B. Besharati
Ph.D. Candidate
Department of Mechanical Engineering,
A. J. Clark School of Engineering,
University of Maryland,
College Park, MD 20742

L. Luo
Assistant Professor
Department of Marketing,
The Marshall School of Business,
University of Southern California,
Los Angeles, CA 90089

S. Azarm[1]
Professor
Department of Mechanical Engineering,
A. J. Clark School of Engineering,
University of Maryland,
College Park, MD 20742
e-mail: azarm@umd.edu

P. K. Kannan
Associate Professor
Department of Marketing,
Robert H. Smith School of Business,
University of Maryland,
College Park, MD 20742

Multi-Objective Single Product Robust Optimization: An Integrated Design and Marketing Approach

We present an integrated design and marketing approach to facilitate the generation of an optimal robust set of product design alternatives to carry forward to the prototyping stage. The approach considers variability in both (i) engineering design domain, and (ii) customer preferences in marketing domain. In the design domain, the approach evaluates performance and robustness of a design alternative due to variations in its uncontrollable parameters. In the marketing domain, in addition to considering competitive product offerings, the approach considers designs that are robust in customer preferences with respect to: (1) the variations in the design domain, and (2) the inherent variations in the estimates of preferences given the fit of the preference model to the sampled data. Our overall goal is to obtain design alternatives that are multi-objectively robust and optimal, i.e., (1) are optimal for nominal values of parameters, and (2) are within a known acceptable range in their multi-objective performance, and (3) maintain feasibility even when they are subject to applications and environments that are different from nominal or standard laboratory conditions. We illustrate the highlights of our approach with the design of a corded power tool example. [DOI: 10.1115/1.2202889]

Keywords: robust design, integration of design and marketing, multi-objective optimization

1 Introduction

A successful product design requires, among others, an efficient and effective integration of engineering design and marketing domains [1]. In the engineering design domain, design alternatives can be generated by a number of means—for example, by a combinatorial permutation of attribute levels or by a multi-objective optimization method (e.g., Refs. [2,3]). A limitation of such reported methods often is that they are developed solely based on "design attributes" and entirely ignore "marketing attributes" that impact customer preferences. The literature in engineering design has looked into the integration of engineering design and marketing aspects for product design (e.g., Refs. [4–9]). These methods either ignore robustness in the design and marketing [4–8], or might be too conservative: selecting designs that have the best possible performance under a worst case condition [9].

In product design, both design and marketing attributes are likely to have variability. The source of this variability is parameters that the designer does not have control over. Such variations can cause unwanted changes in product performance that in turn may affect customers' preferences for a product. For instance, in a corded power tool product design attributes that might have variability include engineering specifications of the tool such as armature temperature and amp rating. The marketing performance of the tool such as life of the product may also vary due to the changes in the design domain. Also, additional variability can arise due to the variances inherent in the marketing or conjoint model parameter estimates when marketing researchers estimate customer preferences [10].

From an engineering design perspective, a design alternative should maintain feasibility under variability, have variations in its performance that are within an acceptable range,[2] and exhibit an optimum performance under these constraints. The literature reports on a variety of definitions for robustness and in this regard many researchers have investigated the effect of variability and the importance of "robustness" as a critical factor in engineering design, e.g., Refs. [11–18]. Majority of the literature in robust design optimization is focused on product attributes that are directly derived from an engineering design model while the marketing implications of those attributes are not directly considered. On the other hand, the extant literature on the integration of engineering design optimization and marketing (e.g., Ref. [9]) has not fully addressed the issue of design robustness and its impact on the customers' preference. In particular, the approach in Ref. [9] can eliminate potentially optimum designs, with acceptable variability, by designs that have unnecessarily lower variability but with significantly more inferior nominal performance. Unlike the approach in Ref. [9], our robustness measures in this paper eliminate only those designs whose performance variation is beyond an acceptable range. More specifically, our integrated design and marketing robust optimization approach of this paper accounts for: (1) acceptable performance variability and feasibility of a design alternative and (2) the effects of variations in design domain on the marketing domain and criteria (i.e., measures of customer preferences and their variations).

From a marketing perspective, we define "preference robustness" as a criterion that accounts for: (1) the impact of variations in the design domain on the values of marketing attributes; and (2) the variations inherent in the conjoint model parameter estimates due to imperfect model-data fit. Several marketing researchers have suggested that consumer preferences can be influenced by subtle changes in the experimental context (e.g. Refs. [19–22]). In particular, Louviere et al. [23] pointed out that point estimates and

[1]Corresponding author.

Contributed by the Design Automation Committee of ASME for publication in the Journal of Mechanical Design. Manuscript received August 8, 2005; final manuscript received December 19, 2005. Review conducted by Zissimos P. Mourelatos.

[2]In a perfect yet unachievable sense, the variation in performance is desired to be zero.

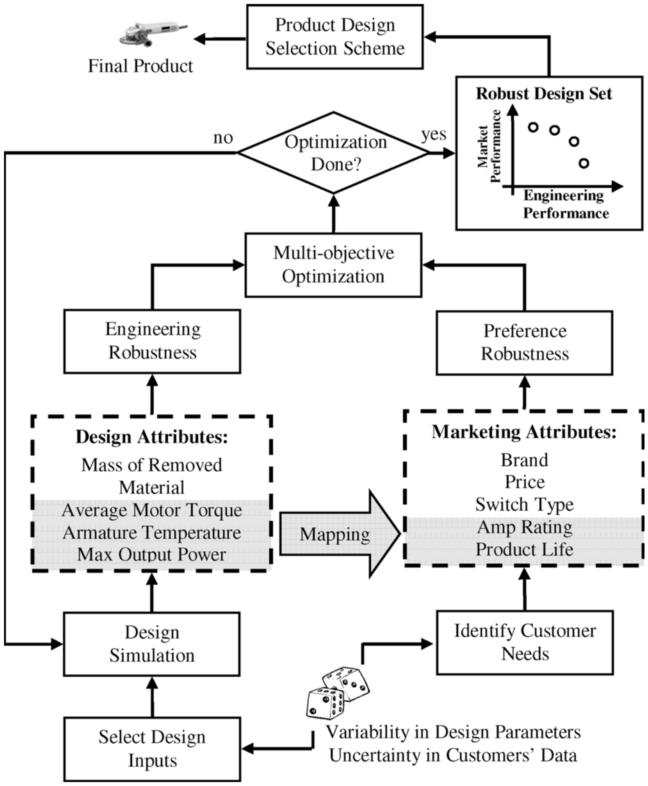

Fig. 1 Overall approach

interval estimates of consumer preferences and context effects can play an important role in the variances of the conjoint estimates. Two different approaches have been proposed to account for this. The approach suggested by Ref. [22] adds an extra error term to the random component of consumer utility. The advantage of this method is that context can be disentangled from preferences in the determination of choice behavior. The drawback is that it requires the collection of additional data on experimental contexts such as attitudes and expectations. In contrast, the study in Ref. [9] specifically identifies and controls for variations in the systematic component of the utility function. We favor the latter approach for two reasons. First, the impact of variations in the design domain can be directly mapped into the consumer utility. Second, this approach allows us to identify robust products in the conventional setting of conjoint surveys without requirement of additional data. However, in Ref. [9], heterogeneity of consumer preferences is not considered. We relax this assumption here by categorizing consumers into different market segments, which provides a better estimate of consumer demand [24]. More important, we improve upon a previously reported preference robustness assessment approach [9] by specifying additional objectives to better identify promising alternatives from the marketing domain.

