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Design of Robust New Products under Variability: Marketing Meets Design*

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In designing consumer durables such as appliances and power tools, it is important to account for variations in product performance across different usage situations and conditions. Since the specific usage of the product and the usage conditions can vary, the resultant variations in product performance also can impact consumer preferences for the product. Therefore, any new product that is designed should be robust to these variations—both in product performances and consumer preferences. This article refers to a robust product design as a design that has (1) the best possible (engineering and market) performance under the worst-case variations and (2) the least possible sensitivity in its performance under the variations. Achieving these robustness criteria, however, implies consideration of a large number of design factors across multiple functions. This article's objectives are (1) to provide a tutorial on how variations in product performance and consumer preferences can be incorporated in the generation and comparison of design alternatives and (2) to apply a multi-objective genetic algorithm (MOGA) that incorporates multifunction criteria in order to identify better designs while incorporating the robustness criteria in the selection process. Since the robustness criteria is based on variations in engineering performance as well as consumer preferences, the identified designs are robust and optimal from different functional perspectives, a significant advantage over extant approaches that do not consider robustness issues from multifunction perspectives. This study's approach is particularly useful for product managers and product development teams, who are charged with developing prototypes. They may find the approach helpful for obtaining customers' buy-in as well as internal buy-in early on in the product development cycle and thereby for reducing the cost and time involved in developing prototypes. This study's approach and its usefulness are illustrated using a case-study application of prototype development for a handheld power tool.

Introduction

It has been long recognized that successful new product development (NPD) involves effective integration of cross-functional processes. Extant research has shown that effective integration can have a positive impact on product development cycle time (Griffin, 1997; Sherman, Souder, and Jenssen, 2000; Urban et al., 1997), project performance (Griffin and Hauser, 1992; Olson et al., 2001), and overall company and market performance (Gemser and Leenders, 2001; Griffin and Hauser, 1996; Tatikonda and Montoya-Weiss, 2001). Consequently, it is no surprise that the specifics of the cross-functional approaches that can lead to such successful impacts have been the focus of research in the last decade—quality function

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deployment (QFD) ("house of quality") (Griffin, 1992; Griffin and Hauser, 1993; Hauser and Clausing, 1988); lead-user analysis (Urban and Von Hippel, 1988); and integrating customer requirements into product designs (Bailetti and Litva, 1995; Urban et al., 1997). The approach described in the present article belongs to the cross-functional genre of research, focusing on the development of specific methodologies to facilitate effective and efficient coordination among engineering design, ergonomics, and marketing functions in developing good candidates for prototypes.

The key characteristic of a cross-functional approach is that it necessarily entails consideration of a large number of factors that contribute to the design. Among these factors, some are specific and unique to individual functions, and some are common across functions. Typically, many of these factors are interrelated and affect the design decisions that fall under the domain of the different functions. The power of a cross-functional approach cannot be harnessed unless all these factors and their interrelationships are systematically considered and are accounted for in the design development. Thus, an effective and efficient method for considering and integrating these factors is critical for reducing the time and cost of developing design prototypes. The current study provides a tutorial on such a method in the context of consumer-durable products. As compared to extant coordinating schemes, this study's approach has two distinguishing characteristics: first, how variations in product performance and consumer preferences due to variations in operating conditions can be incorporated in the generation and comparison of design alternatives are examined in detail; second, a multi-objective genetic algorithm is applied that incorporates multifunction criteria in order to identify good design candidates. This approach thus leads to the identification of "robust" design candidates for prototype development. These distinguishing characteristics are elaborated upon in the following discussion.

Robustness of products is a critical element to consider in the NPD process, especially in the case of consumer durables such as appliances, power tools, and utility vehicles. These products tend to be used in different usage situations and usage conditions in which their performance can vary depending on the operating conditions. For example, a grinder power tool could be used in different applications such as concrete, wood, or metal under operating conditions that could be very different depending on whether it is used in cold or hot weather. In this study, the term *uncontrollable design parameters* is used to indicate such factors that can vary and are not under the control of the designer (e.g., different applications or operating conditions in the power tool example, which are all environmental conditions beyond designers' control).

BIOGRAPHICAL SKETCHES

Ms. Lan Luo is Ph.D. candidate in the marketing department in the Robert H. Smith School of Business at the University of Maryland. Ms. Luo's research interests include new product development, marketing–manufacturing integration, empirical industrial organization, and consumer economics. In 2002, Ms. Luo was selected to be an integral part of a cutting-edge, three-year new product development research project. This major study involves the cross-functional teams of Black & Decker Corporation, and the University of Maryland's marketing and mechanical engineering departments through National Science Foundation support. This project provides the basis for her work in various papers in the field of new product development and marketing–manufacturing integration.

Dr. P. K. Kannan is Harvey Sanders Associate Professor of Marketing in the Robert H. Smith School of Business at the University of Maryland. He is associate director of the Center of E-Service. His current research stream focuses new product development, pricing information products and product lines, e-service, CRM and customer loyalty, and consumer choice. He has received grants from the National Science Foundation, Mellon Foundation, SAIC, and PricewaterhouseCoopers for his work in this area, and research papers have been published in *Management Science, Journal of Academy of Marketing Science*, and *Marketing Science*.

Mr. Babak Besharati is Ph.D. candidate in the Department of Mechanical Engineering in the A. J. Clark School of Engineering at the University of Maryland. The focus of his research is mainly on multidisciplinary design optimization, robust design development, and product design selection. He started his research work with a new product design development project in 2002. Through this research, he has worked on a framework for the integration of robust engineering design and marketing disciplines and particularly has developed metrics for robustness assessment of design alternatives. The support of Black and Decker Corporation and the National Science Foundation has provided a basis to publish his approach and to apply it to a number of real-world product design problems.

Dr. Shapour Azarm is professor of mechanical engineering at the University of Maryland. His current research is in the areas of multiobjective and multidisciplinary (including evolutionary) robust design optimization; approximation of computationally expensive simulations; and robust design selection, with applications to single-product and product-line design. He has authored or coauthored close to 45 journal articles. Since 1998, he has served as associate editor of the *International Journal of Mechanics-Based Design of Structures and Machines* (formerly *Mechanics of Structures and Machines*). He recently became associate editor of the American Society of Mechanical Engineers (ASME) for a second term (2004–07 and formerly 1993–95). He was formerly conference and paper review chair of the ASME Design Automation Conference and chair of the ASME Design Automation Committee. Dr. Azarm is a fellow of the ASME.

