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Evolutionary product line design balancing customer needs and product commonality

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ABSTRACT

Product lines need to constantly evolve in response to market and technology changes. The diverging forces from marketing and engineering entail an intricate balance between satisfying changing customer needs and maintaining commonality in product platforms. This paper reports an evolutionary approach for product line design. Discrete choice analysis and product commonality indices are developed to evaluate the 'fitness' of a product line from marketing and engineering, respectively. Product line adaptation is formulated as a multi-objective optimization problem, whereby a solution framework based genetic algorithms is developed and implemented with a case study of notebook product line design.

1. Introduction

The diversification of customer needs in many industries results in increasingly fragmented market segments, which make it an imperative for manufacturers to compete on product lines instead of single products [1]. The composition of a product line in terms of product models, attributes, and prices not only directly affect customers' purchasing decisions but also have a large impact upon the efficiency of product fulfillment. Product line design has henceforth attracted enormous attention in both marketing and engineering research. Green and Krieger approach product line design as a market positioning problem by formulating it as selection of a subset of products with substitutability/complementarity relationship [2]. Recently, Jiao and Zhang [3], Markus and Vancza [4] extend this formulation to include engineering consideration with customer interaction in product line design.

In practice, however, product lines are rarely centrally designed but dynamically adapted in response to changing market environment. Products are introduced into or phased out of a product line due to changes in customer needs and/or competitive offerings, and different generations of a product line usually display incremental modifications with technological continuity, which mimics the process of biological evolution [5]. Evolutionary design has been recognized as an effective design methodology from both modeling and computational perspective. Maher and Tang develop a computational and cognitive model of design as co-evolution between problem space and solution space [6]. Recently, Bryan et al. propose a co-evolution model for joint design of product families and reconfiguration of assembly systems in response to customer preference changes [7].

This paper considers product line evolution as an integral part of the market eco-system and proposes an evolutionary approach for product line design. Changing customer needs could trigger product line adaptation, which, in return, affects market demand as well as product fulfillment. A key challenge of evolutionary product line design lies in capturing the marketing and engineering implications and finding an optimal balance in product line adaptation. Towards this end, this paper first presents a conceptual framework of product line evolution. Discrete choice analysis (DCA) is then introduced to model the impact of product line adaptation upon market demand, which is utilized to evaluate the 'fitness' of a product line from marketing perspective. Similarly, product line commonality indices are developed to evaluate the 'fitness' of a product line from engineering perspective. A multi-objective optimization model is subsequently developed for product line adaptation, whereby heuristic genetic algorithms (GAs) are developed for problem solving and implemented with a case study of notebook product line design.

2. Evolutionary product line design

Conventional product line design aims to select a subset of product models within a given market or technological context [2]. In contrast, evolutionary product line design is to adapt a given product line in response to environment changes. In other words, evolutionary product line design is not from scratch but path-dependent. Actual product line adaptation is the aggregate result of many forces from both external (e.g. changing customer needs, competitive offerings, etc.) and from internal (e.g. marketing, engineering, manufacturing, etc.). Within a typical organization, product line design is generally situated between marketing and engineering [4]. Fig. 1 presents a conceptual framework of evolutionary product line design. A key issue in evolutionary design is concerning fitness evaluation, which indicates the direction of

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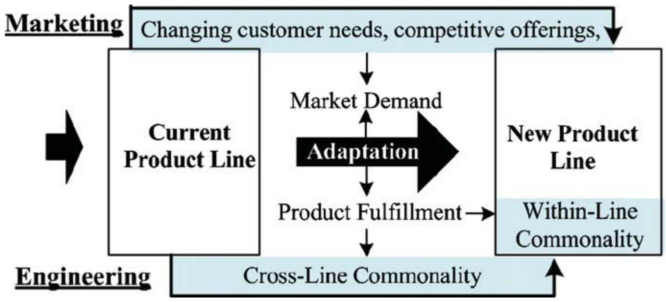

Fig. 1. Evolutionary product line design framework.

evolution. As it is impractical to model a product eco-system in full detail, this paper selects market demand and product fulfillment as two dimensions to measure the fitness of a product line from marketing and engineering perspective, respectively.