The rest of the paper is organized as follows. Section 2 gives a general overview of our approach. Section 3 covers our design robustness approach. Section 4 presents our marketing model. Details of the overall integrated approach are presented in Sec. 5 followed by an example in Sec. 6. Finally, the paper is concluded in Sec. 7.

2 The Overall Approach

Figure 1 gives a flowchart of our overall approach. The approach has two main components: engineering design domain (left column of Fig. 1) and marketing domain (right column of Fig. 1). In the design domain, we first specify the range of variations for uncontrollable design parameters as well as acceptable range of variations for design performance objectives. Next, design inputs are fed into simulation software that calculates an estimate of design attributes (or performance) for each design alternative under consideration. Some design attributes are expected to show little or no variation in their attributes, as a result of variations in uncontrollable design parameters, while others may exceed beyond their acceptable range for their attributes. Depending upon how performance and/or feasibility of a design respond to such variations, two measures are used to measure "engineering robustness," namely multi-objective robustness and feasibility robustness.

In the marketing domain (right column of Fig. 1), the most important customer needs are first identified based on an initial exploratory market study. It is likely that some product attributes not only affect engineering design performance of the product (e.g., maximum output power, in the case of a power tool) but also are key attributes for a customer's purchase decision (e.g., amp rating of a power tool). In our approach, this type of product attribute is designated as "common attributes." It is often necessary to use a mapping (shaded arrow in Fig. 1) to calculate one or more common attributes in the marketing domain from those in the engineering design domain. In our approach, we take into account the variability in customers' preferences (or utilities) for common attributes (such as life and amp rating) that come from both design and marketing domains. On the other hand, there may be product attributes that are not common to both marketing and engineering domains. For example, in a corded power tool, attributes like brand and switch type, which do not affect product's engineering design performance, are quite important to the market performance of a product and hence appear purely as marketing attributes. For these attributes, we only consider the inherent variation in the conjoint estimates. Due to the fact that brand name is generally fixed for a particular manufacturer, we fix the brand name to "own brand" for all product alternatives in our optimization. The output of the marketing model includes estimates of market share and its variation which are used to measure preference robustness.

The preference robustness measures with the engineering design robustness criteria are used in an optimizer, together with other performance criteria, to generate a set of multi-objectively robust product design alternatives. These alternatives not only perform well from both engineering design and marketing performance points of view but also exhibit low variation with respect to their performance due to uncontrollable parameter variations, including the inherent variation in consumer preference elicitation and estimation.

In the final stage of our product design development process, we may need to make a selection among the generated robust product design alternatives (see, e.g., Refs. [3,4,25]). The issue of product design selection is beyond the scope of this paper, and therefore we do not provide a detailed discussion here.

3 Design Model

In this paper, the design model is built based upon the assumption that the simulation software is deterministic and that it receives a set of design variables (e.g., choice of motor, gear ratio) and parameters (e.g., source voltage, ambient temperature) and computes a corresponding set of design attributes (e.g., maximum output power, weight). The design performance attributes are used as objective functions and/or constraints in our robust design optimization approach. The main definitions and terminologies together with our approach for robust design optimization are discussed in the next few sections.

3.1 Definitions and Terminologies. The general formulation of a multi-objective optimization problem is shown in the following:

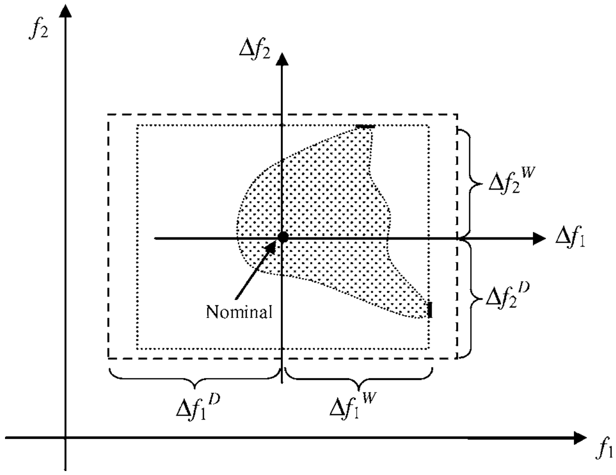

Fig. 2 Multi-objective robustness

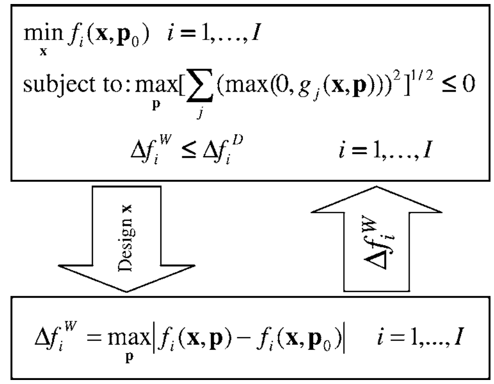

Fig. 3 Robust optimization approach

$$\underset{\mathbf{x}}{\text{minimize}}\ f_i(\mathbf{x},\mathbf{p}) \quad i=1,\ldots,I$$

$$\text{subject to: } g_j(\mathbf{x},\mathbf{p}) \leqslant 0 \quad j=1,\ldots,J \tag{1}$$

where f_i is the ith objective function, g_j is the jth constraint function, $\mathbf{x}=(x_1,\ldots,x_N)$ is the vector of design variables, $\mathbf{p}=(p_1,\ldots,p_V)$ is the vector of design parameters. We assume that the designer has control over design variables $\mathbf{x}$ (i.e., can change them using an optimizer and thus create different design alternatives) but has no control over design parameters $\mathbf{p}$ (i.e., they have uncontrollable variations within a known range). Some researchers prefer to differentiate between variations in design variables and variations in design parameters, the so-called type-1 and type-2 variations [20,27]. For simplicity, we do not make that distinction in this paper. Examples of design variables are motor type, gear ratio, gearbox type, and examples of parameters are ambient temperature, source voltage, and application type. The design variables along with design parameters are fed into the design simulation software. The design simulation software computes the values of design attributes (or performance, e.g., armature temperature, motor speed for a power tool). As highlighted earlier, there are several attributes that are specific to marketing domain and do not play a role in design performance (e.g., brand, price). However, the attributes that are common to both design and marketing domain (such as product life) do have a role in the design module. In this paper, the marketing attributes (excluding the common attributes) are all discrete. Each design alternative can be enumerated over the marketing attribute levels, and thus generate several product alternatives.

