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Product line design for consumer durables often relies on close coordination between marketing and engineering domains. Product lines that evolve as optimal from marketers' perspective may not be optimal from an engineering viewpoint, and vice versa. Although extant research has proposed sophisticated techniques to handle problems that characterize each individual domain, the majority of these developments have not addressed the interdependent issues across marketing and engineering. The author presents a product line optimization method that enables managers to simultaneously consider factors deemed important from both marketing and engineering domains. One major advantage of this method is that it takes into account the strategic reactions from the incumbent manufacturers and the retailer in the design of the product line. The author demonstrates in a simulation study that this method is applicable to problems with a reasonably large scale. Using data collected in a power tool development project undertaken by a major U.S. manufacturer, the study illustrates that the proposed method leads to a more profitable product line than alternative approaches that consider requirements from these two domains separately.

Keywords: product line, product design, marketing engineering integration, optimization methods, genetic algorithm

Product Line Design for Consumer Durables: An Integrated Marketing and Engineering Approach

Product line design is a critical decision that determines many firms' successes (Hauser, Tellis, and Griffin 2006). In a product line design project, close coordination between the marketing and the engineering domains is essential. For example, when designing a power tool product line, the product designer must take into account not only consumers' preferences for the product's features and prices but also other important engineering issues such as whether the products are safe and robust in a variety of usage environments. Similar arguments can be applied to many consumer durable products, such as toys, appliances, trucks, airplanes, and laptops.

In a product line design problem, such marketing and engineering considerations are often highly interdependent. For example, a consumer may think about a power tool in terms of attributes such as power amp and product life, whereas an engineering designer may think of these same concepts in terms of technical variables such as housing, gear ratio, and gearbox type. Such highly interconnected relationships between the two domains imply that any required action in one domain can potentially influence the outcomes in the other domain. Therefore, in the design of an optimal or near-optimal product line, the marketing and engineering requirements often cannot be pursued separately or even sequentially.

Despite the compelling need for a unified framework that integrates design considerations from both disciplines concurrently, the vast majority of extant research has empha-

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ISSN: 0022-2437 (print), 1547-7193 (electronic)

Journal of Marketing Research
Vol. XLVIII (February 2011), 128–139

sized issues from the perspective of each individual discipline. This discipline-centric focus is largely determined by the complexity of the overall product line design problem. When designing a line of consumer durable products, firms need to account for not only the interrelationships between consumer preferences and engineering feasibility/restrictions in the design of each product but also the revenue and cost interactions across the products in the product line. Furthermore, to forecast the revenue from a product line accurately, it is critical for firms to account for the strategic reactions from competing manufacturers and the retailer when the new product line enters the market. In this context, simultaneously considering all these essential issues across both disciplines is challenging both conceptually and computationally.

The primary goal of this research is to propose a product line optimization method to take on this combinatorial challenge. In particular, this research proposes a procedure in which the marketing and engineering criteria are considered concurrently in the search for a profit-maximizing product line. A simulation study demonstrates that this method is applicable to problems with a reasonably large scale. Using data collected in a power tool development project undertaken by a major U.S. manufacturer, the study illustrates that the proposed method leads to a more profitable product line than alternative approaches that consider requirements from these two domains separately.

The rest of the article is organized as follows: First, the relationship of this study to extant literature and the contribution of this research are discussed. Second, the details of the product line optimization are presented. The third section discusses a simulation study in which the computational characteristics of the proposed method are described. Next, the empirical application is described. The article concludes with a summary of contributions and a discussion of limitations and further research.

RELATIONSHIP TO EXISTING RESEARCH

Four streams of research are related to this study. The first stream investigates product line design from a marketing perspective (e.g., Balakrishnan, Gupta, and Jacob 2004, 2006; Belloni et al. 2008; Chen and Hausman 2000; Dobson and Kalish 1988, 1993; Green and Krieger 1985; Kannan, Pope, and Jain 2009; McBride and Zufryden 1988; Moore, Louviere, and Verma 1999; Nair, Thakur, and Wen 1995; Selove and Hauser 2010; Steiner and Hruschka 2003). This research stream employs conjoint data and searches for an optimal or near-optimal product line by selecting levels of consumer attributes. The second research stream examines the product line design problem with an engineering focus (e.g., Farrell and Simpson 2003; Rai and Allada 2003; Simpson, Seeperad, and Mistree 2001). In general, this line of research focuses on platform management in which researchers strive for balance between the commonality of the product platform and the individual product's engineering performance. The third stream consists of studies that investigate how to integrate engineering and marketing considerations into the design of a single product (e.g., Besharati et al. 2004, 2006; Griffin and Hauser 1993; Hauser and Clausing 1988; Li and Azarm 2000; Luo et al. 2005; Luo, Kannan, and Ratchford 2008; Michalek, Feinberg, and Papalambros 2005; Srinivasan, Lovejoy, and Beach 1997; Tarasewich and McMullen 2001; Tarasewich and Nair 2001). Finally, the fourth stream consists of studies that aim to incorporate marketing and engineering considerations in a product line design (e.g., D'Souza and Simpson 2003; Farrell and Simpson 2009; Heese and Swaminathan 2006; Jiao and Zhang 2005; Kumar, Chen, and Simpson 2009; Li and Azarm 2002; Michalek et al. 2006; Michalek et al. 2010).

In the following, I discuss how this study extends the four streams of research. From a substantive perspective, the current study contributes to the literature by providing an effective coordination of several essential issues across both marketing and engineering. Specifically, on the marketing side, the product line's market potential is evaluated by (1) modeling consumers' heterogeneous product preferences and (2) estimating how the competing manufacturers and the retailer will respond to the launch of the new product line. On the engineering side, the focus is on (1) ensuring the engineering feasibility and robustness of the products and (2) maximizing the cost synergy across the products in the product line.

Given the complex nature of product line design, the proposed optimization method by no means exclusively accounts for all the marketing and engineering criteria currently being considered in the design of a product line. I focus on the preceding issues because of their considerable significance in the product design literature. Because any of these issues can have a substantial impact on the profitability of the final product line, the current study contributes to the literature by taking on the combinatorial challenge of integrating them across both disciplines of marketing and engineering. In particular, one major advantage of the proposed model is that it directly accounts for the strategic responses from the competing manufacturers and the retailer. Though recognized as important challenges in product line design problems (Belloni et al. 2008), these issues have not been addressed in previous work.

From a methodological perspective, this study contributes to the literature by searching for an optimal product line in a large design space with a mix of discrete and continuous design variables. Because of the complexity of the product line design problem, previous researchers have limited the composition of a product line to a fairly small set of initial products (e.g., Kumar, Chen, and Simpson 2009; Morgan, Daniels, and Kouvelis 2001; Ramdas and Sawhney 2001). However, in practice, the product design space for a consumer durable product can be very large, even virtually infinite. In an attempt to address this issue, Michalek and colleagues (2006, 2010) propose an analytical target cascading (ATC) method that enables the search of an optimal product line in a complex design space. Although the ATC method is highly efficient in coordinating marketing and engineering considerations (as the simulation study in the current article demonstrates), it is not directly applicable in a product design space with discrete product attributes. Therefore, a major advantage of the proposed method is its ability to accommodate both discrete and continuous variables in a large design space. However, the approach taken here comes with the cost of combinatorial complexity. The ability of this method to scale up to a large problem is discussed subsequently.

