PRODUCT LINE DESIGN, EVOLUTION, AND PRICING

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Abstract

Firms usually design their product lines with products phased in and phased out in response to market or technology changes. This adaption of a product line has complicated implications on market demand and fracturing cost due to the coexistence of both competitive and complimentary relationship among different product models. This paper proposes a computational model to facilitate decision making regarding attribute determination, product line evolution and pricing. A logit discrete choice model is developed to estimate the purchase probability of a product model via the preferences on consumer attributes. An activity-based costing model is developed to estimate the manufacturing costs of a product line by aggregating the volume of components using bill of materials, and considering volume discounts and common overhead activities. Product line design is then formulated as a mixed integer non-linear programming problem with the objective to maximize expected profit by determining new products' attributes, the existence of old products and the price for each product model. The proposed model is illustrated with an example of a mobile phone product line adaptation.

Keywords: Decision making, Computational model, Product line design, Evolution, Pricing

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1 INTRODUCTION

Optimal product line design is one of the crucial decisions for successful operations of many businesses. When determining a product line, some existing product models are eliminated, some are retained, and some new product models are introduced to. In most researches on product line design, the new product models are assumed to be in the pipeline and the decision maker selects a subset from the pool (Green and Krieger, 1985, Nair et al., 1995, Alexouda and Paparrizos, 2001, Li and Azarm, 2002, Kraus and Yano, 2003, Fruchter et al., 2006, Chen et al., 2009, Luo, 2011, Chen et al., 2014). The exclusion of old product models in the candidate pool would lead to the heavy cannibalization among new and old product models due to their functional commonality, which hurts the overall profitability (Mason and Milne, 1994, Kim and Chhajed, 2000, Desai, 2001). Furthermore, the selection decision on predetermined product models also misses the optimal product attribute spaces at the system level. Product line design decisions that factor in attributes of new product models and selection of old product models can be made more comprehensively.

Another limitation of current research on product line design is regarding pricing. Prices directly affect consumers' purchasing decisions and can be used to control cannibalization (Meredith and Maki, 2001). Therefore, pricing is included in most of profit-maximization based product line design models (Dobson and Kalish, 1993, Day and Venkataramanan, 2006). However, most research treats price in the same way as other engineering attributes (Dobson and Kalish, 1988). This research aims to develop a computational model to assist product line design that includes attribute determination, product line evolution, and pricing. As illustrated in Figure 1, the decisions to make simultaneously include: (1) what and how many models from the old product line are to be retained in the new product line?; (2) what are the product attribute levels?; (3) what are the prices of each product model?