From the engineering perspective, ignoring the variation in the performance of the products under various usage situations and conditions may lead to malfunctions of the product and can possibly cause serious failures (Kouvelis and Yu, 1997; Parkinson, Sorensen, and Pourhassan, 1993; Sundaresan, Ishii, and Houser, 1992). Therefore, engineering designers often aim to select designs that meet the following criteria: (1) maintain feasibility under various usage situations and conditions (that is, the product still functions under such variations); (2) show the least possible variation in its performance; and (3) have the best possible performance under the worst case variations in uncontrollable design parameters. This renders *design robustness* a critical factor to consider in the NPD process.

From the marketing perspective, the variations in performance of the product under different usage situations and conditions can have a significant impact on customers' preferences for the product and thus market share. Assume that these variations in performance dimensions can be mapped on to the levels of product attributes that customers typically consider in a preference elicitation process such as conjoint study. The marketing team then can estimate how changes in usage situations and conditions affect the preferences of customers (and thus market shares) for the alternative products and how robust the preferences and market shares for the alternative products are under such variations in performance. This is one component of *preference robustness*—the one that measures robustness under uncontrollable design parameters or environmental factors. In addition, when customer preferences and part-worths for attributes are estimated using choice models, there are sampling errors associated with the estimation procedure. In the literature of choice-based conjoint models, this issue of preference robustness has been virtually ignored. Marketing researchers generally have adopted the point estimates provided by the conjoint model instead of recognizing the degree of error around the point estimates of consumer preferences. In order to account for the uncertainties in customer choices in the preference elicitation process, the variances and co-variances of part-worth estimates from the choice model can be used to construct interval estimates of market shares for each product alternative. When a set of competitive products is defined, the upper and lower limits associated with these interval estimates for market shares can provide a measure of preference robustness with respect to the preference elicitation process. This is the second component of preference robustness. Thus, considering the two components of preference robustness in selecting the design for the new product can help in identifying designs that hopefully dominate other alternatives on the preference dimension given the variability in (1) usage situations and conditions and (2) customers' preferences estimates.

While this study's approach considers both design robustness and preference robustness in evolving new designs, the evolution itself is accomplished using MOGA. Genetic algorithm (GA) is based on the principles of natural selection or "survival of the fittest" in the evolution of species (Holland, 1975). It has been used successfully in various applications including product and structural design optimization (Goldberg, 1989; Holsapple et al., 1993; Narayanan and Azarm, 1999). In marketing, Balakrishnan and Jacob (1996) proposed the use of single-objective GA to solve the problem of identifying an optimal (single) product using conjoint data. More recently, Steiner and Hruschka (2003) extended their approach by applying single-objective GA to solve for optimal product line design. Extending the work of Balakrishnan and Jacob (1996) and Steiner and Hruschka (2003), this study's approach applies GA to a multi-objective optimization problem with multiple constraints to account for robustness in both design and marketing. It also extends the single-objective robustness criteria proposed by Kouvelis and Yu (1997) to the multi-objective robustness domain.

The preceding discussion highlights the contribution of this study's approach from an academic perspective. This approach considers the variations in customer preferences for products due to variations in usage situations and conditions and due to estimation errors in the preference elicitation process, which generally have been ignored in extant research. This variation along with variations in engineering performance are used in multi-objective genetic algorithm to identify robust prototype candidates, thus developing designs that are desirable from different functional perspectives, a significant advantage over extant approaches that do not consider robustness issues from multifunction perspectives.

From a practitioner viewpoint, this approach is particularly useful for product managers and product development teams who are charged with developing prototypes. They may find the approach helpful for obtaining customers' buy-in as well as internal buy-in early on in the product development cycle. This study's customers' preference elicitation process using choice-based conjoint involves both marketing and industrial ergonomics teams in an effort to better link the trade-off between ergonomic features and other product attributes in addition to the integration on the design dimension. This article argues that having such an integration occur early on in the design process affords reduction in the cost and time for the selection of design alternatives because all design factors deemed important from the multiple functional perspectives are considered in a systematic and transparent manner in the prototype selection. This should enable quick buy-in from all functions involved in the design process.

Finally, from a firm's perspective, designing such robust new products will enable all customers to have the same superior experience regardless of their usage environments and situations, which is especially important in the consumer-durable categories. Such robustness will lead to higher quality, better match between the design and customer needs, higher customer satisfaction, and higher repurchase rates—and, in the long run, greater customer loyalty and higher profits for the firm.

The rest of the article is organized as follows. The next section provides a brief description of the NPD case study and an overview of this study's approach. Following that is a description of the study's preference elicitation module and the design module. Next is a description of the integrated multi-objective robustness criteria and the evolution of design alternative to carry forward to the prototype stage. In discussing each of these modules, specifics of the case application are presented to illustrate the application of this approach. Finally, the article concludes with a discussion of the positive aspects of the approach, along with some limitations and directions for future work.

Conceptual Framework

This study's approach has been developed on the basis of an NPD project at a power tool manufacturer. A description[1] of the project is provided to better motivate the approach proposed here. The project involves a handheld power tool (for the sake of exposition, it is called here a *widget*) aimed at the industrial, professional, and do-it-yourself markets. Three functional teams are closely involved in the development project: (1) *industrial design ergonomics team,* which designs the "shape" of the tool, which is an important attribute given the handheld nature of the product; (2) *design team*, which selects the design inputs (such as motor type, gear ratio, and battery type) that affect tool design attributes such as power rating (performance), armature temperature (which determines life of motor/product), motor casing temperature, and so forth, and (3) *marketing team*, which researches and models customer needs, preferences and the competitive landscape to select the appropriate targeting, pricing, and positioning strategies in consultation with the other functional teams. Since the widget being designed either will replace an existing product or will be added to the existing product line, this study's approach is tailored for existing markets and assumes that customers have experience with similar products and will be able to evaluate product features and trade-offs in reliable manner in a preference elicitation process.

Figure 1 shows the overall cross-functional framework for new product development. The framework assumes that initial exploratory studies have been conducted already by the product development teams consisting of marketing, ergonomic, and design experts in understanding the general dimensions on which the new product could perform better compared to the competing products in the market. Such exploratory studies are based on laboratory research, field studies, and focus groups. These studies help the team to identify the important dimensions for marketing and engineering performance of the product. These dimensions form the basis for the design objectives, design attributes, marketing attributes, and ergonomic attributes and their levels to include in the customer preference/part-worth elicitation process.

Figure 1 is a bottom-up flow chart of the overall approach. There are two starting points in the framework. In the preference elicitation module (or conjoint analysis in the right-hand column in Figure 1), the most important customer needs with respect to the new product are first identified based on exploratory studies. These customer needs can translate to levels in marketing attributes such as retail prices, brand name, life of product (in hours), power rating, or ergonomic features such as shape of the product and actuator.[2] Once these attributes and their possible levels (values) are identified, a choice-based conjoint

[1] The specifics of the project and the attributes of the product are modified in this description to maintain confidentiality of the organization involved.