3. Discrete choice demand modeling

The survivability of a product line in a competitive market environment is reflected in market demand for its constituent products. DCA is a systematic method to estimate market demand based on customers' purchasing decisions [8]. Under DCA, a customer's task is simply to choose which product to buy from a choice set, thus avoiding the problem of degree of freedom and alternative ranking as encountered in conjoint analysis (CA) [9]. DCA assumes a probabilistic customer utility function (u) of observable variables including customer attributes ($\mathbf{S}$), product attributes ($\mathbf{Z}$), and an unknown coefficient (α), which takes into account of unobservable variables like tastes, emotions, etc.

$$u = U(\boldsymbol{S}, \boldsymbol{Z}, \alpha) \tag{1}$$

Due to taste variations or measurement errors, a customer's true utility is distorted by some random disturbances. A customer chooses one product alternative over another if the difference in disturbances does not exceed the difference in the deterministic utility. With multiple products and assuming normal distribution of the disturbances, the probability that a customer (m) chooses product (n) out of a choice set (Ω) with N products can be derived as [8]:

$$Pr_m(n)|\Omega = \frac{e^{\eta u_{nm}}}{\sum_{n=1}^{N} e^{\eta u_{nm}}} \tag{2}$$

The above equation indicates that a customer's choice probability for a product is positively related to the product's utility relative to the utility of the choice set on an exponential basis, adjusted by a constant factor η. The choice set (Ω) consists of the firm's product line (Λ) and competitive offerings (Λ^c), i.e. $\Omega = \Lambda \cup \Lambda^c$. Λ can be constructed through a factorial design by combining different product attributes and attribute levels. As the actual choice probability can be observed by the frequency that an alternative is selected, the parameters of the choice model (Eq. (2)) and utility function (Eq. (1)) can be estimated via data fitting. The demand for a product model is the summation of the choice probability of each respondent adjusted by the size of the corresponding market segment (Q_m, $m = 1, 2, \ldots, M$). The total demand for a product line can be derived based on the demand for its constituent products. The market share of a product line can be derived as:

$$\pi(\Lambda) = \frac{\sum_{k=1}^{K^\dagger} \sum_{m=1}^{M} Q_m Pr_m(k)|\Omega}{\sum_{m=1}^{M} Q_m} \tag{3}$$

4. Product line commonality index

The 'fitness' of a product line from the engineering perspective can be generally evaluated based on the efficiency in product fulfillment. Although metrics like cost, lead time, and capacity utilization are commonly used in industry for efficiency measurement, they are generally operation-dependent instead of inherent properties of a product line. Within a given technological context, efficiency derives from "economies of scale" by means of aggregation, repetition, and learning. In the context of a product line, this translates into sharing common components, production processes, and engineering resources across different product models. Thus, commonality is an inherent property of a product line that has a large impact on the efficiency of product fulfillment.

Commonality has been recognized as a key design strategy to provide high product variety while maintaining high fulfillment efficiency, and many indices have been proposed in literature for its measurement [10]. However, the majority of commonality indices are defined based on the degree of sharing within a product line. This paper extends the concept to consider commonality across different generations of a product line, as adding/deleting products is often costly and maintaining continuity is conducive to reuse of previous designs, processes, and equipment.

This paper develops an internal and external product line commonality index (i.e. C_w and C_c) to measure these two types of commonality, respectively. A product line (Λ) can be represented as a hierarchy that is composed of multiple product models ($\mathbf{Z}_k$), each of which can be described as a vector with multiple product attributes (a_i) with multiple levels (a_{ij}) [3]. In a multi-dimensional space of product attributes, a product corresponds to a point while a product line corresponds to a cluster of such points. The 'distance' between different points thus reflects the commonality between the corresponding products. Using techniques of numerical taxonomy [11], this paper defines commonality as the inverse of the average 1-norm distance among the constituent products of a product line for C_w and between the constituent products of two generations of a product line for C_c.

