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

Lan Luo

March 2010

Forthcoming in Journal of Marketing Research

Lan Luo is an Assistant Professor of Marketing, at the Marshall School of Business, University of Southern California, Los Angeles, CA 90089.

The author greatly appreciates P.K. Kannan, Babak Besharati, Shapour Azarm for their valuable inputs to this research. She also wishes to thank the editors-in-chief, the associate editors, the four anonymous reviewers, and seminar attendants at the 2006 INFORMS Marketing Science conference, the 2006 INFORMS Annual Meeting, the 2007 Product and Service Innovations Conference in Utah, the 2008 Research Frontiers in Marketing Science Conference at University of Texas at Dallas, the 2008 Marketing Innovations Conference at Rensselaer Polytechnic Institute for their constructive comments and helpful guidance.
Abstract

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. We present a product line optimization method that enables managers to simultaneously consider factors deemed as important from both domains of marketing and engineering. 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. We demonstrate 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, we illustrate 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, New Products, Product Design, Marketing Engineering Integration, Optimization Methods, Genetic Algorithm, Simulated Annealing
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 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 argument can be applied to many consumer durable products such as toys, appliances, trucks, airplanes, laptops, and etc.

In the design of a product line, 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 emphasized 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 individual product, but also the revenue and cost interactions across the products in the product line. Furthermore, in order to accurately forecast the revenue from a product line,
it is critical to account for the strategic reactions from competing manufacturers and the retailer when the new product line enters into the market. Within this context, a simultaneous consideration of all these essential issues across both disciplines is considerably challenging both conceptually and computationally.

The primary goal of this research is to propose a product line optimization method to tackle this combinatorial challenge. In particular, we propose a procedure in which the marketing and engineering criteria are considered concurrently in the search for a profit-maximizing product line. We demonstrate 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, we illustrate 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 paper is organized as follows. First, we discuss the relationship of this paper to extant literature and the contribution of this research. Second, we present the details of our product line optimization. Third, we describe a simulation study in which we investigate the computational characteristics of our method. Next, we describe the empirical application. We conclude by summarizing contributions and discussing limitations and future research.

RELATIONSHIP TO EXISTING RESEARCH

There are four streams of research related to this paper. The first stream investigates product line design from a marketing perspective (e.g. Balakrishnan, Gupta, and Jacob 2004, 2006; Belloni, Freund, Selove, and Simester 2008; Chen and Hausman 2000; Dobson and Kalish 1988 and 1993; Green and Krieger 1985; Kannan, Pope, and Jain 2009; McBride and Zufryden 1988; Moore, Louviere, and Verma 1999; Nair, Thakur and Wen 1995; Steiner and Hruschka
This research stream utilizes conjoint data and searches for an optimal or near-optimal product line by selecting levels of consumer attributes. The second stream of papers 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). This line of research has generally focused 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 papers investigating how to integrate engineering and marketing considerations into the design of a single product (e.g. Besharati, Luo, Azarm, and Kannan 2004 and 2006; Griffin and Hauser 1993; Hauser and Clausing 1988; Li and Azarm 2000; Luo, Kannan, Besharati, and Azarm 2005; Michalek, Feinberg, and Papalambros 2005; Srinivasan, Lovejoy, and Beach 1997; Tarasewich and McMullen 2001; Tarasewich and Nair 2001). Finally, the fourth stream consists of papers 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, Feinberg, Ebbes, Adiguzel, and Papalambros 2009; Michalek, Ceryan, Papalambros, and Koren 2006).

In the following we discuss how our paper extends the four streams of research.

From a substantive perspective, we contribute to the literature by providing an effective coordination of a number of essential issues across both disciplines of marketing and engineering. Specifically, on the marketing side, we evaluate the market potential of the product line 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, we focus 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, our optimization method by no means exclusively accounts for all the marketing and engineering criteria currently being considered in the design of a product line. We focus on the above issues due to their considerable significance in the product design literature. Since any of these issues can have a substantial impact on the profitability of the final product line, we contribute to the literature by tackling the combinatorial challenge of integrating these essential issues across both disciplines of marketing and engineering. Particularly, one major advantage of the proposed model is that it directly accounts for the strategic responses from the competing manufacturers and the retailer. Although recognized as an important challenge in product line design problem (Belloni et al. 2008), these issues have never been addressed in previous work.

*From a methodological perspective, we contribute to the literature by searching for an optimal product line in a large design space with a mix of discrete and continuous design variables.* Due to the complexity of the product line design problem, a number of previous researchers have limited the composition of a product line within a fairly small set of initial products (e.g. Kumar et al. 2009; Morgan, Daniels, and Kouvelis 2001; Ramdas and Sawhney 2001). In practice, however, the product design space for a consumer durable product can be very large or virtually infinite. In attempts to address this issue, Michalek et al. (2006 and 2009) proposed 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 (we will demonstrate this in a simulation study), it is not directly applicable in a product design space with discrete product attributes.
Therefore, one major advantage of our method is its ability to accommodate both discrete and continuous variables in a large design space. However, the approach we take comes with the cost of combinatorial complexity. The ability of this method to scale up to a large problem is discussed later in the paper.

