Chapter 6

PRODUCT FAMILY POSITIONING

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1. INTRODUCTION

Due to the development of modern technologies and global manufacturing, it becomes harder and harder for companies to distinguish themselves from their competitors. To keep the competitive advantage, the companies intend to provide a variety of products by differentiating their product lines with the belief that product variety may stimulate sales and thus conduce to revenue (Ho and Tang, 1998). A large product variety does improve sales by providing the customers more choices. However, companies with expanding products face with the challenges of controlling costs. The costs exponentially increase with the variety growth. Further, high variety will result in the proliferation of products and processes and in turn inefficiencies in manufacturing (Child, et al., 1991). Mass customization aims at satisfying individual customer needs with the efficiency of mass production (Pine, 1993a). Customization emphasizes the uniqueness of, and the differences among, products (Jiao and Tseng, 2000). To optimize the product variety, a company must assess the level of variety at which customers will still find the company's offerings attractive and the level of complexity that will keep the costs low (Jiao, et al., 1998). Developing product families has been recognized as a natural technique to facilitate increasing complexity and cost-effective product development (Meyer, et al., 1997). In this regard, the manufacturing companies put their effort in organizing, developing, and planning product families to balance the tradeoffs between product diversity and engineering costs.

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Based on the reports of marketing analysis, it turns out that some of the product variants may be more preferred as expected, while others, although they may be equally sound in technical terms, may not be favored by the customers. The errors on expectation and achievement mainly result from the diverse customer requirements. Furthermore, it has been reported that not all the existing market segments create the same opportunity for the companies in the same industry due to the discrepancy of their targets, strategies, technologies, cultures, etc. Therefore, it is most important for the manufacturing companies to make the decisions deliberately that which market segment should be targeted and what products should be planned for the target market, namely, product family positioning.

The involved complexity makes product family positioning very difficult. Proper positioning should help leverage the engineering costs and diverse customer preferences. The prediction of the customer preference is difficult because even the customers themselves do not know why they choose specified products. Moreover, the customers always need to make tradeoffs among diverse product features. For example, the customer must make a compromise between "high product quality" and "high price". It is inhibitive to estimate the value that the customers put on every product feature because the values that the customers perceive are based on their perception of the overall products (Green, et al., 1981). Further, cost estimation is deemed to be inhibited. Traditional cost accounting by allocating fixed costs and variable costs across multiple products may produce distorted cost-carrying figures due to possible sunk costs associated with investment into product and process platforms.

Towards this end, this chapter introduces a systematic approach to product family positioning within the context of mass customization. A comprehensive methodology for product family positioning is developed, aiming at leveraging both customer preferences and engineering costs. The remainder proceeds as follows. In the next section, various existing approaches to product family positioning are reviewed. Section 3 presents the formulation of the product family positioning problem. An optimization framework and the according properties of the model are discussed in Section 4. The developed model is represented in Section 5. A case study of notebook computer family positioning is reported in Section 6. The research is concluded with a summary in Section 7.

2. BACKGROUND REVIEW

In general the literature related to product family positioning stems from two broad fields that are closely correlated: product line design and customer preference analysis for optimal product design, as discussed below.

(1) Product Line Design. For product line design, the objectives widely used in selecting products among a large set of potential products include maximization of profit (Monroe, et al., 1976), net present value (Li and Azarm, 2002), a seller's welfare (McBride and Zufryden, 1988), market share (Kohli and Krishnamurti, 1987), and share of choices (Balakrishnan and Jacob, 1996) within a target market. Pullmana, et al. (2002) have combined QFD and conjoint analysis to compare the most preferred features with those profit maximizing features so as to develop designs that optimize product line sales or profits. Kota, et al. (2000) have proposed a product line commonality measure to capture the level of component commonality in a product family. The key issue is to minimize non-value added variations across models within a product family without limiting customer choices.

Another dimension in product line design research is about the price. Robinson (1988) has suggested that the most likely competitive reaction to a new product in the short term is a change in price. Choi and DeSarbo (1994) have applied the game theory to model competing firms' reactions in price and employed a conjoint simulator to evaluate product concepts against competing brands. Dobson and Kalish (1988; 1993) have discussed the tradeoffs involved in price setting and choice of the number of products. Furthermore, product line design basically involves two issues (Li and Azarm, 2002): generation of a set of feasible product alternatives, and subsequent selection of promising products from this reference set to construct a product line. Along this line, existing approaches to product line design can be classified into two categories (Steiner and Hruschka, 2002). One-step approaches aim at constructing product lines directly from part-worth preference and cost/return functions. On the other hand, two-step approaches first reduce the total set of feasible product profiles to a smaller set, and then select promising products from this smaller set to constitute a product line. Following the two-step approach, Green and Krieger (1985; 1989) have introduced several heuristic procedures with the consideration of how to generate a reference set appropriately. On the other hand, Kohli and Sukumar (1990) and Nair, et al. (1995) have adopted the one-step approach, in which product lines are constructed directly from part-worth data rather than by enumerating potential product designs. In general, the one-step approach is more preferable, as the intermediate step of enumerating utilities and profits of a huge number of reference set items can be eliminated

(Steiner and Hruschka, 2002). Only when the reference set contains a small number of product profiles can the two-step approach work well.