[2] Actuator is similar to a power switch. This attribute is common between ergonomic and marketing functions.

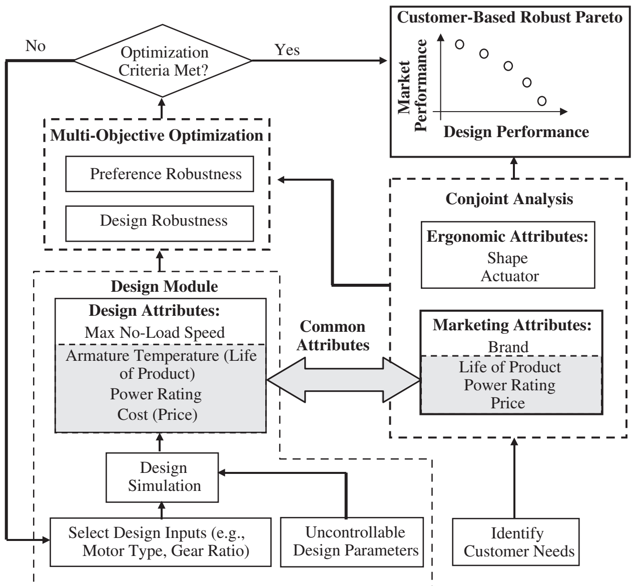

Figure 1. The Overall Framework

analysis is used to estimate consumer preferences (or utilities) for different levels of attributes, while accounting for the uncertainty in customer choices. The output of the preference elicitation module includes estimates of part-worths and the variance and covariance of the estimates, which are necessary to measure the preference robustness. These estimates are also useful to set up objectives and to construct constraints for the multi-objective optimization problem.

In the design module (left-hand column in Figure 1), the engineering design team first identifies a set of design inputs that define the functional design of the new product. Examples of design inputs include motor type, battery type, gear ratios, and gearbox type. For each element of design input, there generally exist one or several design parameters. These design parameters are uncontrollable factors that can have a significant impact on the performance of the tool. For example, a design parameter associated with battery type is battery current. While the designer can assume a nominal (or most likely) value for the current for each type of battery, the actual values of this parameter greatly depend on the usage conditions or situations. These design inputs are fed into a design simulation software. Each combination of the design inputs represents one design alternative. The design simulation software uses these inputs to generate design attributes that describe the performance or other features of the design corresponding to the set of inputs—for example, power rating, armature temperature (closely related to life of product), rotor speed, and cost (related to retail price and profit). The actual values of these design attributes depend on the selection of design inputs and the specific values of the corresponding design parameters.

Some of the attributes considered in this study's framework not only are relevant for engineering of the product but also are key attributes consumers consider when they make the purchase decision (e.g., price, power, life of the product). Such product attributes are considered common to both marketing and design functions. However, there may be other product attributes that are not common across both functions in that the specification of the attributes may rest solely with one function or the other. For example, an attribute such as brand name is relevant mainly for marketing, while the specification of shape is very much under the purview of the ergonomic team. These attributes may not affect the engineering performance of the product per se, although an attribute such as shape can limit what the design input could be. For such uncommon attributes, the specification of the attribute level is left to the function solely responsible for it. For example, the marketing team has the option to choose the specific levels that provide the highest conjoint utilities for such attributes when calculating the interval estimates of market share for each design alternative.

More importantly, it is the common attributes that play a critical role in the fitness assessment of integrated marketing and engineering robustness (the bold arrow linking the two columns at the middle in Figure 1). The part-worth utility estimates and the associated variance and covariance estimates for the attributes common to marketing and design functions are used in the design module in two ways. First, the part-worth utilities help the designer to identify the appropriate objective functions or constraints in optimizing design performance while accounting for design robustness. Second, the part-worth estimates and the associated variances and covariances are used to construct market-share-based measures of preference robustness considering both environmental variability (usage situations) and errors in preference elicitation process. These preference robustness measures, along with design robustness measures, guide the evolution of optimal designs in the multi-objective optimization process. The output of the optimization process generates the set of "customer-based robust pareto" design alternatives. These design alternatives are chosen for prototype development, field performance evaluation, and market simulations.

The following sections provide the specifics of each module and illustrate them in the context of the case study.

Preference Elicitation Module

Choice-based conjoint methodology was used for customer preference elicitation. Conjoint analysis has been a major tool in the process of product design for the last two decades (Chen and Hausman, 2000; Dobson and Kalish, 1993; Green and Srinivasan, 1990; Wittink and Cattin, 1989). In a typical conjoint-based product design procedure, consumers' preferences are estimated through an evaluation of a set of hypothetical product profiles that are specified in terms of levels of different attributes. Estimated part-worth utilities are used to calculate the potential market shares of the proposed product concepts against existing competitors' products.

In this study's framework, instead of just using cards containing verbal representations of the choice options, a combination of verbal descriptions and prototype models is suggested in order to allow both the marketing team and the industrial design ergonomic team to fully characterize the trade-offs between the product attributes for which they have responsibilities. In a traditional conjoint application, the choice options are typically functions of easily specified product attributes, generally using verbal representations. Several marketing researchers have questioned this assumption. Srinivasan, Lovejoy, and Beach's work (1997) suggests that, even though typically not included in conjoint experiment, several important qualitative aspects of the product (such as aesthetics, styling, ergonomics, and usability) have significant impact on consumer preferences. Their study provides empirical support for the need to push beyond hypothetical (verbal) product concepts to more complete customer-ready prototypes before choosing a product to commercialize. Empirical studies involving pictorial representations (Vriens and Loosschilder, 1998) and virtual reality representations (Dahan and Srinivasan, 2000) suggest that these alternate forms of representations improved respondents' understanding of the design attributes. Following Srinivasan, Lovejoy, and Beach's (1997) suggestion, this research included customer-ready prototypes in the choice-based conjoint experiment so that the subjects could evaluate a product based on its overall appeal (such as price, shape, actuator, and power rating). As suggested by Srinivasan, Lovejoy, and Beach (1997), such format of data collection is similar to the situation involving consumers inspecting products in a retail store environment and provides a good approximation to actual consumer evaluation process.

In this case study, based on exploratory research and internal discussions the marketing, design, and ergonomics team chose the following product attributes to obtain customer preference on brand, price, power rating, life of product, actuator type, and shape. The shape attribute consisted of four levels—three shapes that already existed in the market and one new shape the ergonomic team had designed. There are two types of power actuators (A and B). This is a feature that generally is integrated with a specific shape in a prototype. The representation of the combination of shape and power actuator variables was accomplished by using eight prototypes. Some of these prototypes were specifically developed by the industrial design team (nonworking prototypes but models that look, weigh, and feel like a real widget), and some were existing products in the market. All prototypes were colored gray to make them uniform in all dimensions other than shape and actuator.