PROPOSED METHOD

In line with Kaul and Rao (1995) and Michalek and colleagues (2010), a set of consumer attributes and design variables constitutes the starting point of the proposed model. The vector of consumer attributes (denoted as **x**) represents all the attributes consumers directly consider in a product purchase decision (e.g., power amp, product life). The identification of these attributes follows the typical procedure used to determine which product attributes will be included in a conjoint experiment. The design variables (denoted as **y**) are those the product designer needs to decide on in the design of a product (e.g., gear ratio, housing type). These variables determine the values of the consumer attribute vector (excluding brand and price) and are collectively needed for proper functioning of the product. Next, an engineering response function **r[y]** calculates the values of **x** as a function of **y** (i.e., **x = r[y]**). As Michalek and colleagues (2010) discuss, although the specification of the response function **r[y]** should be determined on a case-by-case basis, the general principles of such mapping are well established in the literature (for additional implementation details, see Web Appendix A at http://www.marketingpower.com/jmrfeb11). Given the set of design variables (**y**), consumer attributes (**x**), and their interrelationships (**x = r[y]**), the focal problem of product line optimization is to determine the design variable configuration and the wholesale price of each product in the product line under a set of marketing and engineering criteria. The following section describes the specifics of the marketing and engineering considerations. I then demonstrate how these considerations are merged into a product line optimization procedure.

Marketing Considerations

From the marketing side, I take into account (1) how consumers form their preferences toward each product and (2) how the competitors and the retailer respond to the launch of the new product line.

Consumer preference model. A choice-based finite mixture conjoint model is used to elicit consumers' preferences for different levels of consumer attributes. In this model, the utility of consumer i for profile d in choice set k is defined as follows:

$$U_{idk} = \mathbf{x}_{dk}\boldsymbol{\beta}_{ix} + p_{dk}\beta_{ip} + \varepsilon_{idk}, \tag{1}$$

where $(\boldsymbol{\beta}_{ix}, \beta_{ip})$ is the vector of the conjoint partworths for consumer i, $(\mathbf{x}_{dk}, p_{dk})$ is a vector representing the consumer attributes and the price of product alternative d in choice set k, and ε_{idk} is a random component.

Assuming that the random component ε_{idk} follows an i.i.d. double exponential distribution, the probability of consumer i choosing product d from choice set k is as follows:

$$\Pr_{idk} = \frac{\exp(\mathbf{x}_{dk}\boldsymbol{\beta}_{ix} + p_{dk}\beta_{ip})}{\sum_{d'=1}^{D}\exp(\mathbf{x}_{d'k}\boldsymbol{\beta}_{ix} + p_{d'k}\beta_{ip}) + \exp(\alpha_i)}, \tag{2}$$

where α_i denotes the utility of the "no-choice" option.

Let $\xi_i = (\boldsymbol{\beta}_{ix}, \beta_{ip}, \alpha_i)$; then, ξ_i is defined using a mixture of multivariate normal distributions (Rossi and Allenby 2003):

$$\xi_i \sim \sum_{s=1}^{S}\theta_{is}\mathrm{MVN}(\bar{\xi}_s, \boldsymbol{\Omega}_s), \tag{3}$$

where θ_{is} represents the probability that consumer i belongs to segment s and $\boldsymbol{\Omega}_s$ is a full variance–covariance matrix.

Furthermore, θ_{is} is defined as follows:

$$\theta_{is} = \frac{\exp(\gamma_s\mathbf{z}_i)}{\sum_{s'=1}^{S}\exp(\gamma_{s'}\mathbf{z}_i)}, \tag{4}$$

where $\mathbf{z}_i$ is a vector of covariates (e.g., the respondents' height and weight) and γ_s is the coefficient vector associated with $\mathbf{z}_i$.

The Gibbs sampler and Metropolis–Hastings algorithm are used to obtain the distributions of the posterior estimates (for more estimation details, see Web Appendix B at http://www.marketingpower.com/jmrfeb11). The deviance information criterion measure is used to determine the optimal number of market segments. Thus, the proposed consumer preference model provides the number of segments and the posterior estimates for segment sizes ($\theta_s = \Sigma_{i=1}^{N}\theta_s$ for s = 1, …, S), segment-level conjoint partworths ($\bar{\xi}_1, \bar{\xi}_2, ..., \bar{\xi}_s$), and the variance–covariance matrices ($\boldsymbol{\Omega}_1, \boldsymbol{\Omega}_2, \ldots, \boldsymbol{\Omega}_s$). These posterior estimates can then be used to derive the utility estimate for each product under consideration.[1]

In general, previous research has assumed that the utility of each product is a constant. In reality, this assumption may not hold, because a product might perform differently under different usage situations (e.g., a power tool's power amp may vary from 9 to 10.7 depending on the weather and the application type). The expected utility theory (Quiggin 1982) is adopted to address these inherent variations in each product's utility. Specifically, if the value of a particular consumer attribute (e.g., power amp, product life) varies when the product is used under different usage situations, I obtain the nominal (i.e., the most likely) (v_0), the upper- (v_U), and the lower- (v_L) bound values of the attribute from the engineering simulation (see Web Appendix A at http://

[1]It is worth noting that either the posterior individual- (ξ_i) or segment- ($\bar{\xi}_s$) level conjoint partworths could be considered inputs to the proposed product line optimization. The choice between the two depends on the trade-off between a better representation of consumer heterogeneity and computation time. In the empirical application, when the inputs of the product line optimization changed from $\bar{\xi}_s$ to ξ_i, the average computational time increased 8.59 times when there were one to three products in the product line and 740 respondents in the conjoint experiment. I further examined the impact of ignoring the within-segment heterogeneity when the posteriors of $\bar{\xi}_s$ rather than ξ_i were used in the optimization. Specifically, the individual-level estimates were used to recalibrate the profitability of the final product lines obtained from the segment-level partworths (I thank an anonymous reviewer for suggesting this). It was found that the recalibrated earnings deviated within 3% from the final earnings obtained directly from the individual-level estimates. Given the result of this robustness check, the findings are reported according to the segment-level estimates in the empirical section. I acknowledge that this finding is based only on a single comparison and might not be applicable in different problem settings. In general, segment- (individual-) level estimates can be considered for large- (small-) scale problems. Furthermore, individual-level estimates should be favored when there is a great deal of within-segment heterogeneity. To simplify the notation, the subscript s is used throughout the study to represent the heterogeneous consumer preferences. If the individual-level estimates are used as inputs of the optimization, the subscript s should be replaced with i.

www.marketingpower.com/jmrfeb11). Consequently, the expected utility from the attribute can be computed as follows:

$$\gamma_s = \int_{v_L}^{v_U} u_s(v) f(v)\, dv, \tag{5}$$

where $u_s(v)$ denotes the attribute's conjoint utility as a function of the value of v and f(v) is the density function of a triangular distribution with lower limit v_L, mode v_0, and upper limit v_U.[2] The use of triangular distribution is commonly adopted in business practice when researchers know only the minimum, maximum, and most likely outcomes (e.g., Koller 2005; Li and Azarm 2002). Given Equations 1–5, the expected utility of each product can be obtained as the sum of its respective attribute-level utilities. This utility is used to represent consumers' product preferences and forecast market demand.