(2) Customer Preference Analysis for Optimal Product Design. Measuring customer preferences in terms of expected utilities is the primary concern of optimal product design (Krishnan and Ulrich, 2001) or decision-based design (Hazelrigg, 1998). In typical preference-based product design, conjoint analysis (Green and Krieger, 1985) has proven to be an effective means to estimate individual level part-worth utilities associated with individual product attributes. In order to simulate the potential market shares of proposed product concepts, scaled preference evaluations need to be collected from respondents with regard to a subset of multi-attribute product profiles (stimuli) constructed according to a fractional factorial design. With these preference data, idiosyncratic part-worth preference functions are then estimated for each respondent using regression analysis. Attribute level part-worth utilities can also be computed by respondents' simulated choice data, which is called a choice-based conjoint analysis and hence establishes a direct connection between preference and choice (Kuhfeld, 2004). The conjoint-based searching for optimal product designs always results in combinatorial optimization problems because typically discrete attributes are used in conjoint analysis (Kaul and Rao, 1995; Kohli and Sukumar, 1990; Nair, et al., 1995).

3. PROBLEM DESCRIPTION

This research addresses the product family positioning problem with the goal of maximizing an expected surplus. A large set of product attributes, $A \equiv \{a_k \mid k = 1,\cdots,K\}$, have been identified, given that the firm has the capabilities (both design and production) to produce all these attributes. Each attribute, $\forall a_k \in A$, possesses a few levels, i.e., $A_k^* \equiv \{a_{kl}^* \mid l = 1,\cdots,L_k\}$. Thus, the product family is embodied in the various combinations of the attribute levels, i.e., $Z \equiv \{\vec{z}_j \mid j = 1,\cdots,J\}$. Each product, $\forall \vec{z}_j \in Z$, is defined as a vector of specific attribute levels, i.e., $\vec{z}_j = \left[a_{kl_j}^*\right]_K$, where any $a_{kl_j}^* = \varnothing$ indicates that product $\vec{z}_i$ does not contain attribute a_k; and any $a_{kl_j}^* \neq \varnothing$ represents an element of the set of attribute levels that can be assumed by product $\vec{z}_j$, i.e., $\{a_{kl_j}^*\}_K \in \{A_1^* \times A_2^* \times \cdots \times A_K^*\}$.

The positioned product family, Λ, is a set consisting of a few selected product profiles, i.e., $\Lambda \equiv \{\vec{z}_j \mid j = 1,\cdots,J^\dagger\} \subseteq Z$, $\exists J^\dagger \in \{1,\cdots,J\}$, denotes the number of products contained in the positioned product family. Every product is associated with certain engineering costs, denoted as $\{C_j\}_J$. The manufacturer must make decisions that what products to offer as well as their respective prices, $\{p_j\}_J$. There are multiple market segments, $S \equiv \{s_i \mid i = 1,\cdots,I\}$, each containing homogeneous customers, with a size, Q_i. Various customer preferences on diverse products are represented by respective utilities, $\{U_{ij}\}_{I \cdot J}$. Product demands or market shares, $\{P_{ij}\}_{I \cdot J}$, are described by the probabilities of customers' choosing products, denoted as customer or segment-product pairs, $\{(s_i, \vec{z}_j)\}_{I \cdot J} \in S \times Z$.

4. FUNDAMENTAL ISSUES

4.1 Objective function

Among those customer preference or seller value-focused approaches, the objective functions widely used for solving the selection problem are formulated by measuring the consumer surplus – the amount that customers benefit by being able to purchase a product for a price that is less than they would be willing to pay. The idea behind is that the expected revenue (utility less price) comes from the gain between customer preferences (utilities indicating the dollar value that they would be willing to pay) and the actual price they would pay, whilst the price implies all related costs. With more focus on engineering concerns, the selection problem is approached by measuring the producer surplus – the amount that producers benefit by selling at a market price that is higher than they would be willing to sell for. The principle is to measure the expected profit (price less cost) based on the margin between the actual price they would receive and the cost (indicating the dollar value they would be willing to sell for), whilst the price implies customer preferences.