3.2 Multi-Objective Robustness. We define a design to be multi-objectively robust if the variation in each of its objective function values is bounded within a specified range. In order to formulate the multi-objective robustness, a measure for multi-objective variability is introduced. Our idea is based on the maximum variation of the objective function values from the nominal values, Δf_i^W:

$$\Delta f_i^W = \max_{\mathbf{p}} |f_i(\mathbf{x},\mathbf{p}) - f_i(\mathbf{x},\mathbf{p}_0)| \quad i=1,\ldots,I \tag{2}$$

where $\mathbf{p}_0$ is the vector of nominal parameter values for design $\mathbf{x}$, and $\mathbf{p}$ is between $\mathbf{p}_L$ and $\mathbf{p}_U$, the known lower and upper bounds on design parameters, respectively. Any global optimization technique could be used to find Δf_i^W for each design alternative $\mathbf{x}$.

To assess the multi-objective robustness of each design, first the designer needs to specify the maximum acceptable variation range from nominal for each objective function, Δf_i^D for ith objective function as shown in Fig. 2. The shaded region inside the rectangles in Fig. 2 is the sensitivity region. The sensitivity region for a design $\mathbf{x}$ can be obtained by calculating the objective function values as $\mathbf{p}$ components are varied within their known lower and upper bounds.

For a multi-objectively robust design, the maximum variations of every objective function from its nominal value (e.g., Δf_i^W) should be smaller than an acceptable range (e.g., Δf_i^D) specified by the designer. As shown in Fig. 2, a design is multi-objectively robust, if its sensitivity region or a corresponding maximum variation from the nominal (dotted inner box in Fig. 2) does not go beyond the acceptable range (dashed outer box).

3.3 Feasibility Robustness. The goal of feasibility robustness is to ensure that a design will not violate constraints should the worst case values of uncontrollable parameters occur. The feasibility robustness of a design alternative $\mathbf{x}$ is verified by examining the following inequality:

$$\max_{p}\left[\sum_j (\max(0, g_j(\mathbf{x},\mathbf{p})))^2\right]^{1/2} \leqslant 0$$

$$\mathbf{p}_L \leqslant \mathbf{p} \leqslant \mathbf{p}_U \tag{3}$$

3.4 Robust Design Optimization Approach. Our robust design optimization approach (ignoring the marketing information at this stage for expositional purposes) is encapsulated in Fig. 3. A multi-objective optimization is performed in the upper block of the flowchart. To ensure multi-objective robustness, each feasibly robust design point $\mathbf{x}$ is passed on to the lower block, as shown in Fig. 3, where the maximum variation from the nominal value for each objective function is calculated. This procedure continues until all design alternatives that meet robustness requirements and at the same time have the best possible performance in a multi-objective sense are obtained.

Since we have not considered any marketing information at this stage, the above—mentioned approach that includes multi-objective and feasibility robustness may overlook design candidates that are good alternatives from a marketing performance viewpoint. In Sec. 4 we take the marketing aspects of the product into consideration.

4 Marketing Model

A successful product design should not only satisfy engineering design requirements (in terms of performance and reliability) but it should also perform well commercially in the market based on customer preferences. In Sec. 4.1, a finite mixture conjoint model is used to capture the customers' preferences. Section 4.2 covers the sources of variability in customers' preferences and our approach for modeling such variations.

4.1 Finite Mixture Conjoint Model. In a conjoint-based method, customers' utilities for different levels of marketing attributes are estimated through customers' evaluations of a set of hypothetical product profiles [30]. The simple premise in conjoint models is that customers evaluate the overall utility of a product by combining the separate utility value (i.e., part-worth) of specific levels of marketing attributes that define the product. Since consumers generally have heterogeneous preferences toward the products, a finite mixture conjoint model provides a way to segment the market based on consumers' responses to the conjoint experiment. The details of our model are given below.

A conjoint choice experiment starts with J individuals (consumers), each evaluating K choice sets. Each of the K choice sets contains M product alternatives. Each product alternative is defined by the combination of different levels of marketing attributes. If we assume the existence of $s=1,\ldots,S$ segments with segment sizes SS_s, the utility u of consumer c for product m in choice set k, given that this individual belongs to segment s, is defined as follows[3] [10]:

$$u_{cs}(\mathbf{y}_{mk},P_{mk}) = (\mathbf{y}_{mk}\boldsymbol{\beta}_{sy} + P_{mk}\boldsymbol{\beta}_{sp}) + \varepsilon_{csmk} \tag{4}$$

where $\mathbf{y}_{mk}$ is a vector representing product attributes of product alternative m in choice set k, P_{mk} is the vector of product price in choice set k, $\boldsymbol{\beta}_{sy}$ is a $\alpha\times 1$ vector of parameter coefficients weighting each product attribute levels, $\boldsymbol{\beta}_{sp}$ is a vector of parameter coefficients for prices, and ε_{csmk} is a random component of the utility. Following the tradition in conjoint studies, we use effect-type coding for all the marketing attributes [28]. We assume that the random component $\varepsilon_{\mathrm{csmk}}$ follows an independent identical double exponential distribution. Therefore, the probability $\mathrm{Pr}_{\mathrm{cmks}}$ that product m is chosen from choice set k, subject to consumer c being a member of segment s, can be expressed as

$$\mathrm{Pr}_{cmk} = \frac{\exp(\mathbf{y}_{mk}\boldsymbol{\beta}_{sy} + P_{mk}\boldsymbol{\beta}_{sp})}{\sum_{mm=1}^{M}\exp(\mathbf{y}_{mmk}\boldsymbol{\beta}_{s} + P_{mmk}\boldsymbol{\beta}_{s}) + \exp(\mathrm{cons}_s)} \tag{5}$$

where cons_s represents the constant term representing the utility of the "no-choice" option for consumers in segment s. We denote θ_s as the likelihood that a consumer is a member of market segment s. The unconditional probability of consumer c choosing product m from choice set k can be computed as [29]:

$$\mathrm{Pr}_{cmk} = \sum_{s=1}^{S}\theta_s\,\mathrm{Pr}_{cmks} \tag{6}$$

The log-likelihood of observing all the choices in all the choice sets for all the customers can be written as [29]:

$$\mathrm{LL} = \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{K}\ln(\mathrm{Pr}_{cmk}) \tag{7}$$

Using the maximum likelihood estimation method on Eq. (7), we can calculate a set of segment-level conjoint part-worths and the corresponding segment sizes for the scenarios of one segment, two segments, …, through $S_{\max}$ market segments (a pre-specified maximum number of market segments). Akaike's information criterion (AIC) (defined in Eq. (8)) is used to determine the optimal number of segments in the market. The model (scenario) with the smallest AIC value is the one that best explains the observed choices without overfitting the data (see Refs. [24,30]).

$$\mathrm{AIC} = -\frac{2(\mathrm{LL}-q)}{\mathrm{SS}} \tag{8}$$

where q is the number of part-worth utilities estimated and SS is the sample size (number of customers times the number of choice sets).

The estimation procedure provides us with estimates of the number of segments along with segment sizes, segment-level part-worth utilities, and the asymptotic variance-covariance matrix of part-worth utilities [9,31]. These estimates can be used to calculate the point and interval estimates of market share for each product alternative, given a set of competing products [24,28].