Market responses from competitors and retailer. In what follows, I discuss how the strategic reactions from the incumbent manufacturers and the retailer to the launch of the product line are addressed.[3] Because it is typically difficult to adjust the nonprice attributes in the short run, the reactions from the incumbent manufacturers and the retailer are modeled by changes in prices only (see Hauser 1988; Luo, Kanna, and Ratchford 2007). The rationale is that with the introduction of the new product line, the competing manufacturers and the retailer have incentives to adjust their wholesale and retail prices to maximize own profits. Within this context, after the focal manufacturer configures the design variables of its product line, all the manufacturers and the retailer can reset their wholesale and retail prices. Given the adjusted prices, the focal manufacturer can then reconfigure its design variables to obtain further profit improvement. This cycling process is repeated until no improvement in the profit of the final product line results (for more details of this process, see Figure 1 and the subsection titled "Optimization Procedure"). This approach extends that of Luo, Kannan, and Ratchford (2007) by accommodating a larger-scale product design space in the context of product line design. A major advantage of this method is that the focal manufacturer accounts for the strategic responses from the retailer and the competing manufacturers before the new product line introduction. Extant research in product line design has neglected this aspect.

The price adjustments of the retailer and the manufacturers are modeled as follows: Assume that there are K manufacturers, with the kth (k = 1, …, K) manufacturer selling L_k products. Given the vector of wholesale prices ($w_{11}, w_{12}, \ldots, w_{1L_1}; w_{21}, w_{22}, \ldots, w_{2L_2}; w_{K1}, w_{K2}, \ldots, w_{KL_K}$), the retailer chooses the retail price of each product in its assortment to maximize own profit. The retailer's profit maximization can be written as follows:

$$\max_{p_{11},\ldots,p_{1L_1},\ldots,p_{K1},\ldots,p_{KL_K}} \pi^r = \sum_{t=1}^{T}\left\{\sum_{k=1}^{K}\sum_{l=1}^{L_k}\frac{\left[m_{kl}\times(p_{kl}-w_{kl})\times D_t\right]}{(1+r)^t}\right\} - sc\times\sum_{k=1}^{K}L_k \tag{6}$$

$$\text{with } m_{kl} = \sum_{s=1}^{S}\theta_s \frac{\exp(\mathbf{x}'_{kl}\boldsymbol{\beta}_{sx} + p_{kl}\beta_{sp})}{\sum_{k'=1}^{K}\sum_{l'=1}^{L_{k'}}\exp(\mathbf{x}'_{k'l'}\boldsymbol{\beta}_{sx} + p_{k'l'}\beta_{sp}) + \exp(\alpha_s)}, \tag{7}$$

where π^r is the category profit of the retailer, m_{kl} represents the market share of the lth product from the kth manufacturer, p_{kl} and w_{kl} denote this product's retail and wholesale prices, D_t is the overall market demand in year t, r is a discount rate, and sc is the marginal shelf cost. In line with Gordon (2009), it is assumed that D_t is observed and determined exogenously (e.g., as a function of the products' replacement cycles and overall economic condition). The parameters $\{\theta_s, \boldsymbol{\beta}_{sx}, \beta_{sp}, \alpha_s\}$ in Equation 7 correspond to posterior conjoint partworth estimates obtained from the finite mixture Bayesian estimation.

Given the vector of new retail prices ($p_{11}, \ldots, p_{1L_1}, \ldots p_{K1}, \ldots, P_{KL_K}$), each manufacturer (k = 1, …, K) adjusts the wholesale prices of the L_k products in its product line to maximize profit. Note that this differs from Luo, Kanna, and Ratchford (2007) in that the manufacturer chooses a set of wholesale prices rather than a single price.

$$\max_{w_{k1},w_{k2},\ldots,w_{kL_k}} \pi_k^m = \sum_{t=1}^{T}\left(\sum_{l=1}^{L_k}\frac{\left[(w_{kl}-c_{kl})\times m_{kl}\times D_t\right]}{(1+r)^t}\right) - F_k \tag{8}$$

$$k = 1,\ldots,K,$$

where c_{kl} is the variable cost of the *l*th product from manufacturer k and F_k is the fixed cost of this manufacturer.

Similar to Luo, Kannan, and Ratchford (2007), the new wholesale and retail prices are estimated by solving Equations 6 and 8 iteratively (see details in Web Appendix B at http://www.marketingpower.com/jmrfeb11). A major challenge faced by all existing research in product line design is that multiproduct firms with logit demand do not have log-supermodular profit functions (Hanson and Martin 1996). Therefore, the current model faces the possibility of multiple price equilibriums in the proposed solutions. To alleviate this issue, researchers can empirically investigate the shapes of the profit functions and run the algorithm with different initial prices in attempts to move from a local optimum to a better solution. It is also worth noting that because only the retailer and the incumbents' potential reactions in price adjustments are accounted for, this method does not apply in situations in which the incumbents change their nonprice attributes in response to the entry of the new product line.