Considering both the customer preferences and the engineering costs, the above economic surpluses should be leveraged from both the customer and engineering perspectives. This research proposes to use a shared surplus to leverage both the customer and engineering concerns. Then the objective function can be formulated as the following:

$$\textit{Maximize} \quad E[V] = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{U_{ij}}{C_j} P_{ij} Q_i y_j \,, \tag{1}$$

where $E[\cdot]$ denotes the expected value of the shared surplus, V, which is defined as the utility per cost, is modified by the probabilistic choice model, $\{P_{ij}\}_{I \cdot J}$, and the market size, $\{Q_i\}_I$, C_j indicates the cost of offered product $\vec{z}_j$, and y_j is a binary variable such that $y_j = 1$ if the manufacturer decides to offer product $\vec{z}_j$ and $y_j = 0$ otherwise.

4.2 Customer preference measurement

Volatile market condition, diverse customer preferences, and the competition among similar products make it difficult to measure the customer preference. Conjoint analysis (CA) is perhaps the most widely applied method for modeling consumer preference by marketing researchers. CA is a set of methods originally designed to measure consumer preferences by assessing the buyers' multi-attribute utility functions. The strength of CA is its ability to ask realistic questions that mimic the tradeoffs that respondents make in the real world. In contrast to direct questioning methods that simply ask how important each feature is or the desirability of each level, CA forces respondents to make difficult tradeoffs like the ones they encounter in the real world.

Following the part-worth model that is widely used in CA, the utility of the i-th segment for the j-th product, U_{ij}, is assumed to be a linear function of the part-worth preferences (utilities) of the attribute levels of product $\vec{z}_j$:

$$U_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \left(w_{jk} u_{ikl} x_{jkl} + \pi_j \right) + \varepsilon_{ij}, \tag{2}$$

where u_{ikl} is the part-worth utility of segment s_i for the l-th level of attribute a_k (i.e., a_{kl}^{*}) individually, w_{jk} is the utility weights among attributes, $\{a_k\}_K$, contained in product $\vec{z}_j$, π_j is a constant associated with the derivation of a composite utility from part-worth utilities with respect to product $\vec{z}_j$, ε_{ij} is an error term for each segment-product pair, and x_{jkl} is a binary variable such that $x_{jkl} = 1$ if the l-th level of attribute a_k is contained in product $\vec{z}_j$ and $x_{jkl} = 0$ otherwise.

4.3 Choice model and choice probability

Conjoint analysis yields a preference model, for example a main-effect part-worth model, which defines the functional relationship between attribute levels of a product and a customer's or a segment's overall utility attached to it. Based on this preference model, customers' choices can be modeled by relating preference (utility) to choice. The traditional deterministic first choice rule of preferences assumes that a customer chooses the product from the choice set according to the highest associated utility with certainty. Neglect of uncertain factors in the first choice rule may lead to suboptimal results at the aggregate market level, as market shares of products with higher utilities across customers or segments tend to be overestimated (Kaul and Rao, 1995).

On the other hand, probabilistic choice rules can provide more realistic representations of the customer decision making process (Sudharshan, et al., 1987). Some probabilistic choice rules can offer flexibility in calibrating actual choice behavior such as the option of mimicking the first choice rule (Kaul and Rao, 1995). In general, there are two types of probabilistic choice rules (Ben-Akiva and Lerman, 1985): the generalized (or powered) Bradley-Terry-Luce share-of-utility rule (BTL, also called the α-rule) and the conditional multinomial logit choice rule (MNL).

With the assumption of independently and identically distributed error terms, the logit choice rule suggests itself to be well suited to estimate customer preferences directly from choice data (Green and Krieger 1996).

Under the MNL model, the choice probability, P_{ij}, which indicates how likely a customer or a segment, $\exists s_i \in S$, chooses a product, $\exists z_j \in Z$, among N competing products, is defined as the following:

$$P_{ij} = \frac{e^{\mu U ij}}{\sum_{n=1}^{N} e^{\mu U in}}, \tag{3}$$

where μ is a scaling parameter. As $\mu \to \infty$, the logit behaves like a deterministic model, whereas it becomes a uniform distribution as $\mu \to 0$. Therefore, like with the BTL model, calibration on actual market shares can be carried out subsequently to elaborate preference estimation by post hoc optimization with respect to μ (Train, 2003).