4.2 Preference Robustness. Our model integrates the following types of variations in consumer preference. First, we consider variation from the engineering domain in attributes that are common between the engineering design module and the marketing module. Second, variations inherent in the conjoint part-worth estimation because of the imperfect model-data fit. According to Ben-Akiva and Lerman [32], choice-based conjoint part-worth utility estimates can be considered as asymptotically normal when the sample size is sufficiently large. Therefore, we are able to use the method described in the following paragraphs to construct the interval estimates of the part-worths utilities for various design alternatives.

First, we explain how we obtain the interval conjoint estimates at the segment level. For discrete product attributes (such as brand and switch type), the interval estimate can be obtained by calculating the 95% confidence interval using the point conjoint estimate and the standard error of the estimate.[4] For continuous and non-common product attributes (such as price), we first use pairwise linear interpolation [33] to calculate the point estimate in between specified conjoint levels. For example, for a price (P) that is in between two specified price levels (P_1 and P_2) in the conjoint study, the point estimate of the conjoint part-worth utility can be estimated as follows, where $u(P_1)$ represents the point conjoint estimate at price level P_1 and $u(P_2)$ represents the point conjoint estimate at price level P_2:

$$u(P) = \frac{(P_2-P)}{(P_2-P_1)}u(P_1) + \frac{(P-P_1)}{(P_2-P_1)}u(P_2) \tag{9}$$

Next, we calculate the variance of the part-worth var (u) using Eq. (12) [34]:

$$\mathrm{var}(u) = \left(\frac{P_2-P}{P_2-P_1}\right)^2 z_1^2 + \left(\frac{P-P_1}{P_2-P_1}\right)^2 z_2^2 + 2z_{12}\frac{(P_2-P)(P-P_1)}{(P_2-P_1)^2} \tag{10}$$

where z_1 and z_2 represent the standard errors of the point conjoint estimates at price levels P_1 and P_2, and z_{12} represents the covariance of the two conjoint part-worth utility estimates. Finally, we construct the interval conjoint estimate as the lower and upper bounds of the 95% simultaneous confidence levels.

So far we have only addressed the uncertainties in customer choices in the conjoint experiment. The second component of the preference robustness in our marketing model comes from the variation in the performance of the product in the engineering domain. For example, when the tool is used in different usage situations and under different conditions, the actual amp rating of the power tool may vary, say ±0.5 A from the nominal value. We also consider the impact of such variation on the consumer's preference for the product. This applies to all the common attributes in our study (e.g., power amps and product life). We first calculate the ranges of utility variation for the lower and the upper bounds of the amp rating variation using the method described in Eqs. (9) and (10). Next, we construct the interval estimate of the conjoint utility by identifying the lower and the upper bounds of the conjoint utility variation when amp rating changes.

Once the interval estimates of the conjoint part-worths for each level of the marketing attributes are obtained, we are able to cal-

[3]We also considered alternative models with interaction effects between attributes. We did not find any additional improvement in our model fits. Therefore, only main effects are included in our model.

[4]We use 95% confidence level because this is the most commonly used criterion in statistics literature [34]. This percentage can be adjusted based on the product manager's preference.

culate the upper and lower bounds of the conjoint utility for each product alternative (at the segment level) by summing up the lower and upper bounds of conjoint part-worth utility estimates for each marketing attribute. When calculating the market shares, we consider the impact of variation not only on the product being developed (hereafter called the "own" product) but also on the competing products. The calculation procedure is similar to the one used for "own" product. With regard to the common attributes, we obtain the variation information of the competing products from the engineering lab.

Now we explain how to calculate the upper and lower bounds of market shares for each product alternative. We denote the lower bound of conjoint utility for our own product in sth segment as $U_{\text{lower\_bound},s}$ and the upper bound as $U_{\text{upper\_bound},s}$. For competing products ($\text{cp}_1, \ldots, \text{cp}_R$), we denote the lower bound of conjoint utility for rth product in sth segment as $U_{\text{cp,lower\_bound},s}$ and the upper bound as $U_{\text{cp,upper\_bound},s}$. Our measure of market share variation (MSV) is defined as the difference between $\text{MS}_{\text{upper\_bound}}$ (upper bound of market share estimate) and $\text{MS}_{\text{lower\_bound}}$ (lower bound of market share estimate). Equation (11) provides the formula for $\text{MS}_{\text{upper\_bound}}$ and $\text{MS}_{\text{lower\_bound}}$:

$$\text{MS}_{\text{lower\_bound}} = \sum_{s=1}^{S} \theta_s \frac{\exp(U_{\text{lower\_bound},s})}{\exp(U_{\text{lower\_bound},s}) + \sum_{r=1}^{R} \exp(U_{\text{cp}_r,\text{upper\_bound},s}) + \exp(\text{cons}_s)}$$

$$\text{MS}_{\text{upper\_bound}} = \sum_{s=1}^{S} \theta_s \frac{\exp(U_{\text{upper\_bound},s})}{\exp(U_{\text{upper\_bound},s}) + \sum_{r=1}^{R} \exp(U_{\text{cp}_r,\text{lower\_bound},s}) + \exp(\text{cons}_s)} \quad (11)$$

5 Integrated Design-Marketing Approach

The integrated design-marketing approach is shown in Fig. 4. The approach shown has two starting points, one for the design model and the other for the marketing model. In the design model, the approach starts (from the top of the figure) with a design alternative **x**, and with a known range of parameters and acceptable variation range for each objective function. In the marketing model, the approach starts (from the lower left of the figure) with a marketing survey, including a field and focus group study to identify key marketing attributes and capture customer preferences. In the design model (upper left of the figure) the design **x** is passed on to the design simulation to calculate attributes for the design (i.e., engineering performance objectives and constraints). Next, the design is evaluated for feasibility and multi-objective robustness. If it does not meet the acceptable range for multi-objective robustness (recall Fig. 2), its objective function values are penalized (e.g., a positive penalty is added to the corresponding objective function for the case of minimization). Similarly, any design that does not satisfy the feasibility robustness criterion (recall Eq. (3)) will be penalized. Each design that passes the requirement for feasibility and multi-objective robustness is then enumerated over the marketing attributes (excluding brand) to produce corresponding product alternatives that can be evaluated from the marketing point of view (see the block on the lower right of Fig. 4). In the marketing model, the point estimate of market share and its variation for each design are computed and passed on to the optimizer. The marketing objectives are to maximize the market share and to minimize its variability. Even though past research mainly focuses on market share maximization, we argue that it is also important for product designers to consider both market share and its variability. When two product alternatives have comparable market shares, the product with smaller market share variability should be favored because there is a less amount of uncertainty associated with how this product will perform in the marketplace. The details of our ranking algorithm are given in Sec. 5.1. The procedure embedded in the algorithm continues until a stopping criterion, such as a maximum number of iterations, is reached. The approach ends with the identification of a set of (multi-objectively and feasibly) robust optimum product design alternatives.