Engineering Considerations

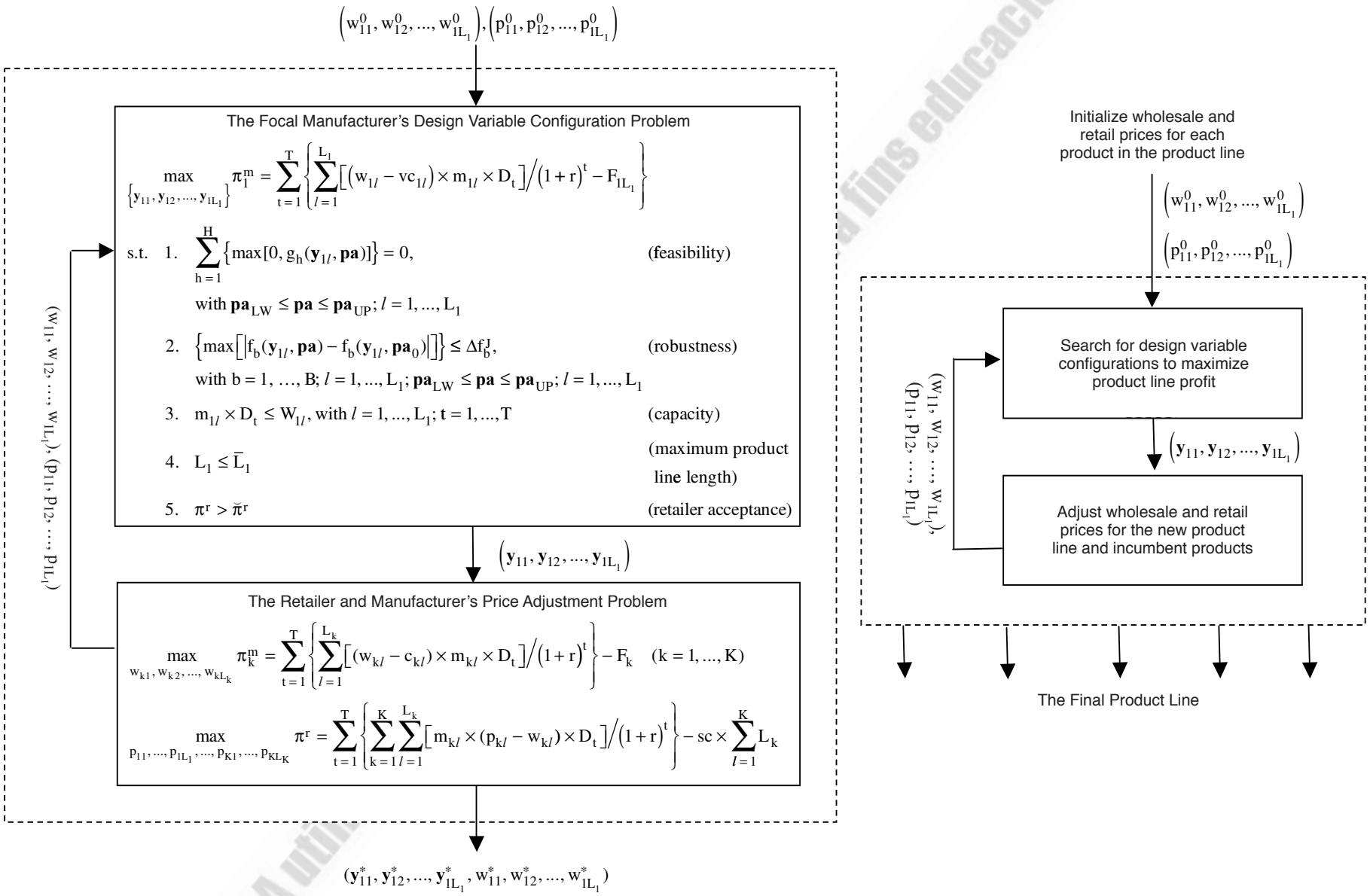
From the engineering side, I take into account (1) the feasibility and robustness of each product in the product line and (2) the cost synergy across the products in the product line.

[2]Within this context, the consumer attribute is continuous and the product designer must decide whether to discretize the attribute. If he or she believes there is a linear relationship between the value of the attribute and consumer preference, a linear function can be used to represent $u_s(v)$. Otherwise, the standard pairwise linear interpolation can be used to calculate $u_s(v)$ when v varies from v_L to v_U (Sawtooth Software 2001).

[3]I decided to focus on one retailer because the distribution channel of consumer durables is often characterized by one powerful retailer (Luo, Kannan, and Ratchford 2007). This also makes the proposed computation tractable. The competitive offerings were defined by the current assortment of the dominant retailer in the focal product category. These products typically represent the major players in the market.

Figure 1

COMPUTATIONAL ALGORITHM OF THE PRODUCT LINE OPTIMIZATION



Engineering feasibility and robustness. It is well established in the engineering literature (e.g., Kouvelis and Yu 1997; Ulrich and Eppinger 2004) that one essential goal of product design in many product categories (e.g., power tools, cars, appliances) is to ensure that products will remain feasible and robust under a variety of usage situations (e.g., different weather conditions, different application types). Therefore, the primary engineering consideration is to evaluate whether each product under consideration satisfies the feasibility and robustness criteria imposed by the engineering designer. A common approach to assess whether a product will satisfy these criteria is to examine the lower and upper bounds of its engineering performance metrics (e.g., motor temperature, motor output speed), which are created as an output of the design simulation (see Web Appendix A at http://www.marketingpower.com/jmrfeb11).

In particular, the goal of the feasibility criteria is to ensure that all the products in the product line do not break down under any known usage situation. Let (y_{11}, y_{12}, …, y_{1L_1}) denote the design variable configurations of the L_1 products in the focal manufacturer's product line (i.e., k = 1 for the focal manufacturer). Adopted from Besharati and colleagues (2004, 2006), the feasibility criteria associated with each product can be expressed as follows (h is the index for the hth feasibility criterion):

$$\sum_{h=1}^{H}\{\max[0, g_h(\mathbf{y}_{1l}, \mathbf{pa})]\} = 0 \tag{9}$$

$$\text{with } \mathbf{pa}_{LW} \le \mathbf{pa} \le \mathbf{pa}_{UP};\ l = 1, \ldots, L_1,$$

where $\mathbf{y}_{1l}$ denotes the design variable vector, **pa** represents the vector of the engineering parameters ranging from the lower bound $\mathbf{pa}_{LW}$ to the upper bound $\mathbf{pa}_{UP}$, and g is a dummy variable indicating whether the product violates the feasibility criterion (g = 1 if violated, and g = 0 if otherwise).

In line with Besharati and colleagues (2004, 2006) and Ulrich and Eppinger (2004), the vector of engineering parameters **pa** characterizes the uncontrollable variations in the product's usage environment. A product line will be penalized in the optimization if it contains any product violating any of the H constraints.

The robustness criteria ensure that undesirable variations in the product's engineering performance are limited to a reasonably small amount. A product satisfies the robustness criteria if the undesirable variations of its engineering performance metrics are bounded within the limits specified by the product designer. In line with Besharati and colleagues (2004, 2006), the mathematical representation of the robustness criteria is given in Equation 10:

$$\left\{\max\left[\left|f_b\left(\mathbf{y}_{1l}, \mathbf{pa}\right) - f_b\left(\mathbf{y}_{1l}, \mathbf{pa}_0\right)\right|\right]\right\} \le \Delta f_b^J \tag{10}$$

$$\text{with } b = 1, \ldots, B;\ \mathbf{pa}_{LW} \le \mathbf{pa} \le \mathbf{pa}_{UP};\ l = 1, \ldots, L_1,$$

where the index b (b = 1, …, B) denotes the bth robustness constraint, $\{\max[|f_b(\mathbf{y}_{1l}, \mathbf{pa}) - f_b(y_{1l}, \mathbf{pa}_0)|]\}$ is the observed maximum variation in the product's engineering performance when the engineering parameters deviate from the nominal value $\mathbf{pa}_0$, and Δf_b^J denotes the maximum acceptable variation specified by the engineering designer. A product line will be penalized in the optimization if it contains any product violating any of the B constraints.