Based on a customer survey, the response rate - how often each product alternative is chosen - can be depicted as a probability density distribution. The demand for a particular product is the summation of the choice frequency of each respondent, $\forall s_i \in S$, adjusted for the ratio of respondent sample size versus the size of the market population (Train, 2003). The accuracy of the demand estimates can be increased by identifying unique customer utility functions per market segment, or class of customers to capture systematic preference variations (Ben-Akiva and Lerman, 1985). Estimates of future demand can also be facilitated using pattern-based or correlation-based forecasting of existing products. Forecasts of economic growth and changes of the socioeconomic and demographic background of the market populations help to refine these estimates.

4.4 Dealing with engineering costs

Traditional cost accounting by allocating fixed costs and variable costs across multiple products may produce distorted cost-carrying figures due to possible sunk costs associated with investment into product and process platforms. It is quite common in mass customization that design and manufacturing admit resources (and thus the related costs) to be shared among multiple products in a reconfigurable fashion, as well as per-product fixed costs (Moore, et al., 1999). In fact, Yano and Dobson (1998) have observed a number of industrial settings, where a wide range of products are produced with very little incremental costs per se, or very high development costs are shared across broad product families, or fixed costs and variable costs change dramatically with product variety. They have pointed out that "the accounting systems, whether traditional or activity-based, do not support the separation of various cost elements".

Furthermore, the cost advantages in mass customization rest with the achievement of mass production efficiency. Rather than the absolute amount of dollar costs, what important to justify optimal product offerings is the magnitudes of deviations from existing product and process platforms due to design changes and process variations in relation to product variety. To circumvent the difficulties inherent in estimating the accurate cost figures, this research adopts a pragmatic costing approach based on standard time estimation developed by Jiao and Tseng (1999). The idea is to allocate costs to those established time standards based on well-practiced work and time studies, thus relieving the tedious tasks for identifying various cost drivers and cost-related activities. The key is to develop mapping relationships between different attribute levels and their expected consumptions of standard times within legacy process capabilities. These part-worth standard time accounting relationships are built into the product and process platforms (Jiao, et al., 2003). Any product configured from available attribute levels is justified based on its expected cycle time. This expected cycle time is accounted by the aggregation of part-worth standard times. The rationale is particularly applicable to family positioning, where "the optimal product profiles are not as sensitive to absolute dollar costs as they are to the relative magnitudes of cost levels" (Choi and DeSarbo, 1994).

Introducing a penalty function, the cost function, C_j, corresponding to product $\vec{z}_j$, can be formulated based on the respective process capability index, PCI_j, that is,

$$C_j = \beta e^{\frac{1}{PCI_j}} = \beta e^{\frac{3\sigma_j^T}{\mu_j^T - LSL^T}}, \tag{4}$$

where β is a constant indicating the average dollar cost per variation of process capabilities, LSL^T denotes the baseline of cycle times for all product variants to be produced within the process platform, μ_j^T and σ_j^T are the mean and the standard deviation of the estimated cycle time for product $\vec{z}_j$.

The meaning of β is consistent with that of the dollar loss per deviation constant widely used in Taguchi's loss functions. It can be determined ex ante based on the analysis of existing product and process platforms. Such a cost function produces a relative measure, instead of actual dollar figures, for evaluating the extent of process variations among multiple products. Modeling the economic latitude of product family positioning through the cycle time performance and the impact on process capabilities can alleviate the difficulties in traditional cost estimation.

5. MODEL DEVELOPMENT

Treating the price of each offered product as a decision variable will make the problem nonlinear (Yano and Dobson, 1998). To avoid explicitly, nor necessary, modeling of the price, the general practice is to treat price as a separate attribute that can be chosen from a limited number of values for each product (Nair, et al., 1995; Moore, et al., 1999). Adding price as one more attribute, the attribute set becomes $A \equiv \{a_k\}_{K+1}$, where a_{K+1} represents the price possessing a few levels, i.e., $A^*_{K+1} \equiv \{a^*_{(K+1)l} \mid l = 1, \cdots, L_{K+1}\}$. Further, let $\vec{p} = [a^*_{(K+1)1}, \cdots, a^*_{(K+1)L_{K+1}}]$ be the vector of feasible price levels.