**PROPOSED METHOD**

Following Kaul and Rao (1995) and Michalek et al. (2009), we begin by defining a set of consumer attributes and design variables as the starting point of our model. The vector of consumer attributes (denoted as \( x \)) represents all the attributes directly considered by consumers 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. And the design variables (denoted as \( y \)) are variables that the product designer needs to decide upon 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, we proceed to define an engineering response function \( r(y) \) that calculates the values of \( x \) as a function of \( y \) (i.e. \( x = r(y) \)).

As discussed by Michalek et al. (2009), while the specification of the response function \( r(y) \) needs to be determined on a case-by-case basis, the general principles of such mapping are well established in the literature (see Web Appendix A for additional implementation details). Given the set of design variables \( y \), consumer attributes \( x \), and their interrelationships \( x = r(y) \), the focal problem of our 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.
In the following we first describe the specifics of our marketing and engineering considerations. We then demonstrate how we merge these considerations into a product line optimization procedure.

**Marketing Considerations**

From the *marketing* side, we take into account: 1) how consumers form their preferences towards 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 (FM) 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:

\[
U_{idk} = x_{id} \beta_{i\alpha} + p_{id} \beta_{i\beta} + \varepsilon_{idk}
\]

where \((\beta_{i\alpha}, \beta_{i\beta})\) is the vector of the conjoint part-worths for consumer *i*, \((x_{id}, p_{id})\) is a vector representing the consumer attributes and the price of product alternative *d* in choice set *k*, and \(\varepsilon_{idk}\) is a random component.

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

\[
Pr_{idk} = \frac{\exp(x_{id} \beta_{i\alpha} + p_{id} \beta_{i\beta})}{\sum_{d' = 1}^{D} \exp(x_{id'} \beta_{i\alpha} + p_{id'} \beta_{i\beta}) + \exp(\alpha_i)}
\]

where \(\alpha_i\) denotes the utility of the “no-choice” option.

Let \(\xi_i = (\beta_{i\alpha}, \beta_{i\beta}, \alpha_i)\), we define \(\xi_i\) using a mixture of multivariate normal distributions (Rossi and Allenby 2003):
where $\theta_{is}$ represents the probability that consumer $i$ belongs to segment $s$ and $\Omega_s$ is a full variance-covariance matrix.

Furthermore, we define $\theta_{is}$ as follows:

\[(4)\]

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

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

We use Gibbs Sampler and Metropolis-Hastings algorithm to obtain the distributions of the posterior estimates (see Web Appendix B for more estimation details). The Deviance Information Criterion (DIC) measure is used to determine the optimal number of market segments. Our consumer preference model, thus, provides us with the number of segments and the posterior estimates for segment sizes ($\theta_s = \sum_{i=1}^{N} \theta_{is}$ for $s=1,…,S$), segment level conjoint part-worths ($\xi_{1s}, \xi_{2s},…, \xi_{Ss}$), and the variance-covariance matrixs ($\Omega_1, \Omega_2,…, \Omega_s$). These posterior estimates can then be used to derive the utility estimate for each product under consideration.\(^1\)

\(^1\) It is worth-noting that either the posterior individual- ($\xi_i$) or segment- ($\xi_s$) level conjoint part-worths may be considered as inputs to our product line optimization. The choice between the two depends on the tradeoff between a better representation of consumer heterogeneity and computation time. In our empirical application, when the inputs of the product line optimization changed from $\xi_s$ to $\xi_i$, the average computational time increased 8.59 times when there are 1-3 products in the product line and 740 respondents in the conjoint experiment. We further examined the impact of ignoring the within-segment heterogeneity when the posteriors of $\xi_s$ rather than $\xi_i$ were used in the optimization. Specifically, we used the individual-level estimates to recalibrate the profitability of the final product lines obtained from the segment-level part-worths (we thank an anonymous reviewer for suggesting this). We 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, we reported the findings based on the segment-level estimates in the empirical section. We acknowledge that this finding is only based on a single comparison and may not be applicable in different problem settings. In general, segment- (individual-) level estimates can be considered for large- (small-) scale problems. And individual-level estimates should be favored when there is a great deal of
Previous research has generally assumed that the utility of each product is a constant. In reality, this assumption may not hold because a product may 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). We adopt the expected utility theory (Quiggin 1982) to address these inherent variations in each product’s utility. In particular, if the value of a particular consumer attribute (e.g. power amp and product life) varies when the product is used under different usage situations, we 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 (Web Appendix A). Consequently, the expected utility from the attribute can be computed as below:

\[
\gamma_s = \int_{v_L}^{v_U} u_s(v) f(v) dv
\]

with \( u_s(v) \) denoting the attribute’s conjoint utility as a function of the value of \( v \), and \( f(v) \) being 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 only the minimum, maximum, and most likely outcomes are known to the researchers (e.g. Koller 2005; Li and Azarm 2002).

Given Equations (1) to (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.