Cost synergy. Given the increasing popularity of platform production (Morgan, Daniels, and Kouvelis 2001), the proposed cost model is constructed for platform-based product categories. Within this context, the manufacturer purchases the components from outside vendors, assembles the components into the final products, provides after-sale maintenance support, and salvages the product at the end of its life cycle. Accordingly, the variable cost of product l is computed as follows:

$$vc_{1l} = \sum_{r=1}^{R}(1 - \lambda_{rwl}) \times c_{rwl} + c_{al} + c_{ml} + c_{sl} \qquad l = 1, \ldots, L_1. \tag{11}$$

In Equation 11, the variable cost v_{c1l} is jointly determined by the component cost c_{rwl} (r is the index for the component—e.g., motor type; w is the index for the type of the component—e.g., motor #1), a discount factor λ_{rwl} associated with component sharing, the assembly cost c_{al}, the maintenance cost c_{ml}, and the salvage cost c_{sl}.

In general, in the platform-management literature, researchers refer to the parts firms use to build the product as components. For example, some major components related to a power tool are the motor, gearbox, and housing. Because they define the product from the designer's perspective, within this context, these components are essentially a part of the product's design variables. When different products within a product line share the same types of components, the cost associated with acquiring each unit of the shared component is scaled down because of economy of scale. The proposed method uses a discount factor λ_{rwl} to capture this effect (for more details on how to define λ_{rwl} and the other cost elements in Equation 11, see Web Appendix B at http://www.marketingpower.com/jmrfeb11).

Optimization Procedure

Figure 1 provides the overall procedure of the product line optimization. As shown, the proposed product line optimization includes two inner loop optimizations (denoted as the focal manufacturer's design variable configuration problem and the retailer and manufacturers' price adjustment problem) and an outer loop optimization (i.e., the procedure that solves the two inner optimizations iteratively until convergence).

This optimization begins with initializing the vectors of wholesale prices (w_{11}^0, w_{12}^0, ..., $w_{1L_1}^0$) and retail prices (p_{11}^0, p_{12}^0, ..., $p_{1L_1}^0$) for the focal manufacturer (denoted as the first manufacturer; i.e., k = 1). Given these initial wholesale prices, the focal manufacturer searches for vectors of design variables ($\mathbf{y}_{11}$, $\mathbf{y}_{12}$, …, $\mathbf{y}_{1L_1}$) to maximize its product line profit, subject to a set of constraints (i.e., the first panel of Figure 1). The first two constraints ensure that each product in the product line satisfies the engineering feasibility and robustness criteria. The third constraint is the capacity constraint. Note that the assembly of platform products typically requires different machine setup for each product. Therefore, the capacity constraint is set according to the production of each product (i.e., W_{1l}) rather than the sum of production across all the products in the product line. When a product's market demand exceeds the capacity constraint, the product's production volume will be set at the level of the capacity constraint. The fourth constraint sets the maximum length of the product line (i.e., $\overline{L}_1$), which typically the focal manufacturer prespecifies. Several previous studies

have assumed a fixed number of products in the product line (e.g., Balakrishnan, Gupta, and Jacob 2004; Belloni et al. 2008). The proposed method relaxes this assumption by allowing an upper limit of product line length. Finally, the channel acceptance criterion is determined by comparing the retailer's new category profit with its current category profit (denoted as $\breve{\pi}^r$).

The outputs of this inner loop optimization are the vectors of the design variables ($\mathbf{y}_{11}, \mathbf{y}_{12}, \ldots, \mathbf{y}_{1L_1}$) and their corresponding nonprice consumer attributes ($\mathbf{x}_{11}, \mathbf{x}_{12}, \ldots, \mathbf{x}_{1L_1}$). Next, the retailer and the manufacturers (including the focal and the competing manufacturers) adjust the retail and wholesale prices in response to the market entry of this product line (second panel of Figure 1).

Given the adjusted prices, the focal manufacturer researches vectors of design variables to maximize its product line profit. This cycling process continues until no improvement in the profit of the final product line results. The dotted box in Figure 1 depicts this outer loop optimization.

This procedure is performed for each possible product line length. The final product line is chosen as the one that maximizes the firm's profit as the product line length varies from 1 to $\overline{L}_1$. Note that if product line length is fixed (e.g., Balakrishnan. Gupta, and Jacob 2004; Belloni et al. 2008), the optimization needs to be performed only once. In addition, if the retailer were to consider only part of the product line acceptable, the method indirectly accounts for this because the shorter product line lengths have been considered under this procedure.

Because the product line design is NP-hard (Kohli and Sukumar 1990), the primary goal of previous research in this area has been finding near-optimal solutions in a reasonable amount of time. The current research follows this line of work by using heuristic methods to solve the focal manufacturer's design variable configuration problem (first panel of Figure 1) and gradient search methods to search for the adjusted wholesale and retail prices (second panel of Figure 1). Although prior research has suggested that the heuristic methods of genetic algorithm and simulated annealing have the ability to escape from a locally optimal solution (Balakrishnan, Gupta, and Jacob 2004; Belloni et al. 2008), the solutions these methods provide do not ensure global optimality. Similarly, multiple price equilibriums may exist when the manufacturers and the retailer make price adjustments. Therefore, a global maximum cannot be guaranteed in the optimization results. This is a common limitation shared by all extant research in product line design. To alleviate this issue, researchers can run the optimization multiple times with different starting values to assess the overall quality of the final solution. On a related note, because the focal manufacturer's ultimate goal is to maximize its profit and multiple product lines might generate identical (or highly similar) profits, the quality of the final solution is evaluated by the earning levels associated with the product line (Belloni et al. 2008) rather than the closeness in the configurations of the products. In a similar spirit, the convergence criterion of the proposed product optimization is based on the level of the final earning rather than the closeness of the solutions.

SIMULATION STUDY

In this section, I examine the computational characteristics of the proposed optimization procedure using simulated data. The primary goals of this simulation study are to empirically investigate (1) the use of different computational algorithms in the focal manufacturer's design variable configuration problem (the first panel of Figure 1), (2) the applicability of the overall procedure to large-scale problems, and (3) the convergence property of this procedure. All the computations were conducted in Matlab on a Pentium 4 personal computer.

The performance of three algorithms in the focal manufacturer's design variable configuration problem (the first panel of Figure 1) is compared. Note that because this comparison pertains only to the first panel of Figure 1, the wholesale prices and the retail markups were assumed to be fixed so that comparison could be confined to this particular part of the overall problem. Specifically, genetic algorithm (GA), simulated annealing (SA), and ATC were included in the comparison because previous research has shown that these methods perform well in product line design problems (e.g., Balakrishnan, Gupta, and Jacob 2004; Belloni et al. 2008; Michalek et al. 2010). In this simulation study, the focal manufacturer designs a product line consisting of one to eight products, each composed of four design variables. (I extend this to include more design variables in the second part of the simulation study.) Because the ATC method only handles continuous design variables, 16 problem sizes were investigated (8 with a mix of discrete and continuous variables and 8 with continuous variables only). For each problem size, five problem instances were created, which resulted in 80 simulated problems. (For more details of the simulation procedure and a brief description of these optimization methods, see Web Appendix C at http://www.marketingpower.com/jmrfeb11.)