By combining Eqs. (1), (2), (3) and (4), the product family positioning problem can be formulated as a mixed integer program, as below:

$$Maximize \quad E[V] = \sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{U_{ij}}{\beta e^{\frac{3\sigma_j^T}{\mu_j^T - LSL^T}}}\right)\left(\frac{e^{\mu U_{ij}}}{\sum_{n=1}^{N} e^{\mu U_{in}}}\right)Q_i y_j \,, \tag{5a}$$

$$s.t. \quad U_{ij} = \sum_{k=1}^{K+1}\sum_{l=1}^{Lk}\left(w_{jk} u_{ikl} x_{jkl} + \pi_j\right) + \varepsilon_{ij} \,, \forall i \in \{1, \cdots, I\}, \forall j \in \{1, \cdots, J\}, \tag{5b}$$

$$\sum_{l=1}^{Lk} x_{jkl} = 1 \,, \forall j \in \{1, \cdots, J\}, \forall k \in \{1, \cdots, K+1\}, \tag{5c}$$

$$\sum_{k=1}^{K+1}\sum_{l=1}^{Lk}\left|x_{jkl} - x_{j'kl}\right| > 0 \,, \forall j, j' \in \{1, \cdots, J\}, j \neq j' \,, \tag{5d}$$

$$\sum_{j=1}^{J} y_j \leq J^{\dagger} \,, \forall J^{\dagger} \in \{1, \cdots, J\}, \tag{5e}$$

$$x_{jkl}, y_j \in \{0, 1\}, \forall j \in \{1, \cdots, J\}, \forall k \in \{1, \cdots, K+1\}, \forall l \in \{1, \cdots, L_k\}. \tag{5f}$$

Objective function (5a) is to maximize the expected shared surplus by offering a product family consisting of products, $\{\vec{z}_j\}_J$, to customer segments, $\{s_i\}_I$. Constraint (5b) refers to conjoint analysis – ensures that the composite utility of segment s_i for product $\vec{z}_j$ can be constructed from part-worth utilities of individual attribute levels, $\{A_k^*\}_{K+1}$. Constraint (5c) suggests an exclusiveness condition – enforces that exactly one and only one level of each attribute can be chosen for each product. Constraint (5d) denotes a divergence condition – requires that several products to be offered must pairwise differ in at least one attribute level. Constraint (5e) indicates a capacity condition – limits the maximal number of products that can be chosen by each segment. $J^\dagger$ is the upper bound of the number of products that the manufacturer wants to introduce to a product family. Constraint (5f) represents the binary restriction with regard to the decision variables of the optimization problem.

There are two types of decision variables involved in the above mathematical program, i.e., x_{jkl} and y_j, representing the composite attribute levels and the products included in the positioned product family, respectively. Both types of decisions depend on a simultaneous satisfaction of the target segments. The manufacturer's decisions about what (i.e., layer I decision-making) and which (i.e., layer II decision-making) products to offer to the target segments are implied in various instances of $\{x_{jkl} \mid \forall j,k,l\}$ and $\{y_j \mid \forall j\}$, respectively. As a result, the positioned product family, $\Lambda^\dagger \equiv \{\vec{z}_j^\dagger \mid j = 1,\cdots,J^\dagger\}$ is yielded as a combination of selected products corresponding to $\{y_j \mid \forall j\}$, where each selected product , $\vec{z}_j^\dagger$, comprises a few selected attributes and the associated levels corresponding to $\{x_{jkl} \mid \forall j,k,l\}$.

6. CASE STUDY

6.1 Application case

The proposed framework has been applied to the notebook computer family positioning problem. For illustrative simplicity, a set of key attributes and available attribute levels for the notebook computer are listed in Table 6-1. Among them, "price" is treated as one of the attributes to be assumed by a product.

With regard to the class-member relationships, notebook computer family comprises a four-layer AND/OR tree structure, as shown in Figure 6-1. The first layer is the product family, each of which consists of one or more products. Each product consists of a few attributes, thus constituting the second layer. The third layer represents the levels for each attribute, indicating the instantiation of an attribute by one out of many levels.

Table 6-1. List of attributes and their feasible levels for notebook computers.

Attribute		**Attribute Levels**		
a_k	Description	a^*_{kl}	Code	Description
a_1	Processor	a^*_{11}	A1-1	Pentium 2.4 GHz
		a^*_{12}	A1-2	Pentium 2.0 GHz
		a^*_{13}	A1-3	Centrino 1.6 GHz
		a^*_{14}	A1-4	Centrino 1.7 GHz
a_2	Memory	a^*_{21}	A2-1	256 MB DDR SDRAM
		a^*_{22}	A2-2	512 MB DDR SDRAM
		a^*_{23}	A2-3	1 GB DDR SDRAM
a_3	Hard Disk	a^*_{31}	A3-1	60 GB
		a^*_{32}	A3-2	80 GB
		a^*_{33}	A3-3	120 GB
a_4	Weight	a^*_{41}	A4-1	Low (below 2.0 KG with battery)
		a^*_{42}	A4-2	Moderate (2.0 - 2.8 KG with battery)
		a^*_{43}	A4-3	High (2.8 KG above with battery)
a_5	Battery Life	a^*_{51}	A5-1	Regular (around 6 hours)
		a^*_{52}	A5-2	Long (7.5 hours above)
a_6	Price	a^*_{61}	A6-1	\$800 - \$1.3K
		a^*_{62}	A6-2	\$1.3K - \$1.8K
		a^*_{63}	A6-3	\$1.8K - \$2.5K
		a^*_{64}	A6-4	\$2.5K above