² Within this context, the consumer attribute is continuous and the product designer needs to decide whether to discretize the attribute. If he/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 pair-wise linear interpolation can be used to calculate \( u_s(v) \) when \( v \) varies from \( v_L \) to \( v_U \) (Sawtooth User’s Manual 2001).
Market Responses from Competitors and Retailer

In the following we discuss how we address the strategic reactions from the incumbent manufacturers and the retailer to the launch of the product line. Because it is typically difficult to adjust the non-price attributes in the short run, we model the reactions from the incumbent manufacturers and the retailer by changes in prices only (this is also in line with Hauser 1988 and Luo et al. 2007). Our 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 seek further profit improvement. We repeat this cycling process until no improvement in the profit of the final product line can be found (see more details of this process in Figure 1 and the sub-section titled “Optimization Procedure” below). This approach extends Luo et al. (2007) by accommodating a larger scale product design space in the context of product line design. One major advantage of this method is that, prior to the new product line introduction, the focal manufacturer already accounts for the strategic responses from the retailer and the competing manufacturers. This has been neglected by extant research in product line design.

The price adjustments of the retailer and the manufacturers are modeled as follows. Assuming that there are \( K \) manufacturers with the \( k \text{th} \) \((k = 1, \ldots, K) \) manufacturer sells \( L_k \) products. Given the vector of wholesale prices \( (w_{11}, w_{12}, \ldots, w_{1L_1}, w_{21}, w_{22}, \ldots, w_{2L_2}, \ldots, w_{K1}, w_{K2}, \ldots, w_{KL_K}) \), the

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3 We decided to focus on one retailer because the distribution channel of consumer durables is often characterized by one powerful retailer (Luo, Kannan, Ratchford 2007). This also makes our 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.
retailer chooses the retail price of each product in its assortment to maximize own profit. The retailer’s profit maximization can be written as:

\[
\max_{p_{kl}} \pi^r = \sum_{t=1}^{T} \left( \sum_{k=1}^{K} \sum_{l=1}^{L_k} \left[ m_{kl} \ast (p_{kl} - w_{kl}) \ast D_t \right] \left(1 + r\right) \right) - sc \ast \sum_{k=1}^{K} L_k
\]

(7) with

\[
m_{kl} = \frac{\exp(x^\prime_{kl} \beta_{sp} + p_{kl} \beta_{sp})}{\sum_{k=1}^{K} \sum_{l=1}^{L_k} \exp(x^\prime_{kl} \beta_{sx} + p_{kl} \beta_{sp}) + \exp(\alpha_s)}
\]

where \(\pi^r\) is the category profit of the retailer, \(m_{kl}\) represents the market share of the \(l^{th}\) product from the \(k^{th}\) 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. Following Gordon (2009), we assume that \(D_t\) is observed and determined exogenously (as a function of the products’ replacement cycles, overall economic condition, and etc.). The parameters \(\{\theta_s, \beta_{sx}, \beta_{sp}, \alpha_s\}\) in Equation (7) correspond to posterior conjoint part-worth estimates obtained from the finite mixture Bayesian estimation.

Given the vector of new retail prices \(\{p_{11}, p_{1L_1}, \ldots, p_{KL_K}\}\), each manufacturer \((k = 1, \ldots, K)\) will adjust the wholesale prices of the \(L_k\) products in its product line to maximize its profit. Note that this differs from Luo et al. (2007) in that the manufacturer will choose a set of wholesale prices rather than a single price.

\[
\max_{w_{kl}} \pi^m_k = \sum_{t=1}^{T} \left( \sum_{l=1}^{L_k} \left[ (w_{kl} - c_{kl}) \ast m_{kl} \ast D_t \right] \left(1 + r\right) \right) - F_k \quad k = 1, \ldots, K
\]

(8) where \(c_{kl}\) is the variable cost of the \(l^{th}\) product from manufacturer \(k\), \(F_k\) is the fixed cost of this manufacturer.

Similar to Luo et al. (2007), the new wholesale and retail prices are estimated by solving Equations (6) and (8) iteratively (details in Web Appendix B). A major challenge faced by all
existing research in product line design is that multi-product firms with logit demand do not have log-supermodular profit functions (Hanson and Martin 1996). Therefore, we face the possibility of multiple price equilibria in our 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, since we only account for the retailer and the incumbents’ potential reactions in price adjustments, this method does not apply in situations where the incumbents change their non-price attributes in response to the entry of the new product line.

**Engineering Considerations**

From the *engineering* side, we 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.

*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 and application types). Therefore, our 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).

In particular, the goal of our *feasibility criteria* is to ensure that all the products in the product do not break down under any known usage situation. Let \((y_{11}, y_{12}, \ldots, y_{1L})\) denote the
design variable configurations of the $L_1$ products in the focal manufacturer’s product line (i.e. we set $k=1$ for the focal manufacturer). Adopted from Besharati, et al. (2004) and (2006), the feasibility criteria associated with each product can be expressed as follows ($h$ is the index for the $h^{th}$ feasibility criterion):

$$\sum_{h=1}^{H} (\max[0, g_h(y_{1l}, p_a)]) = 0$$

with $p_{a_{LW}} \leq p_a \leq p_{a_{UP}} ; l = 1, \ldots, L_1$

where $y_{1l}$ denotes the the design variable vector, $p_a$ represents the vector of the engineering parameters ranging from the lower bound $p_{a_{LW}}$ and the upper bound $p_{a_{UP}}$, and $g$ is a dummy variable indicating whether the product violates the feasibility criterion ($g = 1$ if violated; $g = 0$ otherwise).