Table 1 provides the result comparisons. When the design variable vector included both discrete and continuous attributes, the average earnings of the product lines were com-

Table 1

ALGORITHM COMPARISONS FOR THE FOCAL MANUFACTURER'S DESIGN VARIABLE CONFIGURATION PROBLEM (FIRST PANEL OF FIGURE 1)

	Mix of Discrete and Continuous Variables				*Continuous Variables Only*					
	GA		*SA*		*GA*		*SA*		*ATC*	
Number of Products	*Average Profit*	*Average CPU Time*	*Average Profit*	*Average CPU Time*	*Average Profit*	*Average CPU Time*	*Average Profit*	*Average CPU Time*	*Average Profit*	*Average CPU Time*
Small (1–3)	65.5	.9	63.9	29.0	68.8	1.1	68.1	40.8	69.0	.9
Medium (4–5)	105.2	1.2	107.8	78.8	103.2	1.3	105.1	117.5	104.7	2.3
Large (6–8)	92.2	1.8	90.9	195.7	87.4	1.9	88.6	232.9	90.5	3.6

Notes: The average profits are presented in millions of U.S. dollars, and the average CPU time is presented in seconds.

parable, regardless of whether GA or SA was used to solve the optimization. However, in terms of CPU time, GA is much more efficient than SA. These findings are consistent across different problem sizes. When the design variable vector included only continuous attributes, the same pattern resulted between the methods of GA and SA. Note that the results of the comparison for these two algorithms are also in line with Belloni and colleagues' (2008) findings. It is possible that the computational inefficiency of SA results from its extensive search process because SA sometimes accepts product line configurations that reduce earnings in attempts to escape from a local optimum. With regard to ATC, this method performs well in terms of both the quality of the solutions and the computation time. In particular, ATC seems to generate better solutions than GA and SA as the problem size increases. It is conjectured that when there are many products in the product line, the decompositional-based ATC approach facilitates a more effective and efficient search than the combinatorial-based GA and SA approaches. Given the previously mentioned findings, I suggest using GA in the focal manufacturer's design variable configuration problem when the products contain both discrete and continuous design variables. When the products consist of only continuous variables, the ATC method may be superior, particularly when there are a great number of products in the product line.

Next, the computation time required to obtain a final solution based on the overall procedure (the entire Figure 1) across different problem sizes was further investigated. In this simulation task, the focal manufacturer designs a product line consisting of one to eight products, each composed of 4, 8, 12, 16, 20, or 24 design variables. This results in 48 simulation problems. In this task, GA was used to solve the focal manufacturer's design variable configuration problem (the first panel of Figure 1). The reason for choosing GA was that it not only handles both continuous and discrete design variables but also is computationally desirable. The required computation time for the overall procedure (the entire Figure 1) varied between 2 and 10.4 hours when the problem sizes ranged from a small problem with one to three products and 4–8 design variables to a large problem with six to eight products and 20–24 design variables. (For more details, see Web Appendix C at http://www.marketingpower.com/ jmrfeb11.)

Finally, the proposed procedure converged within a reasonable amount of time for all the simulation problems discussed previously. These results suggest that, by and large, the overall proposed procedure is applicable to problems with a reasonably large scale.[4]

EMPIRICAL APPLICATION

The proposed product line optimization was applied in a case study using data collected in a power tool product development project undertaken by a large U.S. manufacturer. The industrial partner and I conducted exploratory research (e.g., field trips, focus group studies) to identify the set of consumer attributes the end users of this power tool deemed most critical. The identification of these attributes follows the typical procedure used in determining which attributes to include in a conjoint experiment. It was discovered that, in general, consumers take into account the power tool's brand, price, power amp, product life, switch type, and girth type in a purchase decision. (For more details of the conjoint design, see Web Appendix D at http://www.marketingpower.com/jmrfeb11.[5]) Given these consumer attributes, I proceeded to determine the set of design variables. The following design variables were identified because they determine the values of the consumer attribute vector and are collectively needed for proper functioning of the product: motor type, speed reduction unit or gearbox type, gear ratio, switch type, and housing type. (For more details on the design space defined by these design variables, see Web Appendix D.)

After the vectors of the consumer attributes and design variables were identified, the mapping between the two vectors was established. The consumer attributes switch type and girth type are identical to their corresponding design variables (with a small girth mapped from a small housing and a large girth mapped from a large housing). For power amp and product life, an engineering simulation similar to the one described in Web Appendix A (http://www.marketingpower.com/jmrfeb11) was used to establish the mapping relationships. Specifically, the inputs of the simulation are the configuration of the design variables motor type, gearbox type, and gear ratio. The outputs of the simulation are the values of the product's (1) power amp and product life (consumer attributes) and (2) motor temperature, motor output speed, and mass material removal per application (engineering performance metrics). The former directly influence consumers' purchase decisions. The latter were used to evaluate whether the product satisfies the feasibility and robustness constraints the product designer specified. The uncontrollable variations in the product's usage environment were represented by a set of engineering parameters (for more details, see Web Appendix D at http://www.marketingpower.com/jmrfeb11). The outputs of the simulation provided the nominal, lower-, and upper-bound values of each output variable. Given the sets of consumer attributes, design variables, and their mapping relationships, the focal problem of the product line optimization is to search for a profit-maximizing product line.

Marketing Considerations

A choice-based conjoint study was conducted with 740 power tool users across the U.S. market. Each respondent was given 18 choice sets, with each choice set including two products and a no-choice option (for more details of the conjoint design, see Web Appendix D at http://www.marketingpower.com/jmrfeb11). In addition, each respondent provided some demographic information including trades, glove size, height, and age. These covariates were used to identify segment membership and facilitate the estimation of the conjoint partworths.

[4]The performance of the proposed product line optimization was also compared with the global optimum (obtained through complete enumeration) for the case of four design variables with one to two products in the product line. This comparison was limited to only small-scale problems for which the global optimum could be obtained in a reasonable amount of time. The average final earnings from the proposed optimization are at 96% of the true optimum.

[5]Some actual attribute names were camouflaged as well as the values of attribute levels, cost estimates, and capacity constraints to protect the proprietary information of the industrial partner.

The finite mixture conjoint model was estimated on the basis of scenarios of one to five market segments. With the use of the deviance information criterion measure, the optimal number of market segments was selected as two. Table 2 shows the estimation results (for the estimates related to the covariates, see Web Appendix D at http://www.marketingpower. com/jmrfeb11). The hyperparameter of the no-choice option in Segment 1 was fixed to zero for identification. In each market segment, the sum of the conjoint partworths across the different levels of a product attribute was fixed to zero for identification. To make the scale of the conjoint partworths comparable across different attributes, the continuous variable price was also mean centered.