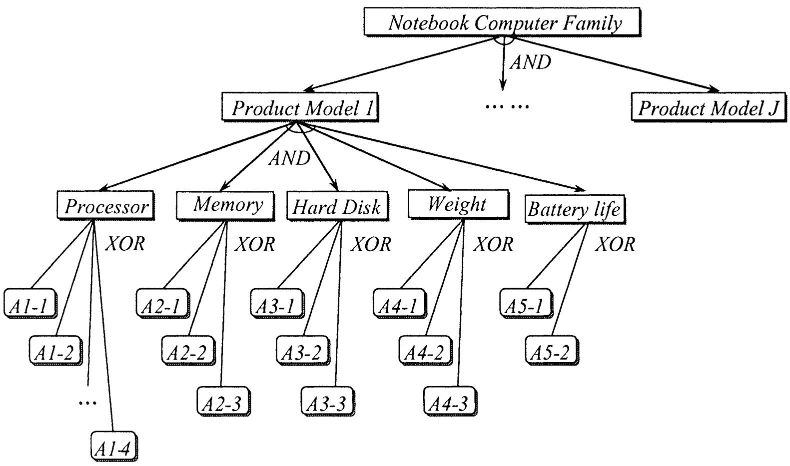


Figure 6-1. Generic structure for notebook computer family.

6.2 Customer preference

It is required to construct testing profiles for conjoint analysis. Given all attributes and their possible levels as shown in Table 6-1, a total number of $4 \times 3 \times 3 \times 3 \times 2 \times 4 = 864$ possible combinations may be constructed. To overcome such a combinatorial explosion, the Taguchi Orthogonal Array Selector provided in SPSS software (http://www.spss.com) is used to generate a total number of 27 orthogonal product profiles. With these profiles, a fractional factorial experiment is designed for exploring customer preferences, as shown in Table 6-2. In Table 6-2, columns 2-7 indicate the specification of offerings that are involved in the profiles and column 8 collects the preferences given by the customers.

Table 6-2. Response surface experiment design.

Conjoint Test							Preference Scale least — most
Profile	Processor	Memory	Hard Disk	Weight	Battery Life	Price	1 … 9
1	P-2.0	256	60	Low	Regular	\$800-1.3K	9
2	C-1.7	256	80	Low	Regular	\$1.8-2.5K	3
3	P-2.4	512	60	Moderate	Long	\$800-1.3K	4
4	C-1.7	512	120	Low	Regular	\$1.3-1.8K	7
...	...	...	...	...	...	...	...
25	C-1.7	256	80	Moderate	Regular	\$1.8-2.5K	2
26	P-2.0	1	120	Low	Regular	\$800-1.3K	8
27	C-1.6	1	80	High	Regular	\$1.3-\$1.8K	6

A total number of 20 customers are selected to act as the respondents. Each respondent is asked to evaluate all 27 profiles one by one by giving a mark based on a 9-point scale, where "9" means the customer prefers a product most and "1" least. With these data, clustering analysis is run to find customer segments based on the similarity among customer preferences. Three customer segments are formed: s_1, s_2, and s_3, suggesting home users, regular users, and professional/business users, respectively.

For each respondent in a segment, 27 regression equations are obtained by interpreting his original choice data as a binary instance of each part-worth utility. With these 27 equations, the part-worth utilities for this respondent are derived. Averaging the part-worth utility results of all respondents belonging to the same segment, a segment-level utility is obtained for each attribute level. Columns 2-4 in Table 6-3 show the part-worth utilities for three segments with respect to every attribute level.

6.3 Engineering costs

Table 6-3 also shows the part-worth standard times for all attribute levels. The company fulfills customer orders through assembly-to-order production while importing all components and parts via global sourcing. The part-worth standard time of each attribute level is established based on work and time studies of the related assembly and testing operations. With assembly-to-order production, the company established standard routings as the basis for its process platform. Based on empirical studies, costing parameters are known as $LSL^T = 2518$ (second) and $\beta = 0.006$.

Table 6-3. Part-worth utilities and part-worth standard times.