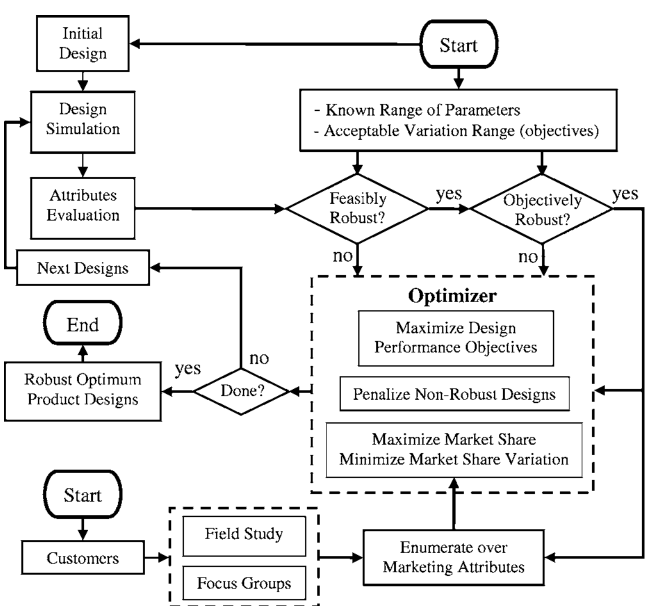

Fig. 4 Integrated design-marketing approach

5.1 Design-Marketing Evaluation of Product Alternatives. The optimizer used in our approach (see Fig. 4) evaluates and compares products based on their predicted engineering design as well as market performance. The performance measures in both domains were defined in previous sections. Here the product evaluation is performed at the domain level (i.e., marketing or engineering design domain).

In the engineering design domain, we consider robust products (from both feasibility and multi-objective robustness points of view) and evaluate their performance and feasibility using the design objective and constraint functions. In the marketing domain, we consider both market share and market share variations (MSV) to assess the predicted marketing performance and robustness of the products (maximize market share and minimize varia-

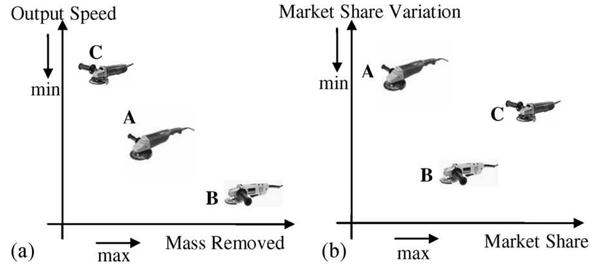

Fig. 5 Rank ordering of design alternatives in (*a*) design domain, and (*b*) marketing domain

Table 1 Design parameters; information

Design parameter	Nominal	Lower bound	Upper bound
Source voltage (V)	110	95	125
Ambient temperature (C)	25	-10	50
User load bias (lb)	6	3	9
Fan CFM degradation (%)	20	0	80
Application torque adjustment (%)	0	-20	20

tion, given a set of competitive products). Our rank ordering rule, which is used in the optimizer, is as follows: product **X** dominates product **Y** if **X** dominates **Y** (i.e., has a better performance) in at least one of the domains (i.e., design or marketing) while not dominated in the other. Alternatively, product **X** is dominated by **Y** if it does not dominate **Y** in any domain while being dominated by **Y** in at least one domain. If neither of these conditions holds, then products **X** and **Y** are nondominated.

Figure 5 shows an example in which three product designs **A**, **B**, and **C** are rank ordered. Figure 5(*a*) depicts the engineering design domain in which output speed is minimized while mass removed is maximized. Figure 5(*b*) shows the marketing domain in which the market share of the product is maximized while the variation in market share estimates is minimized. In order to rank order the designs shown, we need to compare each pair separately. **B** dominates **A** in both design and marketing domains, and therefore, overall **B** dominates **A**. However, **A** dominates **C** in the design domain, but **C** dominates **A** in the marketing domain. Such a conflict leads to **A** and **C** to be nondominated. Furthermore, between **B** and **C**, **B** dominates **C** in the design domain. However in the marketing domain, **B** and **C** are nondominated. Therefore, based on the above-mentioned ranking rule, **B** dominates **C**. In short, considering both design and marketing domains, **B** gets the highest (i.e., first) rank (no product dominates it), while both **A** and **C** are nondominated with respect to each other, and are ranked second.

6 Example

In the following, we demonstrate our approach with an example in the design of a corded small angle grinder.

6.1 Preliminaries. To begin with, it is necessary to survey the market for such corded power tools to identify key attributes of the product that are important to customers and then establish a set of common attributes between engineering design and marketing domains. Working as a team with our industrial partner, we conducted several focus group studies to first identify a set of attributes that are considered as the most critical by the end users. Six marketing attributes have been identified for this product: brand, price, amp rating, switch type, life, and girth size. The engineering design attributes (i.e., output from the design simulation) are maximum output power, output speed, armature temperature, and brush temperature. Among these attributes, amp rating and life of the product are attributes common between the design and marketing domains. Amp rating is obtained using maximum motor output power, and an estimate of product life can be obtained by a heuristic that takes motor output speed and armature temperature. The application (i.e., type of material and the duration of use of the tool on that material) is assumed to be the same for all design alternatives. The set of design variables are: choice of motor (x_m) which is a discrete variable between 1 and 10, choice of speed reduction unit or gearbox (x_g) which is a discrete variable between 1 and 6, the gear ratio (x_r) which is a continuous variable between 3.5 and 5. There are five design parameters that affect the performance of each design alternative. The design parameters with their uncontrollable variability information are given at Table 1.

The variability in the marketing is discussed in Sec. 6.3. We assume that in the market for this power tool, there are three competitive products. Their specifications in terms of marketing attributes (including the common attributes) are given in Table 2.

The set of robust design alternatives considering only engineering design robustness aspects are discussed in the next section.

6.2 Robust Designs using Engineering Design Robustness. The product's output motor speed is minimized, to reduce the effects of vibration to the user, while the amount (i.e., mass) of material removed is maximized, to ensure performance and efficiency of the product. To guarantee that the product does not fail (due to burn out) under demanding application conditions, a design constraint is imposed to keep the motor temperature (which is the larger of armature temperature and field temperature) less than 220°C. Given these two objectives and constraint, without considering the effects of parameter variations on them, a multi-objective genetic algorithm (MOGA) [35] with Kurapati et al.'s constraint handling technique [36] was used as an optimizer to obtain the set of (nominal) Pareto designs. The reason for choosing an optimizer based on genetic algorithm is that our case study involves both discrete and continuous variables. Figure 6 shows the results. Nominal Pareto design points are highlighted by diamonds in Fig. 6. There are gaps among the clusters of design alternatives as depicted in Fig. 6. The primary reason for these gaps is due to dramatic changes in performance based on the choice of available components in the database. At this point, for expositional purposes, the marketing module is not considered.