$$C_w(\Lambda) \equiv \left(\frac{1}{K^\dagger (K^\dagger - 1)} \sum_{k=1}^{K^\dagger} \sum_{t=1}^{K^\dagger} \left| \boldsymbol{\beta} \cdot (\boldsymbol{Z}_k - \boldsymbol{Z}_t) \right|_1 \right)^{-1} \tag{4}$$

$$C_c(\Lambda, \Lambda') \equiv \left(\frac{1}{K^\dagger K'^\dagger} \sum_{k=1}^{K^\dagger} \sum_{k'=1}^{K'^\dagger} \left| \boldsymbol{\beta} \cdot (\boldsymbol{Z}_k - \boldsymbol{Z}_{k'}) \right|_1 \right)^{-1} \tag{5}$$

β is a vector coefficient that normalizes the distances along different product attributes. It can be calculated based on the relative cost of design changes along different product attributes. The reason for using 1-norm for distance measurement is because of the discrete nature of product attributes. Without loss of generality, distance is measured in the functional domain but can be extended to physical and process domains based on product family architecture [1].

5. Optimal product line adaptation

The demand model (Eq. (1)–(3)) and product line commonality indices (Eq. (4)–(5)) provide a set of metrics to evaluate the fitness of a product line, but they point in different directions concerning product line adaptation in response to diversifying customer needs. The marketing incentive to increase demand requires higher $K^\dagger$ and u_{nm}, which means larger variety of products and higher level of customization, leading to a broader but more dispersed product line. The engineering incentive to increase C_w demands a tighter product line with less variety and customization; and the incentive to increase C_c restricts the magnitude of design change across different generations of a product line, which further constrains the degree of customization. This paper develops a multi-objective optimization model to balance the diverging forces between marketing and engineering in evolutionary product line design (Fig. 2).

The weighting factors λ_1, λ_2, and λ_3 represent the relative contribution of market demand, in-line commonality, and cross-line continuity to the new product line's overall fitness. These

Given:

Current: $\Lambda^0 = \{z^0_{k_0}, k_0 = 1, \ldots, K_0\}$,

$\Lambda^c = \{z^0_{k_c}, k_c = 1, \ldots, K_c\}$,

$\boldsymbol{S} = [S_1, S_2, \ldots, S_M]$, $Q_m, m = 1, \ldots, M$

Changes: $\Delta\boldsymbol{S}$, $\Delta\Lambda^c$, ΔQ_m

Find:

A new product line: $\Lambda = \{z_k, k = 1, \ldots, K\}$

Satisfy:

$\Lambda \subseteq Z$

Maximize:

$$f(\Lambda) = \lambda_1 \pi(\Lambda) + \lambda_2 C_w(\Lambda) + \lambda_3 C_c(\Lambda, \Lambda^0)$$

Fig. 2. Optimal product line adaptation.

factors can be estimated based on the manufacturer's strategic priority, e.g. setting λ_1 to be relatively high if market share is the top priority. It is worth pointing out that the formulation above implicitly admits that market dynamics is too complex to be fully modeled and absolute measures like profit maximization is too complicated to be obtained. Instead, the optimization model aims to complement practitioners' experience in product line adaptation towards higher *fitness*, which contributes to profit maximization in an indirect way.

6. A GA-based solution framework

Implementation of the optimization model (Fig. 2) involves finding an optimal subset of products out of feasible configurations and determining the attributes as well as attributes levels for each product, which is combinatorial in nature [2]. As the number of attributes and levels are usually large, complete enumeration becomes numerically prohibitive. GA is an effective heuristic method for solving combinatorial optimization problem via probabilistic search based on the principle of natural selection and survival of the fittest [12], which is also the foundation of product line evolution. Thus, GA is adopted to implement optimal product line adaptation.

Implementation of a heuristic GA involves the representation of a problem to be solved with a genetic structure [12]. This paper presents a genetic encoding scheme (Fig. 3), in which a product line is represented by a *chromosome* consisting of a *string*. Each fragment of the chromosome (*substring*) represents a product. Each element of the string, called *gene*, indicates an attribute of the product. The value assumed by a gene, called *allele*, represents an index of the attribute level instantiated by an attribute. A product line (chromosome) consists of one-to-many products (substrings), exhibiting a type of composition (AND) relationships. Likewise, each product (substring) comprises one or many attributes (genes), each of which can assume one and only one out of many possible attribute levels (alleles), suggesting an exclusive all (XOR) instantiation.