Attribute Level	Part-worth Utility (Customer Segment)			Part-worth Standard Time (Assembly & Testing Operations)	
	s_1	s_2	s_3	μ^t (second)	σ^t (second)
A1-1	0.62	0.71	0.53	485	8.9
A1-2	0.82	0.78	0.81	538	10.3
A1-3	0.80	0.83	1.23	557	11.3
A1-4	0.71	0.73	0.71	521	11.4
A2-1	1.23	1.32	1.25	753	34.2
A2-2	1.26	1.23	1.29	825	36
A2-3	1.32	1.54	1.42	821	35
A3-1	1.17	0.48	0.38	667	23.6
A3-2	1.12	0.88	0.75	703	22.6
A3-3	1.16	1.26	0.89	730	31
A4-1	1.25	0.89	0.72	637	25.5
A4-2	1.44	1.32	0.83	672	27.6
A4-3	1.67	1.21	1.17	715	28.7
A5-1	0.98	0.96	0.85	287	4.32
A5-2	0.82	1.32	0.92	315	5.34
A6-1	0	0	0	N.A.	N.A.
A6-2	-1.55	-0.46	-0.17		
A6-3	-1.38	-0.71	-0.52		
A6-4	-2.21	-2.19	-0.56		

6.4 GA solution

To ensure accurate product family positioning, every possible scenario should be examined. It will result in a combinatorial explosion for the products involved in the product family. Enumeration is inhibitive if a problem is extremely big. Comparing with traditional calculus-based or approximation optimization techniques, genetic algorithms (GAs) have been proven to excel in solving combinatorial optimization problems. The GA procedure is applied to search for a maximum of expected shared surplus among all product alternatives. Assume that each positioned product family may consist of a maximal number of $J' = 4$ products. Then a chromosome string comprises 6 x 4 = 24 genes. Each substring is as long as 6 genes and represents a product that constitutes the product family. During the reproduction process, new product and family alternatives keep being generated through crossover and mutation operations. For every generation, a population size of $M = 20$ is maintained, meaning that only top 20 fit product families are kept for reproduction.

6.5 Results

Adopting the crossover and mutation rate as 0.6 and 0.01, respectively, the results of GA solution are presented in Figure 6-2. As shown in Figure 6-2, the fitness value keeps being improved generation by generation. Certain local optima (e.g., around 100 generations) are successfully overcome. The saturation period (350-492 generations) is quite short, indicating the GA search is efficient. Upon termination at the 492th generation, the GA solver returns the optimal result, which achieves an expected shared surplus of \$792K, as shown in Table 6-4.

As shown in Table 6-4, the positioned product family consists of two products, $\vec{z}_1^1$ and $\vec{z}_2^1$. From the specifications of attribute levels, we can see they basically represent the low-end and high-end notebook computers, respectively. With such a two-product family, all home, regular and professional/business users can be served with an optimistic expectation of maximizing the shared surplus.

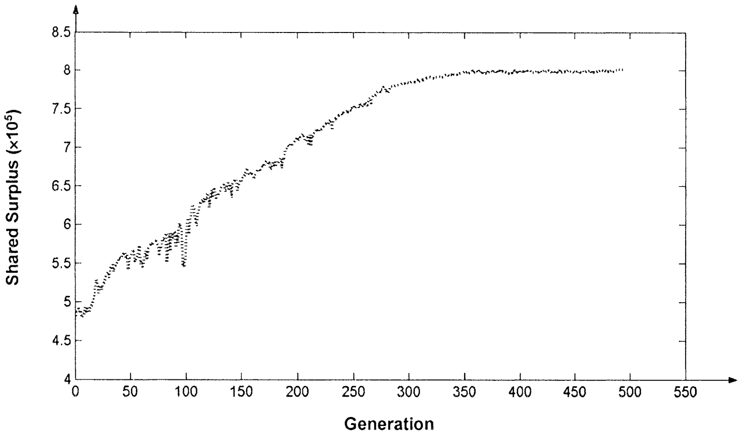


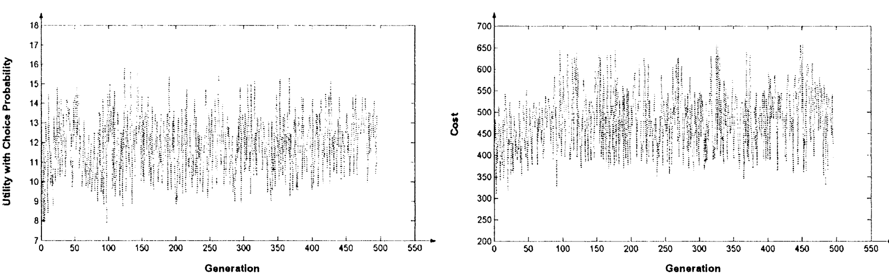
Figure 6-2. Shared surpluses among generations.

Table 6-4. Product family positioning results.