Using the model provided in Sec. 3.2, with a genetic algorithm as the optimizer, the maximum variation from nominal values of motor speed and the mass of removed material are calculated for every design alternative. In this example, the variation from nominal value for motor speed must be less than 8000 rpm. In addition, the variation in the mass of removed material in one application (of the tool on a steel plate) is set to be less than 5 g. The robust designs are those that satisfy these requirements as well as the feasibility robustness requirement. Likewise, the model of Sec. 3.3 is used to identify feasibly robust design alternatives. For a power tool design, to operate for long and intensive applications, the motor temperature should not exceed a certain level. There are several parameters that can influence motor temperature in a power tool. Among these, the ambient temperature, user load bias, and power supply voltage and current can have considerable effects on the motor temperature. The design alternatives that are not feasibly robust are eliminated during the optimization.

The robust Pareto design alternatives are obtained following the framework given in Fig. 3, with MOGA used for the optimizer. The robust Pareto points for this example are also shown in Fig. 6 along with the nominal Pareto points. It can be observed that in this example almost all of the robust Pareto points are inferior (in

Table 2 Competitive product specifications

Competitive product	Price	Amp rating	Switch type	Life	Girth size
Brand 1	$99	9	Side Slider	120hrs	Large
Brand 2	$129	12	Paddle	150hrs	Small
Brand 3	$79	6	Paddle	80hrs	Small

terms of performance) to the nominal Pareto points.

In the next section, we study the effect of customer preferences (without using engineering design objectives and constraints mentioned above) in the generation of product design alternatives.

6.3 Preference Robustness Model. Respondents for this study include metal workers and construction workers (who make up 80% of the user base for the tool) recruited from job sites and construction sites. The interviews were conducted with 249 respondents. Each respondent was given 18 choice scenarios (16 were used for conjoint estimations and 2 for verification). Each choice scenario included two product design alternatives and a no-choice option with verbal descriptions indicating the levels of marketing attributes. The data were collected, coded, and analyzed using the finite mixture module of Sawtooth [33]. We examined the scenarios of one through five market segments. The number of market segments is determined by the minimal AIC value, which turned out to be four segments. Therefore, we have four segments in the market. Table 3 provides the part-worth utility estimates associated with each attribute level and the utility estimate for "no-choice" in each market segment. In this table, we also provided the values of segment sizes. In addition, we obtain a 14 $\times$ 14 variance and covariance matrix of the conjoint estimates for each market segment. The diagonal elements of the matrices are all positive numbers and they represent the variances of the conjoint estimates. The off-diagonal elements describe the covariances of the conjoint estimates. (Due to page limitation, the variance and covariance matrices are not shown.)

We now use the information provided in Table 3 to illustrate how the utility of a product is calculated. For a product with own brand, $79 retail price, amp rating of 9, 110 h of product life, top slider switch, and small girth, its utility for consumer segment 1 is 1.3 (i.e., $(-0.54)+(-0.11)+0.13+1.33+(-1.01)+1.5=1.3$). In a similar fashion, we can calculate this product's utility for consumer segment 2 as -1.47, segment 3 as -5.79, and segment 4 as -0.99. A similar approach can be used to obtain the conjoint utility of each competitor product, and based on these values the market share of each product alternative can be predicted. Next, the formulas in Eqs. (9)–(11) are used to construct the market share variation of each alternative.

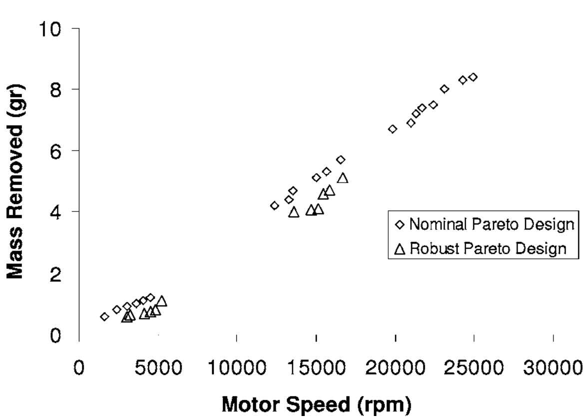

Fig. 6 Set of nominal and robust Pareto design alternatives

Table 3 Conjoint part-worth estimates

	Segment 1	Segment 2	Segment 3	Segment 4
Segment size	0.378	0.248	0.121	0.253
	Part-worth	**Part-worth**	**Part-worth**	**Part-worth**
Brand 0 (own)	-0.54	0.45	2.21	-0.16
Brand 1	0.18	1.06	-2.37	-0.2
Brand 2	0.83	0.11	-1.5	1.15
Brand 3	-0.46	-1.61	1.66	-0.79
Price $79	-0.11	-0.09	0	-0.01
Price $99	-0.89	-1.15	1.91	-0.24
Price $129	1	1.23	-1.91	0.25
Amp 6	1.25	0.45	-1.48	-0.45
Amp 9	0.13	-1.42	-0.65	-2.38
Amp 12	-1.38	0.97	2.13	2.82
Life 80	-0.86	-0.12	-4.71	0.8
Life 110	1.33	-0.47	-5.82	0.74
Life 150	-0.47	0.6	10.53	-1.54
Paddle	0.42	0.29	-3.29	-0.65
Top Slider	-1.01	-0.65	-3.04	0.41
Side Slider	2.39	-0.07	2.46	0.56
Trigger	-1.8	0.42	3.87	-0.31
Small Girth	1.5	0.71	1.51	0.41
Large Girth	-1.5	-0.71	-1.51	-0.41
No Choice	-0.02	-0.02	-0.02	-0.02

To verify our estimates, we compared the estimated market shares for the existing products with actual market share data obtained from Power Tool Institute (PTI). PTI is an organization that provides its member companies with market level data such as the market shares of different power tool products. We found that the discrepancies between the estimated and the actual shares are within 5 to 7 percent. As a result, we believe that our model estimates are reasonably in line with the actual market share values.

6.4 Robust Design Using Integrated Design and Marketing Approach. The integrated robust design and marketing approach discussed in Sec. 5 is now applied to the example. Using the approach described in Sec. 3, design alternatives are generated through feeding numerous combinations of design variables using the optimizer to the corded power tool simulation. The output generated by the design simulation is used to obtain (directly or via mappings) the common attributes. As mentioned before, two common attributes are mapped from design simulation output, namely, amp rating and life of the product. Next, there are three non-common marketing attributes that contribute toward the generation of the set of product alternatives with brand being fixed at "own brand." These attributes are price, switch type, and girth size. After obtaining the product alternatives, the market share and its variation are calculated for each product alternative. The evaluation is performed at the domain level according to the rules given in Sec. 5. For each generated product alternative, using the information provided in Table 3 and Eqs. (9)–(11) the market share and its variation can be estimated. The final set of robust products based on our integrated approach is shown in Fig. 7.