With the coding scheme, a product line can be uniquely identified with a string of predefined numerical codes. The optimal product line adaptation problem (Fig. 2) can be implemented with a standard GA procedure. A new product line can be generated by inheriting and modifying these codes through genetic operations like crossover and mutation. Each offspring of a product line is evaluated using the fitness function (f), and good chromosomes are selected for reproduction. The iterative process could converge to a new product line with higher fitness. Besides computational efficiency, another advantage of using GA heuristics lies in the resemblance of its searching procedure with the actual product line evolution. By selecting the initial population of chromosomes to be around the current product line, the GA heuristic is able to simulate the actual path of product line evolution. This offers empirical insight concerning product line adaptation.

7. A case study

A notebook computer product line is utilized to illustrate the evolutionary design methodology. For simplicity of illustration, a set of key attributes and attribute levels are listed in Table 1.

Table 1
Notebook computer product line.

Attribute		Attribute levels
a_1	Processor	{Pentium 2.4 GHz, Pentium 2.6 GHz, Pentium 2.8 GHz, Centrino 1.4 GHz, Centrino 1.5 GHz, Centrino 1.6 GHz, Centrino 1.7 GHz, Centrino 1.8 GHz, Centrino 2.0 GHz}
a_2	Monitor	{12 in., 14 in., 15.4 in., 13.3 in., 17 in.}
a_3	RAM	{256 MB, 512 MB, 1 GB, 2 GB, 4 GB}
a_4	Hard disk	{80 GB, 120 GB, 160 GB, 250 GB, 500 GB}
a_5	Weight	{Low ($\leq$1.5 KG), moderate (1.5–2.8 KG), high ($\geq$2.8 KG)}
a_6	Battery	{Regular: ~6 h; long $\geq$7.5 h}
a_7	Price	{$\leq$\$800, \$800–\$1.5K, \$1.5K, \$2.5K, $\geq$\$2.5K}
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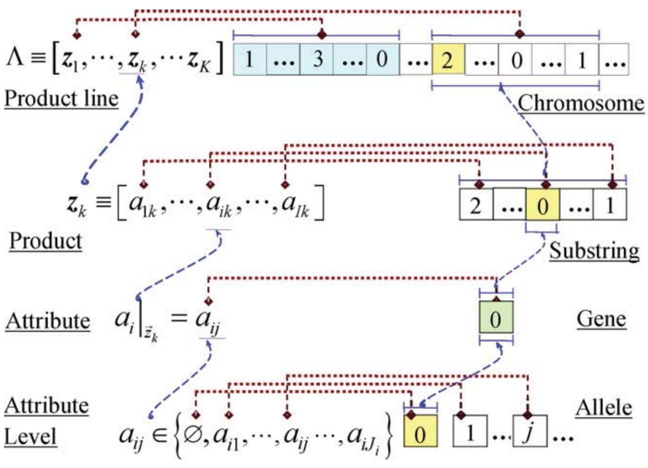

Fig. 3. Genetic encoding of a product line.

Table 2
Context of product line evolution.

	Basic (S_1)	Mobile (S_2)	Gaming (S_3)
Q_m	120,000	40,000	10,000
Λ^0	{2, 1, 1, 1, 3, 1, 1}	{5, 4, 2, 3, 1, 2, 3}	{8, 5, 5, 4, 3, 2, 5}
μ	[0.2, 0.2, 0.5, 0.5, −0.3, 0.5, −1]	[0.5, 0.2, 0.5, 0.5, −1, 0.8, −0.5]	[0.8, 0.8, 0.8, 0.8, −0.2, 0.8, −0.5]
Λ^c	{1, 2, 2, 1, 2, 1, 2}	{4, 3, 2, 2, 1, 1, 2}	{9, 4, 5, 3, 3, 2, 4}
ΔQ_m	−20,000	+10,000	+10,000