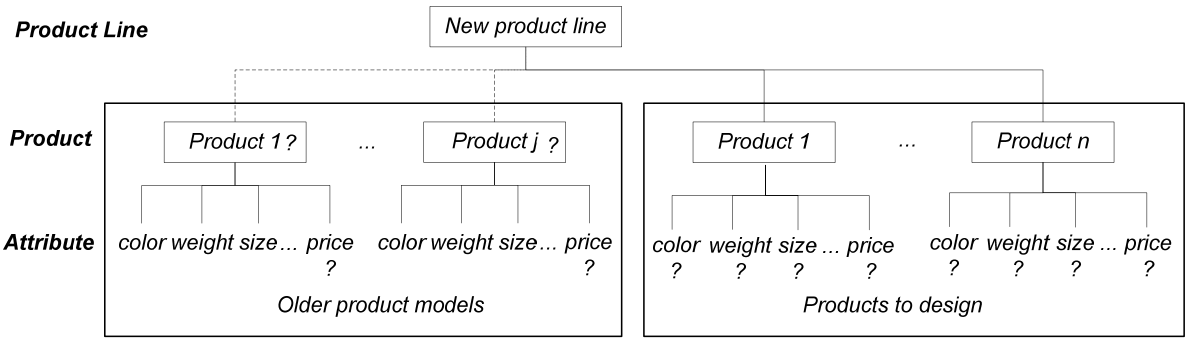

Figure 1. Hierarchical structure of product line, product and attribute

2 LITERATURE REVIEW

There are two streams of research related to this study. The first stream views product line design as a selection of product portfolios from a candidate product models group. The major research objective is maximizing the seller's profit (Green and Krieger, 1985, Alexouda and Paparrizos, 2001, Morgan et al., 2001, Chen et al., 2009, Chen et al., 2014). Besides, Balakrishnan and Jacob (1996) employed genetic algorithm for an optimal product line based on best buyers' welfare. Green and Krieger (1987) and Kohli and Krishnamurti (1987, 1989) developed models and algorithms aiming at the best seller's share-of choice. In this stream of research, each product is represented by a bundle of attributes which, except for price, are predetermined and kept constant in the product line design process. Hence, it is not possible to adjust product attribute levels to align them with the firm-level objective of product line design. Selection of predetermined products may lead to less than optimal product line.

The second stream of research is concentrated on single product or product line attribute design and utilized models to predict the effects of product attributes on the firm-level objectives (Jiao and Zhang, 2005, Michalek et al., 2005, Kumar et al., 2006, Michalek et al., 2006, Albritton and McMullen, 2007, Schön, 2010, Luo, 2011, Tsafarakis et al., 2013). Michalek et al. (2005), Kumar et al. (2006) and Michalek et al. (2011) employed a decomposition approach facilitated by the analytical target cascading in which product planning and design problem are decomposed into a hierarchy of subproblems. Coordinating the solving of the subproblems iteratively leads to the converging of the solution of the joint problem. Some other research solved the problem by relying on the simplification of the problem. For example, Schön (2010) assumed fixed costs at the product or product attribute levels and fixed costs for selling a unit of a product, and developed an exact approach for the product line design by transforming the initial intuitive mixed integer nonlinear programming (MINLP) formulation of the problem to an analytically more convenient mixed integer programming (MIP) problem with concave objective function and linear constraints. Jiao and Zhang (2005) addressed the product portfolio planning as a maximizing shared-surplus problem, with price treated as one of the attributes to be decided by a decision maker. Albritton and McMullen (2007) and Tsafarakis et al. (2013) employed a colony of virtual ants and hybrid particle swarm optimization with mutation for optimizing product lines at product attribute level. All those aforementioned researches exclude the impact of new product models on the existing product models.

3 PROPOSED MODEL

In the proposed method, the starting point of product line design is the consumer attribute vector denoted as x_{nj}. Consumer attributes (such as size, color, weight) collectively determine consumers' preferences on products and therefore impact the market demand. Old products have fixed consumer attributes, except price. The decision to make on the old products is whether to retain them or to eliminate them in the new product line. Consumer attributes of new product models are designed as variables in this proposed methodology. A logit discrete choice model is employed to predict products' market behavior based on their attributes (including price). These consumer attributes can also be linked to production activities and determine manufacturing costs. Activity-based costing is utilized to estimate the total cost of product line fulfillment. Finally, as shown in Figure 2, profit is estimated with known demand, price, revenue and cost information. The focal problem of product line optimization is to determine the consumer attribute configuration of the new product, the existence of old product models, and the sale price of each product in the new product line under a set of marketing and manufacturing criteria. The following section describes how these variables are merged into a product line profit optimization procedure.