Four different brands were considered, along with three levels of price, three levels of power rating and three levels of life of product. Brand, price, and power rating are attributes customers see on the label when they buy the tool at a retail store, so they were directly specified in the verbal description that accompanied each prototype. The average life of the tools is around 1,000 hours of operation. Respondents, who were mainly users of widgets, were generally aware of this, but this information was specified in the verbal description to indicate the differences among average life, below-average life, and above-average life.

Respondents for the study included metal workers and construction workers (who make up 80% of the user base for the tool) recruited from job and construction sites. The interviews were conducted with 210 respondents from different markets, each interview lasting around 25 minutes. Each respondent was given 18 choice scenarios (16 were used for conjoint estimations and 2 for validation). Sawtooth Software (2001) was used to create a fractional factorial design with over 80% efficiency. The choice scenarios were generated using the procedure described in Huber and Zwerina (1996). Each choice occasion included two alternative designs and a no-choice option—each design was represented by its prototype (with shape and

Table 1. 95% Simultaneous Confidence Interval (SCI) for Each Utility Estimate[a]

Attribute/Level	Point Estimate	95% SCI
Brand		
Brand A	−24.81	[−29.36, −20.26]
Brand B	34.02	[30.34, 37.70]
Brand C	25.62	[20.98, 30.26]
Brand D	−34.84	[−40.17, −29.51]
Price		
$179	62.75	[58.52, 66.98]
$199	11.43	[8.62, 14.24]
$229	−74.18	[−80.76, −67.6]
Power		
100 Watts	−46.90	[−51.52, −42.28]
150 Watts	35.86	[32.7, 39.01]
200 Watts	11.04	[5.76, 16.32]
Life of Product		
800 hours	−47.71	[−53.65, −41.77]
1000 hours	1.88	[−1.57, 5.33]
1200 hours	45.83	[40.80, 50.86]
Shape		
Shape A	10.57	[7.41, 13.73]
Shape B	−26.38	[−31.12, −21.64]
Shape C	−40.11	[−42.86, −37.36]
Shape D	55.92	[51.82, 60.02]
Actuator		
Actuator A	60.94	[55.75, 66.13]
Actuator B	−60.94	[−66.13, −55.75]

Consumer Choice Validation		Predicted Share by Conjoint Utilities (%)	Actual Share Indicated by Subjects (%)
Holdout 1	Product1	39.35	45.24
	Product2	33.52	27.62
	No-Choice	27.13	27.14
Holdout 2	Product3	15.27	11.43
	Product4	36.12	45.24
	No-Choice	48.61	43.33

[a] Log-likelihood: −2641.71; chi-square: 2105.98; pseudo R^2: 0.285 (statistics for calibration sample).

actuator attributes) and was accompanying verbal descriptions indicating the levels of other attributes (brand, price, power rating, and life of product). Respondents could touch, feel, pick up, and test each prototype's grip and comfort of handling and so on and could read the verbal descriptions before making their choices. Respondents were asked to consider different usage situations when making their choices. The data were collected, coded, and analyzed using Sawtooth Software and LIMDEP.

The choice-based conjoint model was used to estimate part-worths of the different attribute levels. Table 1 provides these estimates, along with the results of validation on the holdout choice tasks. The fit statistics of the calibration sample and the results of the validation indicate that the model fit is reasonable. The estimation also provides the standard errors for the part-worth utility estimates of each attribute level and the variances and co-variances of the utility estimates. These estimates provide the ability to calculate the 95% simultaneous confidence interval associated with each attribute level. In particular, for continuous attributes such as life of product and power rating, the standard procedure of pair-wise linear interpolation was used (Sawtooth User Manual, 2001) to calculate the point estimate and the lower and upper bounds of 95% simultaneous confidence level for attribute values that are in-between levels.

The use of a choice-based model not only better mirrors the selection process in the market but also allows direct prediction of market shares, avoiding the need for translating predicted ratings or rankings into choices. More importantly, in the context of this study's focus on robust selection, the estimation methodology takes into account the uncertainty in customers' choice that could arise due to different factors. Using the estimates of variances and covariances of the part-worths, interval estimates were constructed for market shares for various alternatives considered in the design process on the basis of a predefined set of competitive products for the new product. The standard errors for the market shares are determined using a simulation procedure where part-worths were drawn from their respective distributions (with associated variances and covariances) and estimate market shares a number of times to obtain the market share distribution. This is useful for determining the preference robustness component due to errors in the preference elicitation process. Market share point estimates also were obtained under environmental variability corresponding to usage situations—best-case situation of the uncontrollable design parameters and worst-case situation of uncontrollable design parameters. Combining both components of market-share variability, overall interval estimates were obtained for market shares for all alternatives under consideration.

The interval estimates of market shares for the alternatives were used to determine whether or not an alternative dominates another alternative. If the interval estimates of two alternatives do not overlap, then there is a basis for dominance. In other words, alternative A dominates alternative B on the preference robustness dimension if and only if the lower limit of alternative A's market share interval estimate is greater than the upper limit of alternative B's market share interval estimate. These preference robustness measures then were combined with the design robustness measures to collectively determine the final robust design set. More details about this study's integrated robust approach are provided later in the article.

Design Module

The design module focuses on the uncertainties in material and usage situations, application type, and conditions (defined here as design parameters) that affect design attributes such as power rating (performance), armature temperature (life of motor/product), motor casing temperature, and cost. While the goal of a deterministic optimization study is to design a product that reaches its optimum performance or a desired level of compromise among its design attributes (i.e., multi-objective optimization) under nominal values of the design parameters, in practical applications of the product the design parameters often deviate from their nominal values. As a result of such deviations, the deterministic optimum design may show a significant degradation in its performance in the field, which also can affect customers' preferences for the product. Therefore, the uncertainties in the design parameters are taken into consideration along with uncertainties in preference estimates in the robust optimization process.

Several researchers in engineering design have investigated the effect of variability in parameters for single-objective design optimization problems (Badhrinath and Rao, 1994; Chen and Yuan, 1999; Gunawan and Azarm, 2004; Parkinson, Sorensen, and Pourhassan, 1993; Sundaresan, Ishii, and Houser, 1992; Taguchi, Elsayed, and Hsiang, 1989) and for multi-objective cases (Besharati et al., 2004). Taguchi, Chowdhury, and Taguchi (2000) define *robustness* as "the state where the technology, product, or process performance is minimally sensitive to factors causing variability (either in manufacturing or in the user's environment) and aging" (p. 4) Parkinson, Sorensen, and Pourhassan (1993) categorized the robustness into two categories: *feasibility robustness*, which refers to satisfaction of the design constraints despite parameter variations, and *sensitivity robustness*, which refers to the degree to which design attributes vary under variations in design parameters.

