\mathbf{x}$ are constrained to feasible values by the constraint functions $\mathbf{g}(\mathbf{x})$; therefore, the resultant product characteristics $\mathbf{z} = \mathbf{r}(\mathbf{x})$ also are restricted to feasible combinations.[4]

Results

The engineering design and marketing subproblems were solved iteratively until convergence using the Matlab function *fmincon*, based on the sequential quadratic programming method (Papalambros and Wilde, 2000), to solve each subproblem. This gradient-based search algorithm generates local optima, and global optima can be found only through multistart. The reported solution represents the best local optimizer found over several starting points based on the dimensions of scales used for reverse engineering.[5] At the solution, shown in 0 the optimal scale design is bounded by active engineering constraints that ensure the dial, the spring plate, and the levers are not too large to fit inside the scale. The optimal scale characteristics are within the range of scales found in online e-commerce, and none of the variable bounds are active except for x_7, which is unique because it is explicitly bound by the specified parameter value of y_2 rather than by an arbitrary bound.

In the engineering model, several product characteristics are functions of the ratios of some of the design variables. For example, an increase in lever length can be traded off for a changed spring constant, force placement, pinion gear pitch diameter, or pivot lever dimensions to yield an equivalent weight capacity. This means that two different designs with appropriate design variable ratios may exhibit the same product characteristics and also that an infinite number of design solutions are equivalent from a marketing perspective. One such design is reported in Table 5. Additional models representing cost structures in terms of design variables or part commonality among product variants in a product line could be used to select a single design among the set of otherwise equivalent designs; however, this possibility has not been explored here.

Comparison of ATC with Disjoint Decision-Making

One might question whether the joint method proposed here has a substantial impact on product design and, ultimately, resulting profit. The role of ATC in avoiding infeasible products has been emphasized; however, this example demonstrates the impact ATC can have on profitability. Let us examine a case of disjoint decision-making by marketing and engineering design, similar to the methodology proposed by Cooper et al. (2003), where (1) marketing defines desired product characteristics; (2) engineering designs a feasible product to meet the requested characteristics as closely as possible; and (3) marketing prices the actualized product.

In the first step, marketing chooses the optimal price and product characteristic combination conditional on the monopolist/single-product framework and known consumer preference data (arrived at using conjoint, a discrete choice model, and the profit function). This step is referred to as analytical target setting (Cooper et al., 2003). Based on the optimal price and characteristics at this stage, expected price, market share, and profit are \$28.04, 64.3%, and \$79.5 M, respectively, as shown in Table 6. There is no guarantee that a feasible product can be designed that exhibits the desired target characteristics. So,

[4] The entire system, including the marketing and engineering design submodels and all supporting data, is available from the authors in the research section of http://ode.engin.umich.edu.

[5] The individual marketing and engineering design subproblems were solved using the Matlab 6.5.1 function *fmincon*, based on the sequential quadratic programming method (Papalambros and Wilde, 2000). Default parameters settings were used to define the *fmincon* algorithm except for a setting of DiffMaxChange $= 10^{-6}$ was used for both subproblems to force tight finite differencing steps for better derivative approximations. Convergence of the ATC subproblem coordination was strictly defined as occurring when the engineering design subproblem and the marketing subproblem each are unable to improve the respective objective function value from the value using the optimal solution in the previous iteration. The number of ATC coordination iterations required to converge varies depending on the starting point and weighting coefficients used. Using the starting point generated by the disjoint case with weighting coefficients of 10^5, the system converged in 1815 ATC iterations (each subproblem solved 1,815 times, taking on the order of one second each iteration), and the resulting inconsistency between marketing targets and engineering design characteristics are less than 0.3% for all characteristics. Use of smaller weighting coefficients yields faster convergence but greater inconsistency between marketing targets and engineering design characteristics [See Michalek and Papalambros (2004a) for details]. For example, weighting coefficients of 10^4 yield convergence in only 31 ATC iterations with inconsistencies less than 10% for all characteristics.