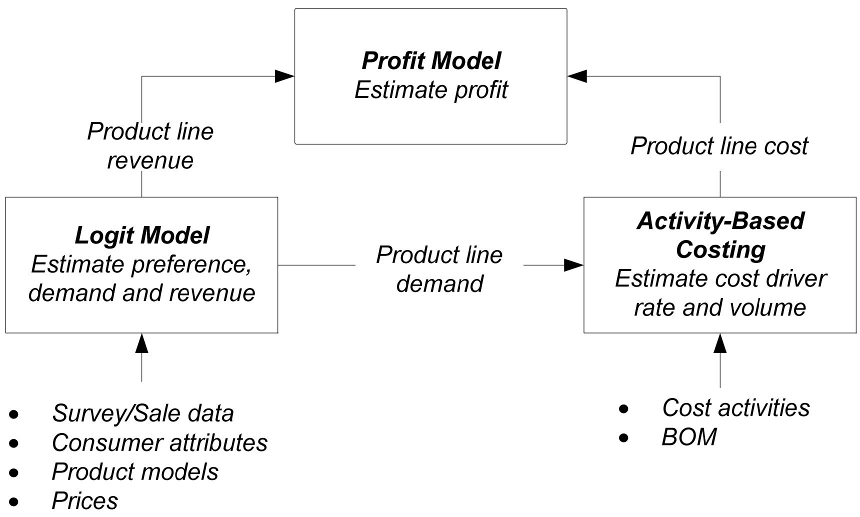

Figure 2. A decision framework for product line design and pricing

3.1 Consumer behavior model

A choice-based logit model is used to elicit consumers' preferences for different levels of consumer attributes and predict demand for a product line. In this model, all consumers from one segment are assumed to be homogenous and possess identical preferences for consumer attributes (Train, 2009). Consumers' utility, U_{nj}, in consumer n is the aggregate of part-worth of observed explanatory variables, x_{nj}, of product j and a stochastic factor ε_{nj}, i.e.

$$U_{nj} = \beta_n' x_{nj} + \varepsilon_{nj} \tag{1}$$

Explanatory variables of old product models are fixed, while attribute variables of new product models could be optimized to achieve a better profit. Prices of both old and new product models are decisions of the manufacturer. β_n is a vector of unobservable coefficients and represents customers' preference to be extracted from survey data. Under the first choice rule and with an independently and identically distributed extreme value of ε_{nj} the logit choice probability of customers in market segment g, choosing an alternative j among all competitive product models i, is derived as:

$$\phi_{gj}(\beta) = \frac{e^{\beta_g' x_{gj}}}{\sum_i e^{\beta_g' x_{gi}}} \tag{2}$$

With $k = 1,2,...,K$ denoting product models from the manufacturer's product line Λ, and M_g denoting market size of market segment $g = 1,2,...,G$, the aggregate demand of product model k over all G segments is:

$$d_k = \sum_{g=1}^{G} M_g \phi_{gk}(\beta) \tag{3}$$

The revenue that the manufacuter obtains from product line Λ with demand d_k price p_k can then be formulated as:

$$R(\Lambda) = \sum_{k=1}^{K} d_k p_k \tag{4}$$

Maximum likelihood method

Maximum likelihood method could be employed to estimate parameter β_g, by selecting the set of values that maximize the likelihood function. The likelihood function $L(\beta_g)$ is defined as the probability of each decision maker n in the sample population of market segment g choosing the alternative that was observed to have been chosen, i.e.:

$$L(\beta_g) = \prod_{n=1}^{N} \prod_{k} (\phi_{nk})^{\tau_{nk}} \tag{5}$$

where ϕ_{nk} refers to Equation (2), indicator $\tau_{nk} = 1$, if decision maker n chooses alternative k, and 0 otherwise. This information is collected from survey or actual sale data. It is more convenient to maximize log-likelihood function since ϕ_{nk} is a positive value and the log function is monotonically increasing. Maximizing $L(\beta_g)$ is equivalent to maximizing the log-likelihood function $LL(\beta_g)$:

$$LL(\beta_g) = \sum_{n=1}^{N} \sum_{j=1}^{J} \tau_{nk} \ln \phi_{nk} \tag{6}$$

3.2 Costing model

Activity base costing is employed to estimate the cost of product line fulfillment. The production activities carried out are identified during the process of purchasing components, transforming them into finished goods, and delivering them to customers. The consumed resources and costs incurred are assigned to activities. The overall costs comprise two main parts: material cost and cost that can be traced by activities. Unit material cost u_{km} for product k consuming material m can be obtained from the product's bill of material (BOM). The quantity of material m consumed by the product line Λ is:

$$q_m(\Lambda) = \sum_{k=1}^{K} d_k u_{km} \tag{7}$$

The demand d_k is pre-estimated in the logit model. The direct material cost of all materials for product line Λ is:

$$C^m(\Lambda) = \sum_{m=1}^{M} q_m(\Lambda) c_m \tag{8}$$

where c_m, material m unit price, is a function of purchasing quantity q_m due to quantity discounts. In line with Schotanus et al. (2009), c_m is modeled as:

$$c_m(q_m) = c_0 + \frac{s}{(q_m)^\eta} \tag{9}$$

where c_0 is the lowest price obtainable; s is the price spread; η is the steepness of the quantity discount rate.

Labor cost and overhead cost can be traced and assigned based on the activities consumed under a hierarchical structure of activities (Schön, 2010). Activity cost for providing all product models in the line is the aggregate of all activities at all levels, and it is modeled as:

$$C^a(\Lambda) = \sum_{l=1}^{L} \sum_{n=1}^{N_l} r_{\ln} u_{\ln}(\Lambda) \tag{10}$$

where $l = 1, 2, ..., L$ denotes level of categorization, and $n_l = 1, 2, ..., N_l$ represents activity at level l. $r_{\ln}$ and $u_{\ln}$ are the cost driver rate and cost driver volume of activity n at level l respectively. The overall cost of product line Λ is:

$$C(\Lambda) = C^m(\Lambda) + C^a(\Lambda) \tag{11}$$

3.3 Profit formulation

The decision regarding retaining product mix, new product attributes, and prices is conceptually modeled as an optimization problem to maximize profit as follows:

$$\max \quad \pi(x_{nj}, \Lambda, p) = R(x_{nj}, \Lambda, p) - C(x_{nj}, \Lambda, p) \tag{12}$$

$$\text{s.t.} \quad p_k > 0 \tag{13}$$

$$\Lambda \subseteq \Lambda^{old} \tag{14}$$

Variables in this function are: a binary vector Λ with length of the number of old product models, indicating the retention of product models from the old product line Λ^{old}; one or more vectors of explanatory variables, x_{nj}, of a new product model; and price vector, p_k, representing prices of the new product line. Explanatory variables, x_{nj}, could be continuous, discrete or mixed variables. Prices are assumed to be continuous and positive in this paper. The profit formula is nonlinear and contains both continuous and integer decision. Due to the complexity of the formula, heuristic algorithms, such as particle swarm optimization, are recommended to solve this optimization problem (Tsafarakis et al., 2013).

4 ILLUSTRATION

The proposed model is applied to solve the product line design of HTC smartphone in a campus shop, which is considered a small market segment. Smartphones are popular consumer products with diverse customer preferences and tastes. Manufacturers keep refreshing their smartphone product lines to cater to changing consumer preferences. In this illustration, there are five HTC smartphone models available in the campus shop, but HTC is planning one new candidate model with several attributes undetermined. Considering the entire new product line's profitability, HTC needs to determine 1) which of these five models should be retained to form a new product line?; 2) what attribute levels of the new product should be selected?; 3) what prices should be charged for each of selected models?.
Table 1 list the smartphone attributes and their levels for both HTC and its competitors' offerings in the campus shop. This was used in the customer survey and 100 responses were collected. Preference

values of attributes are estimated statistically, by inputting data of respondents' choices and applying Logit model and maximum likelihood method. As exhibited in Table 2, the preference values of all attributes except price are positive, indicating that customers prefer higher levels of the corresponding attributes. Preference values of 'HTC', 'Samsung', 'Apple', 'Blackberry' and 'Sony' are mutually relative and only