In this study's approach, the robustness definitions introduced by Kouvelis and Yu (1997) for single-objective problems are extended by considering the case of multiple objectives. In the present study's design robustness assessment, the goal is to identify superior design alternatives based on the following three selection criteria. First, the design should maintain feasibility with regard to design constraints under variations in uncontrollable design parameters. Second, the design should show the least possible variation in its design attributes. Third, the design should have the best possible performance in terms of the design attributes under the worst-case values of uncontrollable design parameters. The following paragraphs provide detailed descriptions of each robustness criterion—that is, feasibility robustness and multi-objective robustness (the Appendix provides additional details and references wherein a technical exposition can be found).

Feasibility Robustness

The goal of feasibility robustness is to ensure that the design will not violate design constraints for the worst case of uncontrollable parameters. Typically, a designer specifies a threshold value (called the "infeasibility threshold") on each important design attribute dimension. If, for a particular design alternative, the value of the design attribute exceeds this threshold level under the worst-case scenario, then the design candidate will be deemed "not feasibly robust." For example, the designer can specify that the armature temperature of the motor in a power tool should not exceed 150^{o} F when the application type (uncontrollable parameter) is varying. This is because armature temperature plays a critical role in determining motor life and the life of the product, and exceeding this temperature may result in product failure. In this case, 150^{o} F is the infeasibility threshold on the armature temperature attribute, and if a design alternative generates an attribute value exceeding the threshold under variations in uncontrollable parameters, it will be eliminated. This criterion is used in the multi-objective optimization problem to eliminate some of the inferior design candidates.

Multiobjective Robustness

This criterion will be explained using an illustration. Consider a motor type (a design input) that impacts design attributes such as armature temperature and

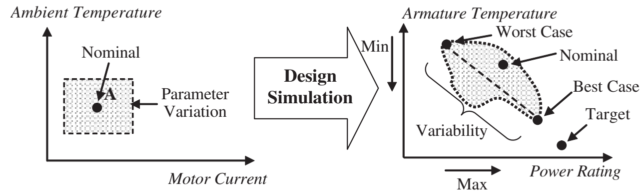

Figure 2. Mapping from Design Parameter Space to the Attribute Space

power rating of a power tool. The values of these design attributes for a given motor type are affected by uncontrollable variations in design parameters such as motor current, type of applications, and ambient temperature. Even though for each type of motor the designer can assume a nominal value for motor current and ambient temperature, the actual values of these design parameters depend greatly on the usage conditions or situations. Once a motor type is chosen by the designer, the variations in the design parameter space (motor current and ambient temperature) can be mapped onto the corresponding sensitivity region in the design attribute space (armature temperature and power rating) using a design simulation method (see Figure 2, where the nominal point and sensitivity region are shown).

Given a design attribute space, the designer typically can specify a target point in terms of design attribute values he or she should aim for. This target becomes the basis for determining the worst-case attribute values and the best-case attribute values under the variations in uncontrollable design parameters. In Figure 2, the point representing the worst-case attribute values is the one (worst-case point) that is farthest from the target point in the sensitivity region, while the point representing the best-case attribute values is the one (best-case point) closest to the target point in the sensitivity region. Multi-objective variability in design attributes is defined here as the distance between the worst-case point and best-case point, as shown in Figure 2.

This study's criterion of multi-objective robustness implies the following in comparing two design alternatives: (1) the closer the worst-case point is to the target, the better the design; and (2) the smaller the multi-objective variability, the better the design. Figure 3 displays two design alternatives, A and B, with their sensitivity regions, nominal points, worst-case points, and best-case points. While in the nominal case design A outperforms design B in the attribute space, in the worst case, design B is better than design A. In addition, design B exhibits a lower variability

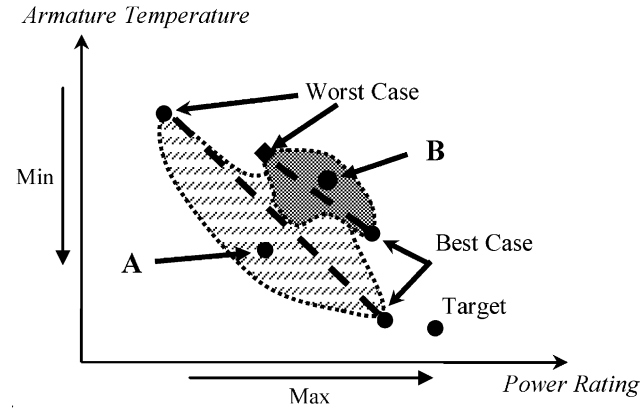

Figure 3. Multi-Objective Robustness Comparison of Two Design Candidates

than design A. Accordingly, design B is multi-objectively more robust than design A. If a design alternative does not perform better compared to another on both (1) and (2), then the designs are referred to as nondominated with respect to each other.

Integrated Robustness Assessment Using MOGA

In search for the final set of robust design alternatives for the prototypes, the design robustness and the preference robustness criteria were integrated using an adaptive search technique called MOGA, which is a multi-objective optimization method able to handle both discrete and continuous design inputs and parameters, as is the case in the problem under consideration (for instance, gear ratio is a continuous variable while motor type is a discrete variable). This technique required the representation of each design alternative in a binary string format. In the context of the present study, each design alternative or "chromosome" was composed of several concatenated strings (design inputs and product features that define the design alternative). Each string was made up of binary substring positions, with each substring indicating the specific level of each design input or product feature. The length of a substring, denoted by k, was dependent on the number of levels of an attribute that needs to be represented. For a substring length of k, GA can represent up to $(2^k - 1)$ different levels (exclude level zero) in the substring. In this case study, for example, if a design has any one of the four possible shapes and one of the two possible types of actuators, its chromosome representation could be "100 01", which corresponds to the fourth shape (i.e.,