There are 18 design alternatives in the design objective space that are identified as robust in design objective space (Figure 7(*a*)). As mentioned before, every design alternative is enumerated over non-common or marketing attributes to produce several

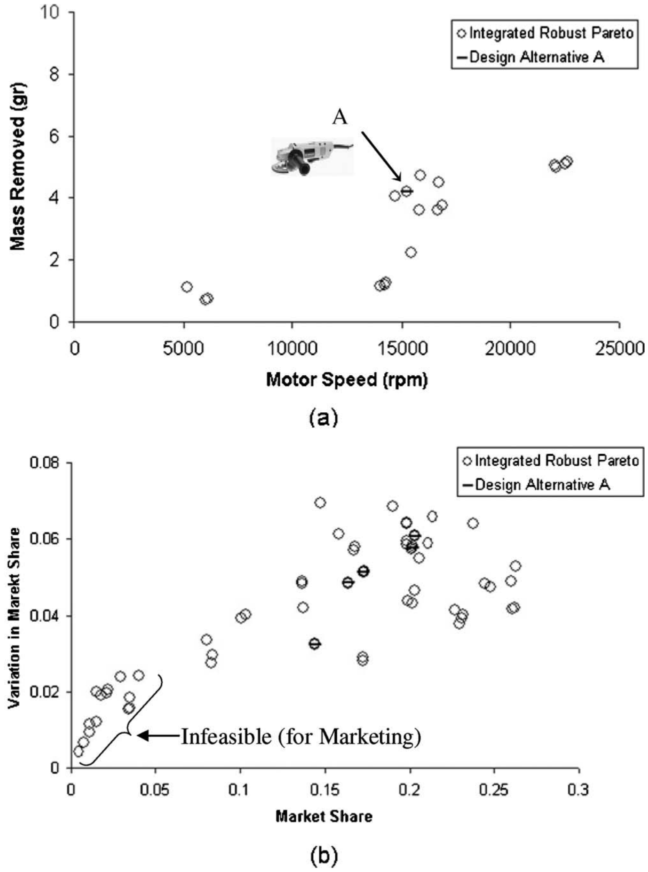

Fig. 7 Final set of robust design and product alternatives: (*a*) engineering design domain, and (*b*) marketing domain

product alternatives. In this example, there are three non-common attributes, namely, switch type, price, and girth size that overall create 24 possible product alternatives for each design. It should be noted that not all of the possible generated combinations for each design have optimum performance in both design and marketing domain. In this example, corresponding to the 18 designs in the design domain (Fig. 7(*a*)), there exist 62 product alternatives in the marketing domain (Fig. 7(*b*)). For example, design alternative **A** in Fig. 7(*a*) corresponds to the five optimum products in Fig. 7(*b*). Table 4 tabulates the specifications of these products.

In the marketing domain (Fig. 7(*b*)), the robust Pareto products have market shares ranging from virtually zero to approximately 28%, all of which have less than 7% of market share variations. We consider the product alternatives in the bottom left corner of Fig. 7(*b*) as infeasible. Even though the market performance of these product alternatives does not vary much, the market shares of these products are all less than 5%. Such low market shares are considered as infeasible because these product alternatives cannot generate requisite revenue to recover the fixed costs needed for the development of these products. This reduces the number of robust products to 48.

Overall, our integrated approach obtains solutions (as shown in Fig. 7) that are superior in terms of design performance, marketing performance or both. The next step in the product development process is to make a selection among the products and then the selected products can be carried forward for the prototyping stage. Using Fig. 7 and locating products in both domains, it would allow a product design manager to evaluate each product from both design performance (and robustness) as well as it market performance. Since it may not be feasible to carry forward 48 products to the prototyping stage, the design and marketing teams may decide to reduce the number of the final products. First, we can eliminate some of these alternatives through a more stringent criteria for robustness (for example, by reducing the acceptable range of variability in the design and/or marketing dimensions), which can reduce the number in the Pareto set. Second, as mentioned before, the marketing team may decide to eliminate solutions that have a low level of predicted market share (e.g., below 10%). Third, the marketing team may prefer to target at a particular price point for the new product after accounting for retailers' existing assortments and their preferences. Finally, a similar procedure can be carried out in design domain and the design team can eliminate the designs that have higher production costs (when offered at the same price) to increase the projected profit. While there are many techniques to aid in making a selection among the final product alternatives, the discussion of such techniques is beyond the scope of this paper.

7 Concluding Remarks

The overall contribution of our approach lies in specifying both design robustness and preference robustness and tying them together in one framework so that an integrated approach for generation of design alternatives, from both design and marketing perspectives, is facilitated. In our approach, we use a bi-disciplinary (i.e., marketing-design) optimization criterion in generating and rank ordering a set of design alternatives, which can then be taken to the prototype development stage. This assures that the prototypes being tested are robust not only from a design perspective but also from a customer preference perspective. In this regard, it is important to note that our integrated approach is not a sequential elimination scheme. Instead every product is evaluated in both design and marketing domains. Only those products that may become infeasible or have inferior performance in at least one domain are eliminated in the process.

From the design perspective, the proposed approach provides the designers a means to assess the performance and feasibility robustness of a design when several uncontrollable parameters exist. Unlike the previous methods in robust design, in particular those in Refs. [9,17,18], our new approach is less conservative and more flexible in that (i) it does not eliminate any design whose performance variation is within an acceptable range, and

Table 4 Product alternatives corresponding to design A

Product	Motor no.	Gear no.	Gear ratio	Price	Switch type	Girth size	Market share	Var. of market share
1	6	4	4.9	$129	Top slider	Small	0.144	0.032
2	6	4	4.9	$129	Trigger	Small	0.164	0.049
3	6	4	4.9	$129	Top slider	Large	0.173	0.051
4	6	4	4.9	$129	Trigger	Large	0.203	0.060
5	6	4	4.9	$129	Side slider	Small	0.201	0.058

(ii) it provides a means to guarantee that a robust design satisfies the acceptable range variation for individual design objectives.

From the marketing perspective, very limited amount of extant research has considered the impact of performance variations in different usage situations and conditions on customer utilities. The uncertainty in estimating customer utilities due to the imperfect data-model fit is also an important factor to consider when specifying preference robustness [20–25]. Building upon the existing research by Ref. [9], we have relaxed the assumption of homogeneous consumer preferences and introduced a multi-objective optimization procedure for the robust marketing criterion.

Our approach despite its strengths in both design and marketing domains has some limitations. Like most robust optimization methods in the literature, our outer-inner optimization approach can be computationally intensive. However, the contribution of this work is mainly in providing a means to integrate design and marketing robustness together. One other potential shortcoming of our approach is when it results in a relatively large set of final product alternatives. A possible remedy to this is to perform design robustness prior to the integration with the marketing model, i.e., in a sequential process. However, such a sequential approach may eliminate potentially good design alternatives.

Acknowledgment

The work presented here was supported in part by the U.S. National Science Foundation through Grant No. DMI 0200029. Such support does not constitute an endorsement by the funding agency of the opinions expressed in the paper. Part of this work was presented at the 2004 ASME IDETC [37].