Table 5. Optimal Scale Design

		Variable and Description	Value	Lower Bound	Upper Bound
Marketing Variables	z_1	Weight Capacity	254 lbs.	200 lbs.	400 lbs.
	z_2	Aspect Ratio	0.997	0.75	1.33
	z_3	Platform Area	133 in^2	100 in^2	140 in^2
	z_4	Tick Mark Gap	0.116 in.	1/16 in.	3/16 in.
	z_5	Number Size	1.33 in.	0.75 in.	1.75
	p	Price	$26.41	$10.00	$30.00
Engineering Variables	x_1	Length from Base to Force on Long Lever	2.30 in.	0.125 in.	36 in.
	x_2	Length from Force to Spring on Long Lever	8.87 in.	0.125 in.	36 in.
	x_3	Length from Base to Force on Short Lever	1.34 in.	0.125 in.	24 in.
	x_4	Length from Force to Joint on Short Lever	1.75 in.	0.125 in.	24 in.
	x_5	Length from Force to Joint on Long Lever	0.41 in.	0.125 in.	36 in.
	x_6	Spring Constant	95.7 lb./in.	1.00 lb./in.	200 lb./in.
	x_7	Distance from Base Edge to Spring	0.50 in.	0.50 in.	12 in.
	x_8	Length of Rack	7.44 in.	1.00 in.	36 in.
	x_9	Pitch Diameter of Pinion	0.25 in.	0.25 in.	24 in.
	x_{10}	Length of Pivot's Horizontal Arm	0.50 in.	0.50 in.	1.9 in.
	x_{11}	Length of Pivot's Vertical Arm	1.90 in.	0.50 in.	1.9 in.
	x_{12}	Dial Diameter	9.34 in.	1.00 in.	36 in.
	x_{13}	Cover Length	11.54 in.	1.00 in.	36 in.
	x_{14}	Cover Width	11.57 in.	1.00 in.	36 in.

engineering designs a *feasible* product that meets the product characteristics requested by marketing as closely as possible. At this point the product design is considered fixed, but price is an easily changed variable, so it can be reconsidered based on the characteristics of the achieved design [a simple form of Cooper et al.'s (2003) "Reduced ATS" problem]. The resulting price, share, and profit in this scenario are $25.54, 54.8%, and $60.8 M, respectively, as shown in Table 6. This involves a sizeable decrease in price and share and a truly enormous drop in profit from what marketing had planned originally using target product characteristics. Consumers often desire combinations of product characteristic values that are difficult or impossible to produce together, so it is important to examine the *realizable* share and profit levels. In a scenario such as this, marketing may accuse engineering design of failing to deliver, while engineering design may blame marketing for requesting a product that could not be built, causing substantial unnecessary compromises in the final product design. With contingent, sequential decision-making each side would be in the right from its own perspective, but the final decisions would be inferior.

Table 6. Optimal Product Characteristic Levels, Prices, Shares and Profits in Three Scenarios

			Disjoint		Joint
	Description	Unit	Initial Marketing Plan	Final Product Design	ATC
z_1	Weight Capacity	lbs	283	222	254
z_2	Aspect Ratio	—	0.946	1.041	0.997
z_3	Platform Area	in.^{2}	124.2	127.8	133.4
z_4	Tick Mark Gap	in.	0.136	0.1322	0.116
z_5	Number Size	in.	1.75	1.478	1.33
p	Price	$	$28.04	$25.54	$26.41
P_j	Market Share	%	64.3%	54.8%	59.0%
Π	Profit	$	$79.5 M	$60.8 M	$68.0 M

For comparison, let these two groups use ATC as a tool for communication, considering both the trade-offs among desirable product characteristics and the feasibility of obtaining these characteristics. In this case, an entirely different product is designed, with price, market share, and profit of $26.41, 59.0%, and $68.0 M, respectively, as shown in Table 6. Although the price is not much higher than in the disjoint case above, share and profit are improved significantly. This difference in profitability is nontrivial, approximately $7,200,000, a 12% increase over the "best feasible" design offered by engineering design based on "optimal" marketing target specifications alone. Thus, ATC, using the same submodels, converges to a jointly optimal solution offering far better market prospects.