$\Lambda^\dagger$	$\Lambda^\dagger = [1,1,2,3,1,1;4,2,3,1,2,3;0,0,0,0,0,0;0,0,0,0,0,0]$			
$\{\vec{z}_j^\dagger\}_{J^\dagger}$	$\vec{z}_1^1 = [1,1,2,3,1,1]$		$\vec{z}_2^1 = [4,2,3,1,2,3]$	
	$a_k^\dagger$	a_{kl}^*	$a_k^\dagger$	a_{kl}^*
$\{a_k^\dagger\}_{(K+l)^\dagger}$	Processor	Pentium 2.4 GHz	Processor	Centrino 1.7 GHz
	Memory	256 MB DDR SDRAM	Memory	512 MB DDR SDRAM
	Hard Disk	80 GB	Hard Disk	120 GB
$\{a_{kl}^*\}_{(K+1)^\dagger}$	Weight	High (2.8 KG above)	Weight	Low (below 2.0 KG)
	Battery Life	Regular (around 6 hours)	Battery Life	Long (7.5 hours above)
	Price	\$800 - \$1.3K	Price	\$1.8K - \$2.5K
$E[V^\dagger]$	\$792K			

6.6 Performance evaluation

Figure 6-3a compares the results of utility with choice probability, $\sum_{i=1}^{3}\sum_{j=1}^{4}(U_{ij}P_{ij})$, among generations. It is interesting to observe that the distribution of utility with choice probability does not tally with that of the fitness shown in Figure 6-2. The optimal solution (i.e., the last generation) does not produce the best utility performance. On the other hand, a number of high utility achievements do not correspond to high fitness. Likewise, as shown in Figure 6-3b, the distribution of cost performance among generations disorders the pattern of fitness distribution shown in Figure 6-2. This may be explained by the fact that high utility achievement is usually accompanied with high costs to incur. Therefore, the shared surplus is a more reasonable fitness measure to leverage both customer and engineering concerns than either utility or cost alone.



(a) Utility with choice probability (b) Cost

Figure 6-3. Distribution of performance of GA by generation.

Figure 6-4 compares the achievements, in terms of the normalized shared surplus, cost, and utility with choice probability, of 20 product families in the 492th generation that returns the optimal solution. It is interesting to see that the peak of utility achievement (family #8) does not conclude the best fitness as its cost is estimated to be high. On the other hand, the minimum cost (family #4) does not mean the best achievement of shared surplus as its utility performance is moderate. Also interesting to observe is that the worst fitness (family #20) performs with neither the lowest utility achievement nor the highest cost figure. The best product family (#1) results from a leverage of both utility and cost performances.

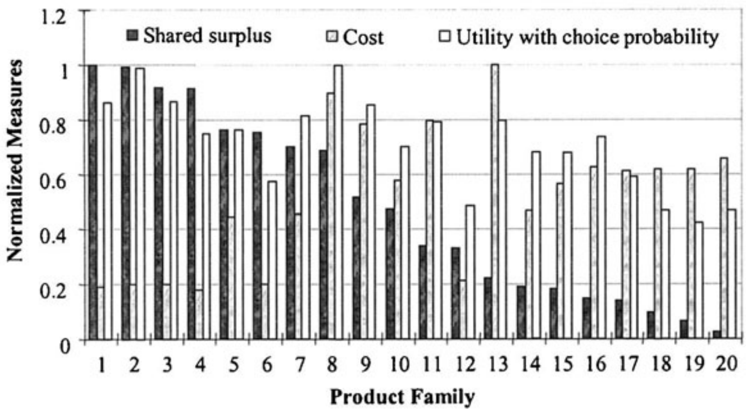


Figure 6-4. Performance comparison of product family population in the 492^{th} generation.

7. CONCLUDING REMARKS

Differing from the conventional product line design problem, product family positioning optimizes both a mix of products and the configurations of individual products in terms of specific attributes. By proposing a shared-surplus model, this research allows products to be constructed directly from attribute levels. Diverse customer preferences across multiple market segments, customer choice probability, and engineering costs for the composition of a product family are all covered by the shared surplus model. Conjoint analysis is adopted to quantify the customer preference. To circumvent the difficulties due to cost estimation, this research adopts a pragmatic costing approach based on standard time estimation to estimate the engineering costs of the products. To deal with the combinatorial explosion during optimization, the GA is used to position the optimal product family to create the highest shared surplus.

To model customers' choices, we employ the logit choice model and implements it in a segment level. The logit choice model implies a property of independence. In addition, the values of scaling parameter μ applied in the logit model are considered to be equal. The simplistic treatment suggests a possible way to improve the predictive quality of a logit model used in measuring the expected shared surplus.