Following Besharati et al. (2004, 2006) and Ulrich and Eppinger (2004), the vector of engineering parameters “$p_a$” characterize 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.

Our 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. Following Besharati et al. (2004) and (2006), the mathematical representation of the robustness criteria is given in Equation (10):

$$\left[ \max\left(\left| f_b(y_{1l}, p_a) - f_b(y_{1l}, p_{a_{b}}) \right| \right) \right] \leq \Delta f_{b}$$

with $b = 1, \ldots, B; \quad p_{a_{LW}} \leq p_a \leq p_{a_{UP}} ; l = 1, \ldots, L_1$
where the index \( b (b = 1, \ldots, B) \) denotes the \( b^{th} \) robustness constraint,

\[
\max \left( f_b(y_{bl}, \mathbf{pa}) - f_b(y_{bl}, \mathbf{pa}_0) \right)
\]

is the observed maximum variation in the product’s engineering performance when the engineering parameters deviate from the nominal value \( \mathbf{pa}_0 \), and \( \Delta f_b \) 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 et al. 2001), our 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:

\[
\begin{align*}
vc_{ll} = \sum_{r=1}^{R} (1 - \lambda_{rwl}) \cdot c_{rwl} + c_{al} + c_{ml} + c_{sl} & \quad l = 1, \ldots, L_l \\
\end{align*}
\]

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

In the platform-management literature, researchers generally refer to the parts firms use to build the product as components. For example, the major components related to a power tool are things like motor, gearbox, housing, and etc. Because they define the product from the designer’s perspective, within our 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 due to economy of scale. We use a discount factor $\lambda_{rel}$ to capture this effect. In Web Appendix B, we provide more details on how to define $\lambda_{rel}$ and the other cost elements in Equation (11).

**Optimization Procedure**

The overall procedure of our product line optimization is provided in Figure 1. As shown in this figure, 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 iterative procedure that solves the two inner optimizations iteratively until convergence).

This optimization starts 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 $(y_{11}, y_{12}, ..., y_{1L_1})$ to maximize its product line profit, subject to a set of constraints (i.e. first block 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, we set the capacity constraint based on the production of each product (i.e. $W_{ij}$) 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. $L_i$), which is typically pre-specified by the focal manufacturer. A number of previous papers assumed a fixed number of products in the product line (e.g. Balakrishnan et al. 2004; Belloni et al. 2008). We relax 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 $\bar{\pi}'$).

The outputs of this inner loop optimization are the vectors of the design variables $\left( y_{11}, y_{12}, ..., y_{1L} \right)$ and their corresponding non-price consumer attributes $\left( x_{11}, x_{12}, ..., x_{1L} \right)$. 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 block of Figure 1).

Given the adjusted prices, the focal manufacturer re-searches 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. This outer loop optimization is depicted by the dotted box in Figure 1.

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 $L_1$. Note that if product line length is fixed (as in Balakrishnan et al. 2004 and Belloni et al. 2008), we only need to perform the optimization once. Additionally, although the retailer may only consider part of the product line as acceptable, we indirectly accounted for this because the shorter product line lengths have been considered under this procedure.

Due to the NP-hard property of the product line design (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. We follow this line of work by using heuristic methods to solve the focal manufacturer’s design variable configuration problem (first block of Figure 1) and gradient search methods to search for the adjusted wholesale and retail prices (second block of Figure 1).
Although past research has suggested that the heuristic methods of genetic algorithm and simulated annealing do have the ability to escape from a locally optimal solution (Belloni et al. 2008; Balakrishnan et al. 2004), the solutions provided by these methods do not ensure global optimality. Similarly, multiple price equilibria may exist when the manufacturers and the retailer make price adjustments. Therefore, we cannot guarantee a global maximum in our 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 may 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 our product optimization is based on the level of the final earning rather than the closeness of the solutions.

**SIMULATION STUDY**

In this section we 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 block 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.

First, we compared the performance of three algorithms in the focal manufacturer’s design variable configuration problem (the first block of Figure 1). Note that because this comparison is only related to the first block of Figure 1, the wholesale prices and the retail
markups were assumed to be fixed so that we can confine our comparison to this particular part of the overall problem. Specifically, genetic algorithm (GA), simulated annealing (SA), and analytical target cascading (ATC) were included in our comparison because previous research has shown that these methods perform well in product line design problems (e.g. Balakrishnan et al. 2004; Belloni et al. 2008; and Michalek et al. 2009). In this simulation study, the focal manufacturer designs a product line consisting of 1 to 8 products, each composed of 4 design variables (we will extend this to include more design variables in the second part of the simulation study). Because the ATC method only handles continuous design variables, we investigated 16 different problem sizes (8 with a mix of discrete and continuous variables and 8 with continuous variables only). For each problem size, we created 5 problem instances, which results in a total of 80 simulated problems. Web Appendix C provides more details of our simulation procedure and a brief description of these optimization methods.