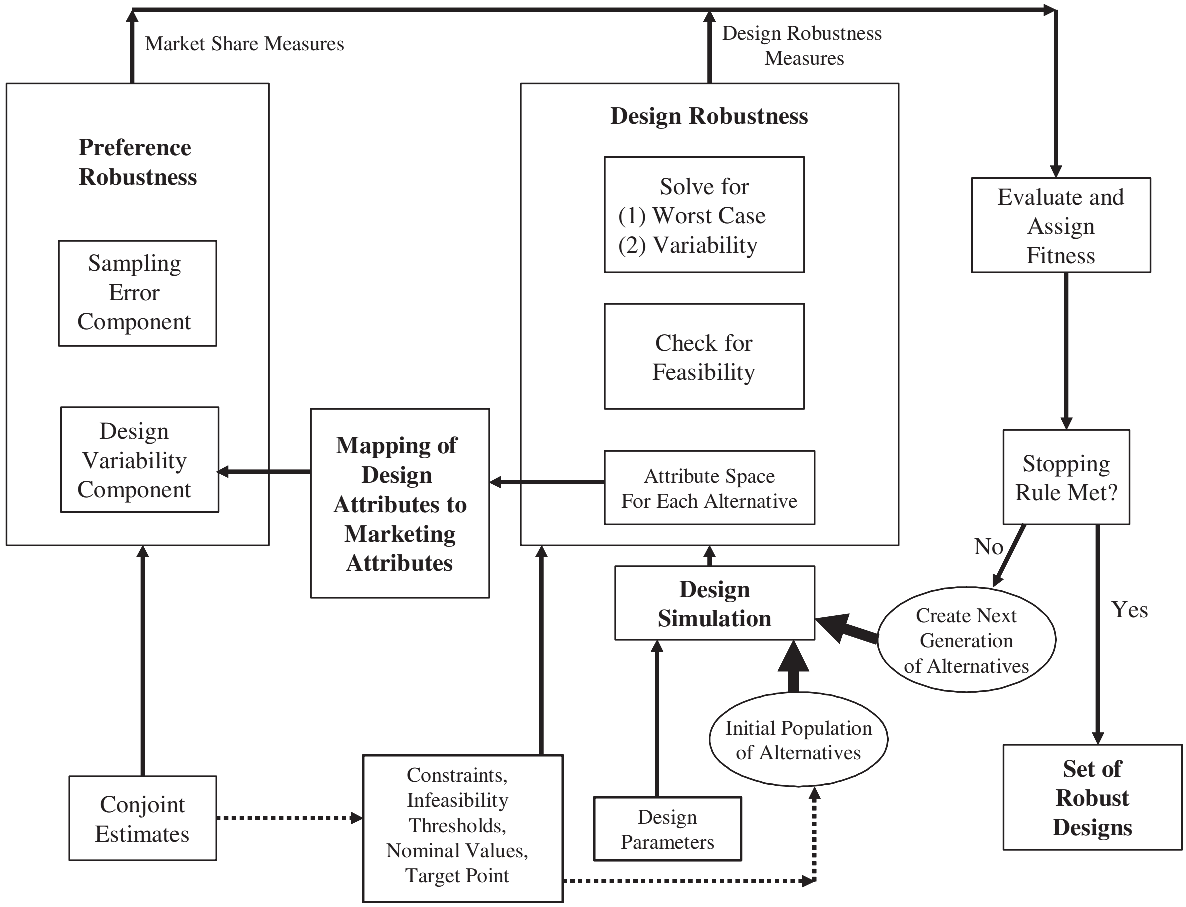

Figure 4. Integrated Robust Optimization Approach

$0 \times 2^0 + 0 \times 2^1 + 1 \times 2^2 = 4$) and the first type of actuator (i.e.,$1 \times 2^0 + 0 \times 2^1$). For continuous design inputs such as gear ratio, the string presentation is illustrated by the following example: a gear ratio of 5.3 is represented as "0101 0011", since $1 \times 2^0 + 0 \times 2^1 + 1 \times 2^2 + 0 \times 2^3 = 5$ and $1 \times 2^0 + 1 \times 2^1 + 0 \times 2^2 + 0 \times 2^3 = 3$.

The multi-objective robust optimization process with the present case study is explained using only two objectives so that it can be illustrated graphically. (Note that this problem has been significantly simplified for expositional purposes.) The set of design inputs included were motor type (160 levels), battery type (100 levels), gearbox type (80 levels), and gear ratio (continuous within a given range). The set of (uncontrollable) design parameters considered include motor current (ranging $\pm$ 0.5 amps from the nominal value), ambient temperature (ranging -10 to $+30$°F from the nominal value), battery current (ranging $\pm$ 0.2 amps from nominal value), and battery voltage (ranging $\pm$ 0.5 volts from nominal value). The two objectives were minimize (armature temperature) and maximize (power rating). These attributes dimensions are common between the design module and the preference elicitation module (see Figure 1). Power rating appears as is in both modules. Armature temperature affects the life of motor, which is the most critical component of the power tool and determines the life of product.[3]

The schematic in Figure 4 provides an overview of how multi-objective robustness, feasibility robustness, and preference robustness were considered in the application of MOGA (Deb, 2001; Coello, Van Veldhuizen, and Lamont, 2002). The process began with the design team specifying the constraints for the problem. There were many constraints for the case study optimization problem, but a few are highlighted here that are relevant for the objectives considered. Based on the conjoint-analysis results, both the ergonomic team and the marketing team wanted to eliminate

[3] In fact, if the motor fails, widget is generally not repaired but thrown away as repair costs tend to be much more than the price of a new widget.

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shape C (the one with a larger girth) as an alternative, as it has the lowest utility (see dotted line from "conjoint estimates" to "constraints" at the bottom left of Figure 4). This implied that large size motor and gear box combinations had to be restricted. In addition, the price of the new product was restricted to under US$200, which in turn implied a cost constraint in the design module and impacted the various combinations of design inputs that had to be restricted (for example, the more expensive component combinations were restricted—see dotted lines from "constraints" box to "initial population of alternatives"). The armature temperature also was constrained not to exceed 150° F, the threshold beyond which the coils of the motor can burn up and lead to catastrophic failure. There is also a constraint on motor-casing temperature not to exceed 196°F to prevent burns while using the tool.

Next, the design team specified infeasibility thresholds on different dimensions and the target points in the attribute space. The target points were used to normalize the objective and constraint function values so that they were of the same order of magnitude. These specifications, along with design parameters, were sufficient to start the multi-objective optimization process (see bottom of Figure 4). The multi-objective optimization using genetic algorithm works as follows.

Step 1: Initial Population of Alternatives

Fifty design alternatives were picked at random to be evaluated by specifying motor type, battery type, gearbox type, and gear ratio. For each alternative all combinations of the uncontrollable design parameter space (motor current, ambient temperature, battery current and battery voltage, in this case) were defined. Using design simulation, the performance of these designs (in this case, the two objectives of armature temperature and power rating) was evaluated under varying conditions of design parameter values for each design alternative (based on the attribute space for each alternative).