Conclusions

From the perspective of the producer, marketing and engineering design ideally work together to achieve a common goal: creating the product with greatest value for the firm. As detailed here and in earlier cited research, goals, language and modes of operation in the two disciplines tend to insulate each from the other. The practical upshot is that each tends to solve problems relative to constraints "exogenously" set by the other. The proposed methodology, based on analytical target cascading, allows the disciplines to remain independent yet to link their product subproblems formally, using time-tested models from both fields.

It is instructive to consider what this joint methodology offers each of the constituent communities. For the marketing community, ATC goes beyond merely facilitating communication and cutting down time-consuming iterations; it helps whenever marketers confront even moderately complex products and/or production processes in which some combinations of desired characteristics are technologically impractical or even physically impossible. This feasible set of products is seldom one that can be described easily in the product characteristic space and is ordinarily a function of the technical decisions of the product. In short, the method allows marketers to dispense, at least initially, with questions of "what can be made?" and to focus instead on what they do best: discerning what consumers most value.

The method offers distinct benefits for the engineering design community. The main one is that of helping to "contextualize" design decisions within the larger framework of the firm and how it satisfies its customer base. Instead of resolving engineering tradeoffs—for example, among competing performance objectives, as in multiobjective optimization—purely in terms of technological or physical possibility, it allows such decisions to be tied directly into the firm's overall objective, that of producing a successful and profitable product. The proposed methods would allow, for example, sensitivity analysis, where small design changes could be mapped to their eventual profit implications. Such an analysis would be unthinkable without a conjoined system of consumer needs and resultant demand, as provided by the marketing submodel and linked through ATC.

This article is intended as an introduction to a methodology that can be extended readily to far greater complexity using known methods. For example, this study's consumer response model was made as simple as possible, based on a homogenous-coefficient logit model. Well-known hierarchical Bayes methods could be substituted to allow inference for heterogeneous populations, and probit models with full error covariance could help account for potential IIA problems (Kahneman and Tversky, 1979), albeit at great loss of tractability. In turn, models allowing heterogeneous preferences (and thus demand) would allow one to design product *lines*. The present authors intend to report on such an extension in future work. It even would be possible to improve extant conjoint methods by allowing them to generate only *feasible* tasks: those that maximize utility measurement accuracy within the range of technologically possible product configurations.

On the engineering side, great emphasis was placed on an overarching engineering design submodel, which was based on a single product topology appropriate for rectangular dial-readout scales. Product variety could be enhanced by incorporating multiple product topologies, with the potential for automatic topology generation (as in, for example, Campbell et al., 1998). A deliberately simplistic cost model also was chosen for illustration; however, more detailed cost models can be integrated to the engineering decision model. By doing so, it would be possible to have another sort of feedback, wherein the marketing submodel sets target production cost and the engineering design submodel designs feasible products that meet cost targets. Product lines or families can be accommodated on the engineering side as well, enabling study of component- and process-sharing effects on the production cost structure (Fellini et al., 2003) or the use of flexible and reconfigurable manufacturing equipment (Koren et al., 1999).

In closing, there are several points to stress for both communities. The first involves the viewpoint, common in marketing, that design constraints generally can be overcome by allotting appropriate funds. In some cases they cannot. Marketing methods must learn to take note not only of costly designs but also of utterly infeasible ones, a concept foundational in the ATC formulation presented here. The present authors believe this can only improve predictive accuracy and simultaneously can reduce data requirements for the dominant models used in new product forecasting. In parallel, the engineering design community must accept that price and consumer preferences are aspects of design just as real as those determined by physics. Second, determining which product characteristic combinations are infeasible can be exceptionally difficult even when producing only a single product as simple as the scales considered in this article. Even if infeasible combinations are eliminated in conjoint questions, optimal designs still may be infeasible; this is particularly important for continuous variable formulations. The ATC approach allows marketing and engineering design to formulate their own submodels, using methods most familiar to each, and to link them afterward, so that an optimal joint decision can be reached. Finally, designs reached using ATC necessarily converge on joint optimality and, as such, guarantee better profitability—or any other chosen metric—than the suboptimal solutions achieved by solving the engineering design and marketing design problems sequentially. Given its relative ease of implementation, this last benefit may prove a deciding factor in the willingness of firms to adopt ATC processes for complex design projects.

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Appendix
Spline-Interpolated Part-Worths