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 quite comparable, regardless 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 our comparison for these two algorithms are also in line with the findings of Belloni et al. (2008). It is possible that the computational inefficiency of SA results from its extensive search process, as SA sometimes accept product line configurations that reduce earnings in attempts to escape from a local optimum. With regard to ATC, this method performs quite well in terms of both the quality of the solutions and the computation time. In particular, we noticed that ATC seems to generate
better solutions than GA and SA as the problem size increases. Our conjecture is that, when there are many products in the product line, the decompositional-based ATC approach facilitates a more effective and efficient search as compared to the combinatorial-based GA and SA approaches. Given the findings above, we 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.

<Insert Table 1 about here>

We further investigated the computation time required to obtain a final solution based on our overall procedure (the entire Figure 1) across different problem sizes. In this simulation task, the focal manufacturer designs a product line consisting of 1 to 8 products, each composed of 4, 8, 12, 16, 20, or 24 design variables. This results in a total of 48 simulation problems. In this task, we used GA to solve the focal manufacturer’s design variable configuration problem (the first block of Figure 1). We chose GA because it not only handles both continuous and discrete design variables but also is computationally desirable. The required computation time for our overall procedure (the entire Figure 1) varied between 2 to 10.4 hours, as the problem sizes range from a small problem with 1-3 products and 4-8 design variables to a large problem with 6-8 products and 20-24 design variables (more details in Web Appendix C).

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

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4 We also compared the performance of our product line optimization to the global optimum (obtained through complete enumeration) for the case of 4 design variables with 1-2 products in the product line. We limited this comparison to only small scale problems for which the global optimum could be obtained in a reasonable amount of time. The average final earnings from our optimization are at 96% of the true optimum.
EMPIRICAL APPLICATION

We applied the proposed product line optimization in a case study using data collected in a power tool product development project undertaken by a large U.S. manufacturer. Teaming with our industrial partner, we conducted exploratory research (e.g. field trips, focus group studies) to identify the set of consumer attributes deemed as the most critical by the end users of this power tool. The identification of these attributes follows the typical procedure used in determining which attributes to be included in a conjoint experiment. We discovered that consumers generally take into account the power tool’s brand, price, power amp, product life, switch type, and girth type in a purchase decision. More details of the conjoint design are provided in Web Appendix D. Given these consumer attributes, we 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. See Web Appendix D for more details on the design space defined by these design variables.

After identifying the vectors of the consumer attributes and design variables, we proceeded to establish the mapping between the two vectors. 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). As for power amp and product life, an engineering simulation similar to the one described in Web Appendix A was used to establish the mapping relations. Specifically, the inputs of the simulation are the configuration of the design variables motor type, gearbox type, gear ratio. The outputs of the

---

5 We camouflaged some actual attribute names as well as the values of attribute levels, cost estimates, and capacity constraints to protect the proprietary information of our industrial partner.
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 influences consumer’s purchase decision. The latter were used to evaluate whether the product satisfies the feasibility and robustness constraints specified by the product designer. The uncontrollable variations in the product’s usage environment were represented by a set of engineering parameters (see Web Appendix D for more details). And the outputs of the simulation provided the nominal, the lower, and the upper bound values of each output variable.

Given the sets of consumer attributes, design variables, and their mapping relationships, the focal problem of our 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 US market. Each respondent was given 18 choice sets with each choice set including two products and a no-choice option (see Web Appendix D for more details of the conjoint design). Additionally, each respondent provided some demographic information including trade(s), glove size, height, and age. These covariates were used to identify segment membership and facilitate the estimation of the conjoint part-worths.

We estimated the finite mixture conjoint model based on scenarios of one to five market segments. Using the DIC measure, the optimal number of market segments was selected as two. The estimation results are shown in Table 2 (see Web Appendix D for the estimates related to the covariates). The hyper-parameter of the no-choice option in segment 1 was fixed to zero for identification. In each market segment, the sum of the conjoint part-worths across the different
levels of a product attribute was fixed to zero for identification. To make the scale of the conjoint part-worths comparable across different attributes, the continuous variable price was also mean-centered.

<Insert Table 2 about here>

Note that a power tool’s power amp and product life may differ under various usage situations. Equation (5) was used to calculate their expected conjoint part-worths given their nominal, lower, and upper bounds values. We also relaxed the assumption of a total drop-off at the end points by allowing the probabilities at the minimum and maximum outcomes to be 2.5%.

Prior to the entry of the new product line, there were three incumbent manufacturers. Two manufacturers offer product lines with two products and one manufacturer sells one product (see Web Appendix D for their consumer attribute specifications). For each product line under consideration, we used the algorithm described in Web Appendix B to calculate the wholesale and retail price adjustments.

**Engineering Considerations**

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

With regard to robustness requirements, the following two criteria were considered: 1) the variation between the actual and the nominal motor output speed must be less than 4,000 rpm; 2) the variation between the actual and the nominal mass material removal per application must
be less than 5 grams. Consequently, for each product under consideration, we calculated the
maximum variation associated with each of the above engineering performance metric (for
example, if a product’s nominal, lower, and upper bounds of mass material removal rates are 12,
5, 16 grams respectively, the maximum variation is calculated as \( \max(|5 - 12|, |12 - 16|) = 7 \). In
our optimization, a product line will be penalized if it consists of product(s) 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
look-up table. The specific combination of these components determined the assembly cost,
which was also obtained from a look-up table. The maintenance cost was calculated based on 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 our 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 our engineering and marketing considerations, we searched for a
profit-maximizing product line using the procedure described in Figure 1. Brand was fixed at the
level of own brand. We used GA to solve the focal manufacturer’s design variable configuration
problem (first block 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 (see Web Appendix D for more estimation details). 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 to be three. As a result, we repeated the proposed optimization procedure when there were one, two, and three products in the product line. The product line with the following specifications provided the highest earning (see Table 3). We observed that the high earning level of this product line benefited a great deal from component sharing (the first two products shared the same gear box 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 amp, product life, and prices of these products). Over a five-year horizon, the discounted long-term profit is estimated to be $52.8 million. We also conducted some robustness checks and found that this final earning level was not overly sensitive to the parameter specifications of the model (see details in Web Appendix D).