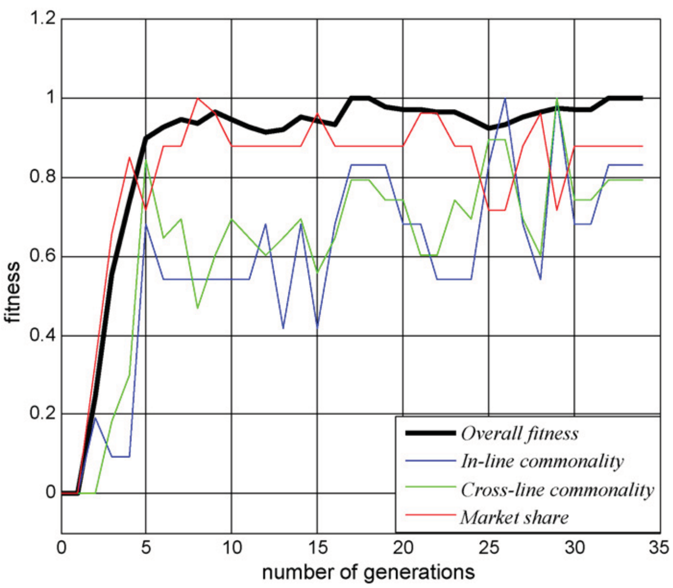

Fig. 4. Fitness change with product line evolution.

Among them, "price" is treated as one attribute to be assumed by a product. Every notebook computer is thus described as a configuration of available attribute levels, for example {1, 1, 1, 1, 1, 1, 1} represents a product model of {Pentium 2.4 GHz, 12 in. monitor, 256 MB RAM, 80 GB hard disk, low weight, regular battery, ≤\$800}.

The manufacturer currently offers a product line (Λ^0) that consists of three product models in three market segments categorized as *basic*, *mobile*, and *gaming*, respectively. The customer utility function in each market segment can be estimated by discrete choice analysis [9]. For illustrative simplicity, utility is assumed as linear functions of the product attributes with the coefficients (μ) indicating the customer's relative preferences along different attributes. The market demand is shifting from *basic* towards *mobile* and *gaming* segments. Table 2 summarizes the market situation that confronts the manufacturer in product line evolution.

This paper selects the current product line as the initial population of product line and employs mutation as the primary method for reproduction. Although this may sacrifice the speed of convergence in locating the optimal solution, it simulates the path of evolution and offers practical insight regarding the market dynamics. The evolution of the fitness function and its components with respect to the number of generations of reproduction is displayed in Fig. 4. As the relative trend of market share and commonality is the main concern in product line evolution, data is normalized to be within [0, 1] with the current product line set at the origin. The graph shows that both product line commonality indexes and market share are increasing and leveling off after a certain number of iterations. The new product line converges to {3, 1, 2, 2, 4, 1, 2}, {6, 5, 2, 3, 2, 3, 3}, and {8, 6, 5, 5, 4, 3, 5}, which gives the highest overall fitness.

8. Conclusions

As customer needs continue to diversify and product variety continues to grow in many industry sectors, product line design is becoming increasingly important. This paper reports an evolutionary approach for product line design and develops an optimization model to balance the diverging incentives between marketing and engineering in product line adaptation. As product lines are rarely designed from scratch but incrementally evolved in response to market changes, the evolutionary approach provides a practice-oriented conceptual framework that meets two seemingly conflicting goals of product line design: sustaining the continuity of product line but also adapting to the diverse and changing market force. The optimization model provides a foundation to capture these forces. A key challenge in evolutionary design lies in the difficulty of evaluating the fitness of a large variety of potential design outcomes. In this regard, this paper makes contribution by introducing discrete choice analysis for demand modeling on the marketing side and product line commonality indexes on the engineering side. The case study illustrates a conceptual and methodological framework for evolutionary product line design. Further research is needed to include product commonality, dynamic competition demand models, and supply chain issues in commonality modeling. Large scale case studies are also needed to determine empirically the application boundaries.

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