Note that a power tool's power amp and product life might differ under various usage situations. Equation 5 was used to calculate their expected conjoint partworths given their nominal, lower-, and upper-bound values. The assumption of a total drop-off at the end points was relaxed by allowing the probabilities at the minimum and maximum outcomes to be 2.5%.

Before the entry of the new product line, there were three incumbent manufacturers. Two manufacturers offered product lines with two products, and one manufacturer sold one product (for their consumer attribute specifications, see Web Appendix D at http://www.marketingpower.com/jmrfeb11). For each product line under consideration, the algorithm described in Web Appendix B was used to calculate the wholesale and retail price adjustments.

Engineering Considerations

The feasibility criterion required that the product's motor temperature be less than 125°C under any usage situation. This constraint was imposed to ensure that the product would not break down under demanding application conditions. Therefore, for each product under consideration, the upper bound of its motor temperature (provided as an output variable from the engineering simulation) was checked. If this upper bound value was greater than 125°C, the product line consisting of this product would be penalized in the optimization.

With regard to robustness requirements, the following two criteria were considered: (1) the variation between the actual and nominal motor output speeds must be less than 4000 revolutions per minute, and (2) the variation between the actual and nominal mass material removals per application must be less than 5 grams. Consequently, for each product under consideration, the maximum variation associated with each of the preceding engineering performance metric was calculated (e.g., if a product's nominal, lower, and upper bounds of mass material removal rates are 12, 5, and 16 grams, respectively, the maximum variation is calculated as $\max[|5 - 12|, |12 - 16|] = 7$). In the proposed optimization, a product line will be penalized if it consists of products violating any of these robustness requirements.

The variable cost of each product in the product line was calculated using Equation 11. The major components of this product are motor, gearbox, product switch, and housing type. The unit cost of each component type and the associated discount factor were obtained from a lookup table. The specific combination of these components determined the assembly cost, which was also obtained from a lookup table. The maintenance cost was calculated using the lower bound of product life, and the salvage cost for each product was estimated to be $3. The fixed cost estimates were given by the industrial partner. For product lines consisting of one, two, and three products, the fixed costs were estimated to be $15 million, $18 million, and $25 million, respectively.

Product Line Optimization Results

Given the specifics of the engineering and marketing considerations, a profit-maximizing product line was searched for using the procedure described in Figure 1. Brand was fixed at the level of own brand. The GA was used to solve the focal manufacturer's design variable configuration problem (first panel in Figure 1). The initial population of product lines was randomly chosen. Given the products' initial wholesale and retail prices, the focal manufacturer first searched for the design variable configurations of a profit-maximizing product line. Next, the retailer and the manufacturers reset prices to maximize own profit. On the basis of the adjusted prices, the focal manufacturer re-searched a set of design variables to maximize its profit. This cycling process continues until no improvement in the profit of the final product line results (for more estimation details, see Web Appendix D at http://www.marketingpower.com/jmrfeb11).[6]

Because the dominant retailer rarely accepts more than three products from the same manufacturer in the focal product category, the maximum length of the product line was set at three. As a result, the proposed optimization procedure was repeated when there were one, two, and three products in the product line. The product line with the fol-

Table 2
BAYESIAN FINITE MIXTURE CONJOINT PARTWORTH ESTIMATES

	Segment 1 (Size = .147)		Segment 2 (Size = .853)	
	M	*SD*[a]	*M*	*SD*
Own brand	.859	.857	.164	.205
Brand 1	1.077	.533	–.299	.270
Brand 2	2.233	1.139	.298	.268
Brand 3	–4.169	1.885	–.163	.362
Price (mean centered)	–.342	.181	–.044	.517
Power amp: 6	–1.630	.577	–.318	.412
Power amp: 9	.240	.376	.090	.427
Power amp: 12	1.390	.434	.228	.603
Product life: 80 hours	–3.682	1.636	–.334	.476
Product life: 110 hours	–1.346	1.602	.028	.525
Product life: 150 hours	5.028	1.436	.306	.584
Switch type 1: paddle	–1.503	.661	–.333	.588
Switch type 2: top slider	1.966	.676	.320	.485
Switch type 3: side slider	.593	.565	.517	.305
Switch type 4: trigger	–1.056	.608	–.504	.414
Girth type 1: small	1.173	1.006	–.035	.180
Girth type 2: large	–1.173	1.006	.035	.180
No choice	—	—	.477	.211

[a]These entries are the posterior estimates of the square roots of the diagonal terms in the variance–covariance matrix (i.e., Ω_s). They represent the degree of heterogeneity within each consumer segment.

[6]The GA parameters used here are the same as those used in the simulation study. The GA parameters were varied several times to evaluate how sensitive the final earning level was to the GA parameters. The quality of the solution was assessed by using different starting values. No major differences were found in the final earnings.

lowing specifications provided the highest earning (see Table 3). It was evident that the high earning level of this product line benefited a great deal from component sharing. (The first two products shared the same gearbox type, the last two products used the same switch type, and all three products consisted of the same girth type.) Meanwhile, the product line also exploits the heterogeneous consumer preferences in the marketplace (see the different power amps, product life, and prices of these products). Over a five-year horizon, the discounted long-term profit is estimated to be $52.8 million. Some robustness checks were also conducted and indicated that this final earning level was not overly sensitive to the parameter specifications of the model (see details in Web Appendix D at http://www.marketingpower.com/jmrfeb11).

Comparison with Benchmark Approaches

Next, this study compares the empirical results obtained from the proposed procedure with two benchmark approaches in which the marketing and engineering considerations are addressed in a sequential order. Both approaches comprise two stages. In the marketing-first approach, the marketing team's primary goal in the first stage is to search for vectors of consumer attributes that maximize the product line profitability. The key differences between the optimization at this stage and the one described in Figure 1 are that (1) the decision variables $\{\mathbf{y}_{11}, \mathbf{y}_{12}, \ldots, \mathbf{y}_{1L_1}\}$ are replaced by $\{\mathbf{x}_{11}, \mathbf{x}_{12}, \ldots, \mathbf{x}_{1L_1}\}$ and (2) the five constraints in the first block of the figure are reduced to constraints 3–5. Because a product's variable cost is an inherent function of a product's design variable configuration and its cost interactions with the other products in the product line, the product's cost based needed to be approximated using a weighted sum of its attribute levels (excluding brand and price).[7] The other aspects of this optimization are identical to the ones Figure 1 describes. In the second stage, given the consumer attribute specification of each product in the final product line, the engineering team searches for a combination of design variables that best match the required values of consumer attributes at the nominal operation condition. In addition, the engineering team evaluates whether these design variable configurations satisfy the engineering feasibility and robustness criteria (the first two constraints in the first panel of Figure 1). If the product violates one or more engineering requirements, the engineering team will move on to a design variable configuration that produces the second smallest deviation from the required consumer attribute values. This process continues until all products satisfy the engineering requirements.