<Insert Table 3 about here>

**Comparison to Benchmark Approaches**

We now compare 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

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6 The GA parameters used here are the same as the parameters used in the simulation study. We varied the GA parameters several times to evaluate how sensitive the final earning level is to the GA parameters. We also assessed the quality of the solution by using different starting values. No major differences were found in the final earnings.
that maximize the product line profitability. The key differences between the optimization at this stage and the one described in Figure 1 are that: a) the decision variables $\{y_{11}, y_{12}, ..., y_{1L}\}$ are replaced by $\{x_{11}, x_{12}, ..., x_{1L}\}$ and b) the five constraints in the first block of the figure are reduced to constraints 3) to 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, we had to approximate the product’s cost based on a weighted sum of its attribute levels (excluding brand and price). The other aspects of this optimization are identical to the ones described in Figure 1. 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. Additionally, the engineering team evaluates whether these design variable configurations satisfy the engineering feasibility and robustness criteria (the first two constraints in the first block of Figure 1). If the product violates one or more engineering requirements, the engineering team will move onto 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 following specifications (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 sub-optimal product line. In

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7 We obtained the weights from a multiple regression using the cost estimates of current products and some hypothetical products. We thank two anonymous reviewers for this suggestion. Additionally, we would like to point out that if the marketing team were able to incorporate cost synergy into the variable cost estimation, the primary advantage of our approach vs. the marketing-first approach hinges on the rigidity of the engineering criteria. If there are a substantial number of engineering requirements, the marketing-first approach may result in a local search in a sub-optimal space. On the other hand, if the vast majority of product candidates satisfy the engineering requirements, the results may not differ much between the proposed and the marketing-first approaches.
particular, since 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 as compared to the product line shown in Table 3. As a result, although this product line was predicted to capture a larger market share (34.08% vs. 29.63% in our approach), the average markup between the wholesale prices and variable costs was lower ($6.10 vs. $7.93 in our approach). Consequently, this product line was not as profitable as the one obtained from our approach (long-term profit: $46.5 million vs. $52.8 million in our approach).

<Insert Table 4 about here>

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 described in Figure 1 are that: a) the product line configurations are limited among the pool of product candidates retained from the first stage (rather than the entire design space); and b) the five constraints in the first block of the figure are reduced to constraints 3) to 5). The other aspects of this optimization procedure were identical to those described in Figure 1.

Given that the design space for a consumer durable product is usually very 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 candidates. Therefore, heuristic methods are often used to pre-select a set of product candidates for the composition of the final product line. In order to demonstrate the drawback of the engineering-first approach if the product designer could not identify the complete pool of
product candidates satisfying the engineering criteria in the first stage, we randomly sampled the
design space until obtaining 1,000 products satisfying the engineering criteria. Next, an
exhaustive search was conducted to obtain the profit-maximizing product line when there are 1-3
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 1,000 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 our approach (profit: $48.3 million vs. $52.8 million in our approach).  

<Insert Table 5 about here>

CONCLUSIONS

In this paper, we introduced a procedure of product line optimization where the
marketing and engineering criteria are considered concurrently in the search for a profit-
maximizing product line. We propose that the product designer needs to take into account both
marketing and engineering considerations concurrently in a product line design. In particular, our
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, we demonstrated that the
proposed optimization procedure provides an effective solution to this challenging problem.

We also contribute to the literature by proposing an optimization method that works in
relatively large-scale design problems consisting of both discrete and continuous design
variables. Particularly, we suggest that genetic algorithm (GA) provides an efficient and effective

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8 Note that since the design space in our empirical application is relatively small, we could technically discretize the
continuous design variable gear ratio and perform an exhaustive search in the first stage. Under this scenario, the
results from the engineering-first approach should be similar to that of ours.
solution to the focal manufacturer’s design variable configuration problem in a variety of problem settings. In contrast, despite of their comparable performance in finding profit-maximizing product lines, the heuristic method of simulated annealing (SA) is only suitable for small-scale problems (given its computational inefficiency) and the decompositional method of analytical target cascading (ATC) is applicable to problems with only continuous design variables.