Step 2: Mapping Design Attribute Space to Marketing Attribute Space

Once the attribute space was developed for each alternative, it had to be mapped to marketing attributes (that are common to both design and marketing functions) to understand the impact of design variability on customers' preferences (the first component of preference robustness). For example, the design attribute of armature temperature affects life of the product (a marketing attribute). Based on product testing in laboratory studies, the relationship between armature temperature and life of product was determined by the design team and was incorporated in the mapping. Thus, when armature temperature varies, the life of product varies and, consequently, can impact consumers' preference for the product. Similarly, cost of the design and price of the product (which are common between the two modules) are related using manufacturer margin goals.[4] This mapping function provided the important link between design module and preference robustness module and allowed for an estimation of the changes in customers' preferences (and thus market shares) under design variability.

Step 3: Feasibility Robustness

The feasibility robustness of each design alternative was evaluated taking the infeasibility thresholds into account. For example, one of the constraints shown in the study's illustration—motor casing temperature not to exceed 196°—eliminated eight designs from the initial population, as illustrated in Figure 5. Those designs exceeding the infeasibility threshold were eliminated from further consideration.

Step 4: Integrated Robustness Assessment

Preference robustness was combined with design robustness to identify nondominated designs. For the successful candidates that remain (i.e., those that pass the feasibility requirements), the sensitivity region for each design alternative was formed (e.g., Figure 5 shows the regions for two designs). Using the approach described in the design module, the worst-case point distance from the target point and multi-objective variability were calculated for every design alternative. Using the approach described in the preference elicitation module, the interval estimate of market share for each design alternative was calculated as the measure for preference robustness. The trade-off

[4] Price has been computed as cost plus manufacturer margin plus retailer margin. In actual practice, the price is determined by the marketplace. In such as a case, the manufacturer can determine the impact on her or his margins based on their costs and prices commanded in market.

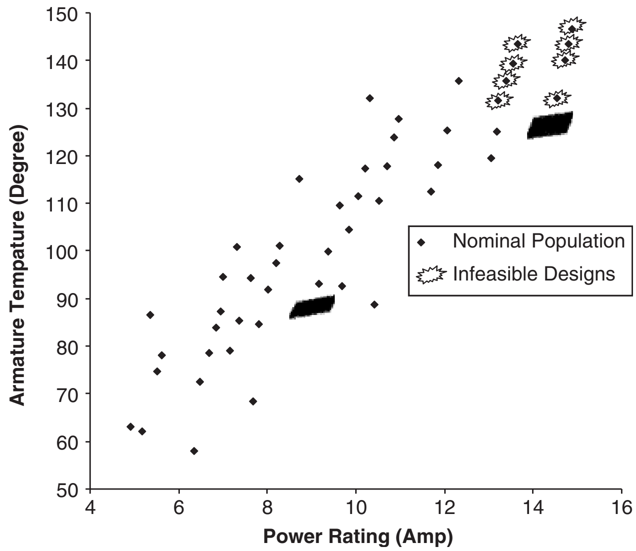

Figure 5. Set of Design Alternatives for Initial Population

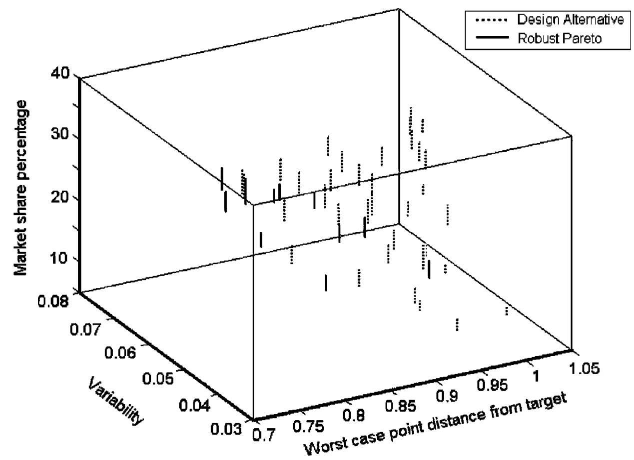

Figure 6. Retained Robust Designs after First Fitness Assessment for Initial Set of Feasible Design Alternatives

among these three measures is shown in Figure 6. The multi-objective optimization technique guides the search based on the multi-objective ranking (a fitness measure) of design robustness and preference robustness (Zenios, 1995). The integrated design and preference robustness assessment was based on the criterion that given two design alternatives A and B, alternative A is preferred to B if and only if A is superior in both design and preference robustness assessments. Eleven designs were determined to be robust after the first iteration of the integrated robustness assessment.

Step 5: Check-Stopping Criteria

A moving average rule was employed as the stopping criterion (Balakrishnan and Jacob, 1996; Steiner and Hruschka, 2003). Namely, if the average fitness of the best chromosomes (or designs) of the current generation increased by less than a small percentage as compared to the average fitness of the best designs from a few previous generations, then the identified best designs were stopped. If the stopping criteria for the optimization were not met, the 11 best designs were retained for the next step of the genetic algorithm.

When the stopping criteria were not satisfied, three operators were used to create the next generation of design alternatives: (1) reproduction, wherein a subset of the alternatives were chosen based on their fitness and copies of their profiles were generated; (2) crossover, wherein pairs of design alternatives were chosen and, along specific positions on the strings, genetic material between the two strings were exchanged leading to offspring (i.e. two new design alternatives); and (3) mutation, wherein a design alternative was randomly chosen from the population and the binary value at a specific location (design input and product feature) in the string was modified. At the end of each iteration the stopping criteria were checked, and the iteration continued until the optimizer's stopping criteria were met.

The result of the application of MOGA was a set of robust Pareto solutions that were nondominated by any other alternative considering both the design objectives and the market share objective. In this study's application to the organization's problem, the integrated robustness assessment process using MOGA led to the identification of three design alternatives as the best robust designs from marketing, ergonomic, and design perspectives. The organization picked these three designs for prototype development, performance evaluation in field tests, retailer consultations, and further market simulations.

It should be noted that if MOGA is applied without considering the customer preferences, it would still provide solutions in the Pareto frontier, albeit in the context of only the design objective functions considered. When customer preference and preference robustness are considered in MOGA, then solutions in the Pareto frontier are obtained that have higher market share as well as contain solutions that a MOGA without customer preference considerations may not have generated. However, in a practical application, by considering customer preferences and preference robustness in this study's approach, designs should be identifiable in the Pareto frontier that have potentially higher market share as compared to the case of MOGA without considering customer preferences.

Conclusions

This article has proposed an approach that focuses on the issue of robustness from design and marketing perspectives. In product categories such as consumer durables, which are used under different conditions and for different applications, it is very essential to consider the impact of such variations on performance and customer preference (and market share or profit). This area of research has not received much attention in the NPD literature, and hopefully this study will stimulate some interest.