References

[1] Griffin, A., and Hauser, J. R., 1992, "Patterns of Communications among Marketing, Engineering, and Manufacturing—A Comparison between Two New Product Teams," Manage. Sci., **38**(3), pp. 360–373.
[2] McAllister, C. D., and Simpson, T. W., 2003, "Multidisciplinary Robust Design Optimization of an Internal Combustion Engine," ASME J. Mech. Des., **125**(1), pp. 124–130.
[3] Fuhita, K., and Ishii, K., 1997, "Task Structuring Toward Computational Approaches to Product Variety Design," *Proceedings of ASME DETC '97*, 23rd Design Automation Conference, DETC97/DAC3766, Sep. 14th—17th, Sacramento, CA.
[4] Li, H., and Azarm, S., 2000, "Product Design Selection under Uncertainty and with Competitive Advantage," ASME J. Mech. Des., **122**(4), pp. 411–418.
[5] Urban, G. L., and Hauser, J. R., 1980, *Design and Marketing of New Products*, Prentice-Hall, Englewood Cliffs, NJ.
[6] Michalek, J. J., Feinberg, F. M., and Papalambros, P. Y., 2005, "Linking Marketing and Engineering Product Design Decisions via Analytical Target Cascading," Journal of Product Innovation Management, **22**(1), pp. 42–62.
[7] Wassenaar, H. J., and Chen, W., 2003, "An Approach to Decision Based Design with Discrete Choice Analysis for Demand Modeling," ASME J. Mech. Des., **125**(3), pp. 90–497.
[8] Wassenaar, H. J., Chen, W., Cheng, J., and Sudjianto, A., 2005, "Enhancing Discrete Choice Modeling for Decision-Based Design," ASME J. Mech. Des., **127**(4), pp. 514–523.
[9] Luo, L., Kannan, P. K., Besharati, B., and Azarm, S., 2005, "Design of Robust New Products under Variability: Marketing Meets Design," Journal of Product Innovation Management, **22**(2), pp. 177–192.
[10] McFadden, D., 1986, "The Choice Theory Approach to Market Research," Aviat. Week Space Technol., **5**(4), pp. 275–297.
[11] Taguchi, G., Elsayed, E., and Hsiang, T., 1989, *Quality Engineering in Production Systems*, McGraw Hill, New York.
[12] Parkinson, A., Sorensen, C., and Pourhassan, N., 1993, "A General Approach for robust Optimal Design," ASME J. Mech. Des., **115**(1), pp. 74–80.
[13] Sundaresan, S., Ishii, K., and Houser, D. R., 1992, "Design Optimization for Robustness Using Performance Simulation Programs," Eng. Optimiz., **20**(1), pp. 63–78.
[14] Chen, W., and Yuan, C., 1999, "A Probabilistic-based Design Model for Achieving Flexibility in Design," ASME J. Mech. Des., **121**(1), pp. 77–83.
[15] Rao, S. S., and Cao, L., 2002, "Optimum Design of Mechanical Systems Involving Interval Parameters," ASME J. Mech. Des., **124**(3), pp. 465–472.
[16] Du, S., Sudjianto, A., and Chen, W., 2004, "An Integrated Framework for Optimization Under Uncertainty Using Inverse Reliability Strategy," ASME J. Mech. Des., **126**(4), pp. 562–570.
[17] Gunawan, S., and Azarm, S., 2005, "Multi-Objective Robust Optimization Using a Sensitivity Region Concept," Struct. Multidiscip. Optim., **29**(1), pp. 50–60.
[18] Li, M., Azarm, S., and Boyars, A., 2005, "A New Deterministic Approach Using Sensitivity Region Measures for Multi-Objective Robust and Feasibility Robust Design Optimization," CD-ROM Proceedings of the ASME IDETC/CIE, Paper no. IDETC05–85095, Sep. 24–28, Long Beach, CA.
[19] Hsee, C., and Leclerc, F., 1998, "Will Products Look More Attractive When Presented Seperately or Together?," J. Consum. Res., **25**(2), pp. 175–186.
[20] Camerer, C., 1995, *Handbook of Experimental Economics*, Princeton University Press, Princeton, NJ.
[21] Sudman, S., Bradburn, N., and Schwarz, N., 1996, *Thinking About Answers: The Application of Cognitive Processes To Survey Methodology*, Jossey-Bass, San Francisco.
[22] Swait, J., Adamowicz, W., Hanemann, M., Diederich, A., Krosnick, J., Layton, D., Provencher, W., Schkade, D. and Tourangeau, R., 2002, "Context Dependence and Aggregation in Disaggregate Choice Analysis," Marketing Letters, **13**(3), pp. 195–205.
[23] Louviere, J., Street, D., Carson, R., Ainslie, A., Deshazo, J. R., Cameron, T., Hensher, D., Kohn, R. and Marley, T., 2002, "Dissecting the Random Component of Utility," Marketing Letters, **13**(3), pp. 177–193.
[24] Vriens, M., Wedel, M., and Wilms, T., 1996, "Metric Conjoint Segmentation Methods: A Monte Carlo Comparison," J. Mark. Res., **33**, pp. 73–85.
[25] Besharati, B., Azarm, S., and Kannan, P. K., 2005, "A Decision Support System for Product Design Selection: A Generalized Purchase Modeling Approach," Decision Support Systems, in press.
[26] Chen, W., Allen, J. K., Tsui, K. L., and Mistree, F., 1996, "A Procedure for Robust Design: Minimizing Variations Caused by Noise Factors and Control Factors," ASME J. Mech. Des., **118**(4), pp. 478–485.
[27] Kalsi, M., Hacker, K., and Lewis, K., 2001, "A Comprehensive Robust Design Approach for Decision Trade-Offs in Complex Systems Design," ASME J. Mech. Des., **123**(1), pp. 1–10.
[28] Green, P. E., and Srinivasan, V., 1990, "Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice," J. Marketing, **54**(1), pp. 3–1.
[29] Kamakura, W. A., and Russell, G. J., 1989, "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," J. Mark. Res., **26**, pp. 379–390.
[30] Akaike, H., 1973, "Information Theory and an Extension of the Maximum Likelihood Principle," *Proceedings of the second International Symposium of Information Theory*, pp. 267–281.
[31] Carrol, J. D., and Green, P. E., 1995, "Psychometric Methods in Marketing: Part I, Conjoint Analysis," J. Mark. Res., **32**(1), pp. 385–391.
[32] Ben-Akiva, M., and Lerman, S., 1985, *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT, Cambridge.
[33] Sawtooth Choice-Based Conjoint User Manual, 2001, Sawtooth Software Inc., Sequim, WA, Appendix C, C1–C3.
[34] Greene, W. H., 2000, *Econometric Analysis*, Prentice Hall, Upper Saddle River, NJ.
[35] Narayanan, S., and Azarm, S., 1999, "On Improving Multiobjective Genetic Algorithms for Design Optimization," Struct. Optim., **18**, pp. 146–155.
[36] Kurapati, A., Azarm, S., and Wu, J., 2002, "Constraint Handling Improvements for Multi-Objective Genetic Algorithms," Struct. Multidiscip. Optim., **23**, pp. 204–213.
[37] Besharati, B., Azarm, S., Luo, L., and Kannan, P. K., 2004, "An Integrated Robust Design and Marketing Approach for Design Selection Process," *Proceedings of ASME DETC '04*, Design Automation Conference, DETC04/DAC57405, Sep. 28th—October 2nd, Salt Lake City, UT.