Our research is not without limitations. First, the proposed method is built upon the assumption that the product designer has complete knowledge about the various inputs needed for the optimization. Therefore, exploratory research will be needed if some inputs are unknown. Second, because the product line design problem is NP-hard, our optimization procedure may recover a local maximum rather than a global maximum. Future research may investigate optimization methods that can guarantee a global optimality. Third, although accounting for the retailer and the incumbent’s strategic price reactions, our method is limited in addressing the incumbents’ strategic responses in non-price attributes. Finally, because our optimization method is combinatorial by nature, firms facing extremely large problems may encounter computational difficulty. Future research may develop a decompositional approach that handles both discrete and continuous design variables. In time, as both the algorithm and computational power improve, further research may be able to extend our work by guaranteeing global optimality in a considerably large scale product line design problem.

References


Figure 1: Computational Procedure of the Product Line Optimization

\[ \text{The focal manufacturer's design variable configuration problem} \]
\[ \max_{\{y_{ij}, y_{ij} \rightarrow y_{ij}\}} \pi^*_m = \sum_{t=1}^{T} \left( \sum_{l=1}^{L_t} \left[ (w_{ij} - c_{ij}) * m_{il} * D_t \right] / (1 + r) \right) - F_k \quad k = 1, \ldots, K \]
\[ \text{s.t.} \]
1. \[ \sum_{l=1}^{H} \left( \max(0, g_a(y_{ij}, pa)) \right) = 0 \quad \text{(feasibility)} \]
2. \[ \left( \max(f_b(y_{ij}, pa) - f_b(y_{ij}, pa)) \right) \leq \Delta f_b^j \quad \text{(robustness)} \]
3. \[ m_{il} * D_t \leq W_{ij} \quad \text{with} \quad l = 1, \ldots, L_t; \quad t = 1, \ldots, T \quad \text{(capacity)} \]
4. \[ L_t \leq L_i \quad \text{(maximum product line length)} \]
5. \[ \pi^* > \pi^* \quad \text{(retailer acceptance)} \]

\[ \text{The retailer and manufacturer's price adjustment problem} \]
\[ \max_{w_{11}, w_{12}, \ldots, w_{1L_t}} \pi^*_m = \sum_{i=1}^{T} \left( \sum_{j=1}^{L_t} \left[ (w_{ij} - c_{ij}) * m_{il} * D_t \right] / (1 + r) \right) - F_k \quad k = 1, \ldots, K \]
\[ \max_{p_{11}, p_{12}, \ldots, p_{1L_t}} \pi^* = \sum_{i=1}^{T} \left( \sum_{j=1}^{K} \left( \sum_{l=1}^{L_t} \left[ m_{ij} * (p_{ij} - w_{ij}) * D_t \right] / (1 + r) \right) - c_s * \sum_{k=1}^{K} L_k \right) \]

Initialize wholesale and retail prices for each product in the product line
\[ \left( w_{11}^*, w_{12}^*, \ldots, w_{1L_t}^* \right), \left( p_{11}^*, p_{12}^*, \ldots, p_{1L_t}^* \right) \]

Search for design variable configurations to maximize product line profit
\[ \left( y_{11}, y_{12}, \ldots, y_{1L_t} \right), \left( y_{11}^*, y_{12}^*, \ldots, y_{1L_t}^* \right) \]

Adjust wholesale and retail prices for the new product line and incumbent products
\[ \left( w_{11}, w_{12}, \ldots, w_{1L_t} \right), \left( p_{11}, p_{12}, \ldots, p_{1L_t} \right) \]

The Final Product Line
Table 1: Algorithm Comparisons for the Focal Manufacturer’s Design Variable Configuration Problem (First Block of Figure 1)

<table>
<thead>
<tr>
<th>Number of products</th>
<th>Mix of discrete &amp; continuous variables</th>
<th>Continuous variables only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GA</td>
<td>SA</td>
</tr>
<tr>
<td></td>
<td>Ave Profit</td>
<td>Ave CPU time</td>
</tr>
<tr>
<td>Small (1-3)</td>
<td>65.5</td>
<td>0.9</td>
</tr>
<tr>
<td>Medium (4-5)</td>
<td>105.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Large (6-8)</td>
<td>92.2</td>
<td>1.8</td>
</tr>
</tbody>
</table>

Note: the average profits are presented in millions and the average CPU time is presented in seconds.

Table 2: Bayesian Finite Mixture Conjoint Part-worth Estimates

<table>
<thead>
<tr>
<th>Segment Size</th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD*</td>
</tr>
<tr>
<td>Posterior Part-worth</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Brand</td>
<td>0.859</td>
<td>0.857</td>
</tr>
<tr>
<td>Brand 1</td>
<td>1.077</td>
<td>0.533</td>
</tr>
<tr>
<td>Brand 2</td>
<td>2.233</td>
<td>1.139</td>
</tr>
<tr>
<td>Brand 3</td>
<td>-4.169</td>
<td>1.885</td>
</tr>
<tr>
<td>Price (mean-centered)</td>
<td>-0.342</td>
<td>0.181</td>
</tr>
<tr>
<td>Power amp: 6</td>
<td>-1.630</td>
<td>0.577</td>
</tr>
<tr>
<td>Power amp: 9</td>
<td>0.240</td>
<td>0.376</td>
</tr>
<tr>
<td>Power amp: 12</td>
<td>1.390</td>
<td>0.434</td>
</tr>
<tr>
<td>Product Life: 80 hrs</td>
<td>-3.682</td>
<td>1.636</td>
</tr>
<tr>
<td>Product Life: 110 hrs</td>
<td>-1.346</td>
<td>1.602</td>
</tr>
<tr>
<td>Product Life: 150 hrs</td>
<td>5.028</td>
<td>1.436</td>
</tr>
<tr>
<td>Switch type 1: paddle</td>
<td>-1.503</td>
<td>0.661</td>
</tr>
<tr>
<td>Switch type 2: top slider</td>
<td>1.966</td>
<td>0.676</td>
</tr>
<tr>
<td>Switch type 3: side slider</td>
<td>0.593</td>
<td>0.565</td>
</tr>
<tr>
<td>Switch type 4: trigger</td>
<td>-1.056</td>
<td>0.608</td>
</tr>
<tr>
<td>Girth type 1: small</td>
<td>1.173</td>
<td>1.006</td>
</tr>
<tr>
<td>Girth type 2: large</td>
<td>-1.173</td>
<td>1.006</td>
</tr>
<tr>
<td>No-Choice</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