Table 1. Major Smartphone models for college students

	Brand	***CPU (GHz)***	***RAM (GB)***	***Memory (GB)***	***Network***	***Size (mm)***	***Camera (M pixel)***	***Prices (USD)***
Current product line	HTC	1.5	2	16	3G	159.43	8	719.95
	HTC	1.2	1	8	4G	144.43	5	508.30
	HTC	1.5	1	16	4G	148.03	8	618.80
	HTC	1	0.5	4	3G	135.98	5	338.30
	HTC	1.7	1	64	3G	151.49	8	624.75
Competitors offerings	Samsung	0.8	0.7	4	3G	133.65	5	253.30
	Samsung	1.2	1	16	3G	141.67	8	428.80
	Samsung	1.6	2	16	4G	171.21	8	720.80
	Samsung	1.4	1	16	3G	153.77	8	551.65
	Samsung	0.8	0.5	0.2	3G	119.08	2	135.15
	Apple	1.2	1	16	4G	136.97	8	786.25
	Apple	1	0.5	8	3G	129.25	8	654.00
	Apple	1	0.5	8	3G	129.25	5	488.00
	Blackberry	1	0.7	8	3G	125.30	5	448.80
	Blackberry	1.2	0.7	4	3G	135.07	5	361.25
	Blackberry	1.2	0.7	8	3G	132.59	5	590.75
	Sony	1	0.5	0.3	3G	129.25	5	273.70
	Sony	1	0.5	1	3G	123.00	8	278.80
	Sony	1.4	0.5	1	3G	139.98	8	391.00

Table 2. Preference value for each attribute

Attributes	HTC	Samsung	Apple	Blackberry	Sony	CPU	RAM
Preference value	1.489	1.231	3.638	2.523	0.394	4.153E-4	1.567E-4
Attributes	Storage	3G	4G	Size	Camera	Price	
Preference value	0.012	0.059	0.604	0.075	0.435	-0.008	

Table 3. Cost estimates of HTC's smartphones

Model ID	**Lowest cost (USD)**	**Cost spread (USD)**	**Cost of Phase in/out (USD)**	**Discount rate**
1	525	53	1,200	0.1
2	318	32	1,200	0.1
3	422	45	1,200	0.1
4	151	16	1,200	0.1
5	432	46	1,200	0.1
6	400	70	10,000	0.1

Table 4. New Smartphone's feasible attribute levels and corresponding costs

Attributes	***CPU***		***RAM***		***Memory***		***Network***		***Size***		***Camera***	
Units	*GHz*	USD	*GB*	USD	*GB*	USD		USD	*mm*	USD	*M pixel*	USD
Lower level	1.7	28	1	22	16	24	3G	34	142	52	8	28
Upper level	2.5	46	2	28	32	56	4G	54	162	58	13	50

differences among them matter because they are different levels of the same attribute *'brand'*. So do *'3G'* and *'4G'*. Considering that a single campus is just a minor market segment of HTC smartphone's entire market size, the wholesale prices of currently existing smartphones information (see Table 3) is used as the cost. The new smartphone possesses two kinds of components: fixed components and changeable components. Fixed components are those that are predetermined and excluded in our decisions. Changeable components are those to be determined in this design model. The total material cost of the smartphone, except for changeable components, has the lowest cost of $400 (as shown in Table 3), a cost spread of $70 and a discount rate of 0.1. The new smartphone's changeable attributes, their feasible levels, and corresponding costs are listed in Table 4. The activity cost of phasing in a new candidate smartphone model is assumed to be $10,000, while that of phasing out any current smartphone is $1,200 due to inventory, order cost and so on. The market size is assumed to be 10,000 based on the shop's historical sales data. The Particle Swarm Optimization was implemented in Matlab to optimize variables as specified above. Each old product model is encoded to a bit; 1 indicating the attendance of the corresponding alternative and 0 the absence. As each changeable attribute is given two levels to select from, the new smartphone is encoded to a bit string with a length of the number of changeable attributes; 0 indicating the lower level of attribute and 1 the higher level.