Under this approach, the final product line consisted of three products with the specifications listed in Table 4. The cost and market share estimates in this table are recalibrated using each product's actual design variable configurations. As a result of separating marketing and engineering considerations, this sequential approach led to a suboptimal product line. In particular, because this benchmark approach did not capitalize on the cost synergy among the products in the product line, the final product line had a lower degree of component sharing than the product line Table 3 shows. As a result, although this product line was predicted to capture a larger market share (34.08% versus 29.63% in the proposed approach), the average markup between the wholesale prices and variable costs was lower ($6.10 versus $7.93 in the approach). Consequently, this product line was not as profitable as the one obtained from the proposed approach (long-term profit: $46.5 million versus $52.8 million).

In the second alternative approach (i.e., engineering first), the engineering team first prunes the product design space using the engineering feasibility and robustness criteria. In the second stage, the marketing team composes a profit-maximizing product line among all the products satisfying the engineering constraints. The key differences between the second stage optimization and the one Figure 1 describes are that (1) the product line configurations are limited among the pool of product candidates retained from the first stage (rather than the entire design space) and (2) the five constraints in the first block of the figure are reduced to constraints 3–5. The other aspects of this opti-

[7]The weights were obtained from a multiple regression using the cost estimates of current products and some hypothetical products (I thank two anonymous reviewers for this suggestion). In addition, if the marketing team was able to incorporate cost synergy into the variable cost estimation, the primary advantage of the proposed approach versus the marketing-first approach hinges on the rigidity of the engineering criteria. If there is a substantial number of engineering requirements, the marketing-first approach may result in a local search in a suboptimal space. In contrast, if the vast majority of product candidates satisfy the engineering requirements, the results may not differ substantially between the proposed and the marketing-first approaches.

Table 3
SPECIFICATIONS OF THE FINAL PRODUCT LINE: CURRENT APPROACH

	Motor	*Gear Ratio*	*Gearbox*	*Power Amp (Nominal)*	*Product Life (Nominal)*	*Switch*	*Girth*	*Wholesale Price*	*Retail Price*	*Variable Cost*	*Market Share (%)*
Product 1	4	4.11	3	8.7	123	2	1	$79.22	$109.22	$70.00	7.65
Product 2	10	4.72	3	9.9	117	3	1	$74.03	$100.04	$67.00	14.35
Product 3	9	3.60	2	12.5	125	3	1	$89.55	$118.49	$82.00	7.63

Table 4
SPECIFICATIONS OF THE FINAL PRODUCT LINE: MARKETING-FIRST APPROACH

	Motor	*Gear Ratio*	*Gearbox*	*Power Amp (Nominal)*	*Product Life (Nominal)*	*Switch*	*Girth*	*Wholesale Price*	*Retail Price*	*Variable Cost*	*Market Share (%)*
Product 1	2	3.91	3	6.7	107	2	1	$74.03	$90.02	$70.00	10.98
Product 2	4	4.05	2	9.2	129	3	2	$78.79	$99.77	$71.00	12.70
Product 3	8	4.28	6	10.5	149	3	2	$89.47	$111.03	$83.00	10.40

mization procedure were identical to those Figure 1 describes.

Given that the design space for a consumer durable product is usually large (particularly with the presence of continuous design variables), an exhaustive search is often infeasible in the first stage to identify the complete pool of product candidates that satisfy the engineering criteria. Therefore, heuristic methods are often used to preselect a set of product candidates for the composition of the final product line. To demonstrate the drawback of the engineering-first approach (if the product designer cannot identify the complete pool of product candidates satisfying the engineering criteria in the first stage), the design space was randomly sampled until 1000 products were obtained that satisfied the engineering criteria. Next, an exhaustive search was conducted to obtain the profit-maximizing product line when there were one to three products in the product line. Table 5 provides the specifications of the most profitable product line. Because the composition of the final product line was limited to the set of 1000 products, some promising product candidates from the marketing perspective may be neglected. Therefore, although this product line included some degree of component sharing, it was not as profitable as the one obtained using the proposed approach ($48.3 million versus $52.8 million).[8]

CONCLUSIONS

In this study, I introduce a procedure of product line optimization in which the marketing and engineering criteria are considered concurrently in the search for a profit-maximizing product line. It is proposed that the product designer should take into account both marketing and engineering considerations concurrently in a product line design. In particular, the proposed method extends beyond extant methods in product line design by accounting for the strategic reactions from the competing manufacturers and the retailer in response to the entry of the new product line. Through a simulation study and an empirical application, I demonstrate that the proposed optimization procedure provides an effective solution to this challenging problem.

The study also contributes to the literature by proposing an optimization method that works in relatively large-scale design problems consisting of both discrete and continuous design variables. In particular, it is suggested that GA provides an efficient and effective solution to the focal manufacturer's design variable configuration problem in a variety of problem settings. In contrast, despite their comparable performance in finding profit-maximizing product lines, the heuristic method of SA is only suitable for small-scale problems (given its computational inefficiency) and the decompositional method of ATC is applicable to problems with only continuous design variables.

This research is not without limitations. First, the proposed method is built on the assumption that the product designer has complete knowledge about the various inputs needed for the optimization. Therefore, exploratory research when some inputs are unknown is needed. Second, because the product line design problem is NP-hard, the proposed optimization procedure might recover a local maximum rather than a global maximum. Further research could investigate optimization methods that can guarantee a global optimality. Third, although it accounts for the retailer's and the incumbent's strategic price reactions, the proposed method is limited in addressing the incumbents' strategic responses in nonprice attributes. Finally, because the proposed optimization method is combinatorial, firms facing extremely large problems might encounter computational difficulty. Further research could develop a decompositional approach that handles both discrete and continuous design variables. In time, as both the algorithm and the computational power improve, further research might extend this work by guaranteeing global optimality in a considerably large-scale product line design problem.

[8]Note that because the design space in the empirical application is relatively small, technically, the continuous design variable gear ratio could be discretized and an exhaustive search could be performed in the first stage. Under this scenario, the results from the engineering-first approach should be similar to that obtained here.

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Table 5

SPECIFICATIONS OF THE FINAL PRODUCT LINE: ENGINEERING-FIRST APPROACH

	Motor	*Gear Ratio*	*Gearbox*	*Power Amp (Nominal)*	*Product Life (Nominal)*	*Switch*	*Girth*	*Wholesale Price*	*Retail Price*	*Variable Cost*	*Market Share (%)*
Product 1	3	4.30	2	9.9	107	2	1	$80.72	$101.17	$72.00	10.47
Product 2	3	4.27	3	8.7	119	3	1	$78.79	$103.45	$71.59	10.89
Product 3	2	3.94	1	10.3	128	2	1	$89.29	$115.21	$82.50	6.75

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Fonte: Journal of Marketing Research (JMR), v. 48, n. 1, p. 128-139, 2011. [Base de Dados]. Disponível em: <http://web.ebscohost.com>. Acesso em: 4 fev. 2011.