*These entries are the posterior estimates of the square roots of the diagonal terms in the variance-covariance matrix (i.e. $\Omega_1$). They represent the degree of heterogeneity within each consumer segment.
### Table 3: Specifications of the Final Product Line – Our Approach

<table>
<thead>
<tr>
<th>Product</th>
<th>motor</th>
<th>gear ratio</th>
<th>gear box</th>
<th>power (nominal)</th>
<th>life (nominal)</th>
<th>switch</th>
<th>girth</th>
<th>wholesale price</th>
<th>retail price</th>
<th>variable cost</th>
<th>market share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product 1</td>
<td>4</td>
<td>4.11</td>
<td>3</td>
<td>8.7</td>
<td>123</td>
<td>2</td>
<td>1</td>
<td>$79.22</td>
<td>$109.22</td>
<td>$70.00</td>
<td>7.65%</td>
</tr>
<tr>
<td>Product 2</td>
<td>10</td>
<td>4.72</td>
<td>3</td>
<td>9.9</td>
<td>117</td>
<td>3</td>
<td>1</td>
<td>$74.03</td>
<td>$100.04</td>
<td>$67.00</td>
<td>14.35%</td>
</tr>
<tr>
<td>Product 3</td>
<td>9</td>
<td>3.60</td>
<td>2</td>
<td>12.5</td>
<td>125</td>
<td>3</td>
<td>1</td>
<td>$89.55</td>
<td>$118.49</td>
<td>$82.00</td>
<td>7.63%</td>
</tr>
</tbody>
</table>

### Table 4: Specifications of the Final Product Line – Marketing First Approach

<table>
<thead>
<tr>
<th>Product</th>
<th>motor</th>
<th>gear ratio</th>
<th>gear box</th>
<th>power (nominal)</th>
<th>life (nominal)</th>
<th>switch</th>
<th>girth</th>
<th>wholesale price</th>
<th>retail price</th>
<th>variable cost</th>
<th>market share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product 1</td>
<td>2</td>
<td>3.91</td>
<td>3</td>
<td>6.7</td>
<td>107</td>
<td>2</td>
<td>1</td>
<td>$74.03</td>
<td>$90.02</td>
<td>$70.00</td>
<td>10.98%</td>
</tr>
<tr>
<td>Product 2</td>
<td>4</td>
<td>4.05</td>
<td>2</td>
<td>9.2</td>
<td>129</td>
<td>3</td>
<td>2</td>
<td>$78.79</td>
<td>$99.77</td>
<td>$71.00</td>
<td>12.70%</td>
</tr>
<tr>
<td>Product 3</td>
<td>8</td>
<td>4.28</td>
<td>6</td>
<td>10.5</td>
<td>149</td>
<td>3</td>
<td>2</td>
<td>$89.47</td>
<td>$111.03</td>
<td>$83.00</td>
<td>10.40%</td>
</tr>
</tbody>
</table>

### Table 5: Specifications of the Final Product Line – Engineering First Approach

<table>
<thead>
<tr>
<th>Product</th>
<th>motor</th>
<th>gear ratio</th>
<th>gear box</th>
<th>power (nominal)</th>
<th>life (nominal)</th>
<th>switch</th>
<th>girth</th>
<th>wholesale price</th>
<th>retail price</th>
<th>variable cost</th>
<th>market share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product 1</td>
<td>3</td>
<td>4.30</td>
<td>2</td>
<td>9.9</td>
<td>107</td>
<td>2</td>
<td>1</td>
<td>$80.72</td>
<td>$101.17</td>
<td>$72.00</td>
<td>10.47%</td>
</tr>
<tr>
<td>Product 2</td>
<td>3</td>
<td>4.27</td>
<td>3</td>
<td>8.7</td>
<td>119</td>
<td>3</td>
<td>1</td>
<td>$78.79</td>
<td>$103.45</td>
<td>$71.59</td>
<td>10.89%</td>
</tr>
<tr>
<td>Product 3</td>
<td>2</td>
<td>3.94</td>
<td>1</td>
<td>10.3</td>
<td>128</td>
<td>2</td>
<td>1</td>
<td>$89.29</td>
<td>$115.21</td>
<td>$82.50</td>
<td>6.75%</td>
</tr>
</tbody>
</table>

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