Based on the profit model, we investigate optimizing prices of the old product line, designing a new product line by selecting the old smartphones, introducing one new smartphone and setting prices for each product model in the product line. We compare the resulted profit with the current product line (see Table 5). It is found that the optimal prices of the old product line are $716.98, $499.86, $608.70, $335.67 and $613.15 respectively. The new prices are lower than old prices but not by much, and the total profit of the entire old product line improves slightly from $472,730 to $473,680. The original prices are nearly optimal and the incentive to change prices is not high. If we select a product mix from the old smartphones, add one new smartphone and optimize the prices simultaneously, the best profit is achieved when all the five old smartphone models are selected and the new smartphone has a technical specification of CPU of 2.5GHz, RAM of 1GB, Memory of 16GB, network of 3G, size of 162mm and Camera of 13M Pixel. The prices of the old product models' are reduced from $681.09, $495.11, $605.20, $278.48, and $613.71, respectively; the new product model's price is set at $846.47.

Table 5. Different strategies of product line adaptation and implications

	Current Status	**Repricing of current product line**	**Integrated product line design**
Old product line	[1 1 1 1 1]	[1 1 1 1 1]	[1 1 1 1 1]
New product's attribute			[1 0 0 0 1 1]
Price	[719.95; 508.30; 618.80; 338.30; 624.75]	[716.98; 499.86; 608.70; 335.67; 613.15]	[681.09; 495.11; 605.20; 278.48; 613.71; 846.47]
Demand	[405; 337; 701; 489; 892]	[407; 355; 750; 420; 966]	[464; 311; 649; 574; 808; 1,217]
Revenue	[291,580; 171,300; 433,780; 165,430; 557,280];	[291,890; 177,480; 456,090; 592,040]	[316,400; 154,000; 393,000; 159,900; 496,100; 1,030,500]
Cost	[224,360; 113,230; 312,410; 71,570; 401,970]	[225,570; 119,230; 333,590; 71,750; 434,660]	[257,170; 104,500; 289,310; 97,910; 364,330; 823,710]
Profit	[67,170; 58,130; 121,660; 70, 150; 155,620]	[66,330; 58,260; 122,500; 69,220; 157,370]	[59,230; 49,500; 103,690; 61,990; 131,770; 206,290]
Total Profit	$472,730	$473,680	$612,860

The optimal prices and the market demand of the old product models decline because of the cannibalization by the new product model. With lower demand quantities, the average unit costs of the old product models increases due to economy of scale and, consequently, the profit from the old product model decreases. Nevertheless, the total profit from the new product exceeds the decrease in the total profit from the old product models and the overall profit of the entire product line improves to $612,860.

5 CONCLUSION

This paper proposes an analytical model for product line design based on the observation that product lines are usually not designed from scratch but adapted by the regularly phasing in of new products and phasing out of old product models. The proposed model provides a decision making framework to help make more informed decisions regarding product line design for maximum profit. It delineates the intricate relationships between product line composition, attributes and prices of its constituent product models, and shows the consequent impact on market demand as well as fulfillment. Logit discrete choice model and activity-based costing method are utilized to quantify a product line's demand and manufacturing costs, respectively. Product line design and pricing are then formulated as a mixed integer non-linear programming problem, in order to maximize the profit of the resulting product line. Heuristic algorithm, such as particle swarm optimization, is applied to identify the optimal new product(s), old products selection, and pricing. The proposed methodology is illustrated with a case study on smart phones on a university campus. The result demonstrates the feasibility of the proposed model and its potential of being utilized as a theoretical foundation to develop a decision support system to facilitate integrated and cross-functional decision making regarding product line design. Future research is needed to augment Logit model to more advanced choice based models that considers random preference values within a market segment. To better implement the model, future research is also needed to extend the current study to a bigger market segment, more product attribute levels, and more products to be introduced simultaneously.

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