In an environment where most of NPD work is carried out in cross-functional teams, it is very necessary to have coordination processes that are efficient and effective to harness the power of such teams. The number of design inputs, attributes, and parameters considered are typically large, and they tend to be interrelated and common across many functions. This study's approach provides a clear, systematic method to consider these factors and to integrate them in identifying good design alternatives. The approach is transparent. Thus, every functional team knows exactly how the factors it deems important relates with other factors that other functions consider important and how each factor contributes to in identifying the designs for prototypes. This transparency enables quick internal buy-in within the teams for the chosen alternatives. Overall, this approach has a significant potential to reduce the cost and time of developing prototypes. It also enables the process to be market focused early on in the product development cycle, as customer preferences are already accounted for at the prototype stage.

It is imperative that a successful implementation of this proposed approach requires close coordination among marketing, design, and ergonomics functions. Being closer to the customer and the competition, the onus of leading this coordination effort falls naturally upon the marketing function. As Figure 1 indicates, the marketing team identifies customer needs and the important attributes based on which customers make their purchase decision and the unique attributes offered by competitive products. The marketing team also consults with the design and ergonomic teams on innovations that are distinct possibilities (based on their respective work) and unique features that could provide competitive advantage in the market. These become the starting points for specifying the marketing, ergonomic, and design attributes as shown in Figure 1. The basis for such coordination and an incentive structure may not exist in all organizations. This might entail the creation of product development teams on a project-by-project basis. Such a team draws in experts from marketing, ergonomic, and design functions—all working on a specific product development project with funds/resources earmarked specifically for the project with important milestones and deadlines specified in consultation with top management. Such teams create the necessary incentives for successful coordination as evidenced in many market-focused organizations including the one discussed in this case study.

From an academic viewpoint, this study's methodology integrates issues of design robustness with those of customer preference robustness in evolving new design alternatives using multi-objective genetic algorithms. While the ultimate validation of this approach may be difficult to assess at this stage (and is a topic worthy of future work), it is quite evident that consideration of part-worth of attribute levels and customer utilities for product alternatives in the design stage can lead to a market-focused design evolution process. In the case study, the application of this approach resulted in the generation of a design with higher customer utility (and market share) that was discarded when the MOGA was repeated without considering customer utilities. While this is just anecdotal evidence, this approach confirms some of the common adage in new product development—the design that has the best engineering performance may not be the one most preferred by the customer.

A significant advantage of this approach is that it is flexible enough to accommodate alternative measures in assessing customer preference robustness. This study has used market share variations in Figure 6 as the measure of preference robustness, but this could easily be converted to manufacturer profits. Since each set of design inputs can be associated with a cost attribute, manufacturer margin on each unit sold (retail price minus retail margin minus cost) can be determined for each design alternative. Thus, interval estimates for market shares can be converted to interval estimates for manufacturer profits for each alternative,[5] and this measure can be used for robustness assessment of market profitability. In some instances, manufacturers may specify a retail price point that they target for a new product (this is quite common in the case study as retailers generally specify the price point they are looking for). In such a

[5] Manufacturer Profit = Market Share × Total Market in Number of Units × Manufacturer Margin per Unit.

situation, one could fix the retail price targeted and could use manufacturer profit as a robustness criterion and as an objective in the multi-objective optimization for evaluating alternatives rather than using market share estimates.

This study's framework and methodology do have some limitations. First, given that a customer evaluation of alternatives is the starting point for the coordinated design, if new innovations and attributes evolve during the design process it will be necessary to go back to customers for additional evaluation. Second, while the study has considered the robustness issue in customer preferences using alternate measures, this approach makes a strong assumption that the customers are homogeneous and that the utilities estimated are the same for all customers. The issue of preference heterogeneity can have a more significant impact than the issue of preference robustness, especially with regard to estimated market shares of design alternatives. This is a focus of future research, where robustness issue could be examined in the context of hierarchical Bayes and/or latent segment models.

Finally, with regard to practical uses of this study's framework, it could be argued with some justification that this approach cannot be extended easily to cases where prototypes are expensive to manufacture or where design variables involved are too many or building the simulation models are quite complicated or not possible. However, in such situations, virtual reality representations (Dahan and Srinivasan, 2000) and applying the approach to a smaller component of the design can be attempted before making a large-scale implementation.

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Appendix

In this Appendix, more details are provided into the black boxes used in Figures 1 and 4, given their key role in the framework.

Design Simulation

This software is a collection of special computer programs that perform specific computational analyses to simulate and to predict the performance of a design under varying usage situations and conditions. In this case study, the simulation software consists of a thermal, cost, and finite element analysis assessment programs. The input to the simulation consists of design inputs (motor type, motor number, gear type, gear ratio, and battery number) and design parameters (the nominal and ranges of ambient temperature encountered in using the product, motor current variations for different types of motors, and so forth). The output of the simulation includes values of design attributes such as power rating achieved by the design alternative, overall cost based on the components specified in the design input, weight, and armature temperature attained.

The design simulation software is developed on the basis of extensive laboratory studies where different types of motors, batteries are tested under different environmental conditions using thermal and finite element studies. It also incorporates cost analysis where the standard costs of different components are incorporated to arrive at the overall cost of a design alternative. Such software are developed specifically for each product categories—drills, planers, grinders and such—based on in-house research and studies. Thus, the specific aspects of the simulation used in this case study are useful only for the product lines of the firm, and for new product lines' analysis the firm will require new simulations to be developed. Additional details on building such simulations are available in the text by Doebelin (1998).

Mapping of Design Attributes to Marketing Attributes

The mapping function plays an important role in linking the attributes that are common to the design and marketing function and thus in transmitting the variation that occurs in the design attributes as result of uncontrollable environmental factors (design parameters) to the corresponding marketing attributes. This is necessary for determining the design variability component of preference robustness. With respect to Figure 1, the attribute ‘‘power rating’’ is the just the same across the two functions and so mapping the variability from design to marketing is just a one-to-one linear mapping. However, the design attribute armature temperature affects the attribute "life of product" in a nonlinear fashion. While changes in armature temperature at lower values do not affect the life of the product significantly, changes in armature temperature at higher values do impact the life of product adversely. This nonlinear relationship is determined through laboratory tests and field studies by the design function and is used for mapping the two related attributes. Similarly, the "cost" attribute in the design module is mapped to "price" attribute in the preference module using the relationship: price = cost + manufacturer margin + retail margin, where the margins are constant values and are specified as percentage of costs. As with design simulation, the mapping relationships are specific to the specific product lines analyzed, and analysis of new categories will entail development of such relationships in-house.

Additional details on the black boxes and general and specific technical specifications of the robustness elements discussed in the article can be found in extant references (Kouvelis and Yu, 1999; Besharati et al., 2004; Li and Azarm, 2000).