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An Evolutionary Algorithm Based Method for the Product Line Design using the Share of Choices Criterion

Georgia Alexouda
Department of Applied Informatics, University of Macedonia,
156 Egnatia Str, POB 1591, Thessaloniki 540 06, Greece
e-mail: ageorgia@macedonia.uom.gr

Abstract. An Evolutionary Algorithm (EA) based method for the product line design problem is presented. Optimal product line design is a very important problem in marketing. Before the engineering and manufacture of products a design using buyers' preference data is necessary. The proposed EA uses the share of choices criterion for the fitness evaluation of the candidate product lines. The selection method uses an elitist strategy and strives to maintain population diversity. A uniform crossover operator and a mutation operator are applied. A computational study has been performed in order to compare the EA to the Beam Search (BS) method. The computational results demonstrate that the EA can find near optimal solutions within reasonable computation time. Also, the proposed approach outperforms the BS method with respect to the solution quality. Consequently, the proposed EA can be used in a marketing decision support system for the product line design problem.

1. Introduction

Product design is an important problem in marketing research. There is an increasing research interest in the product design problem because of the high rates of failure of new products and their associated losses [3], [23]. Because the product design problem is NP-Hard [11], heuristic procedures have been proposed for its solution.

When the buyers' preferences are heterogeneous, it is preferable to design a product line than a single product [14]. A product line can be defined as "a group of products that are closely related because they perform a similar function, are sold to the same customer groups, are marketed through the same channels, or fall within given ranges" [12]. In the current paper the term product line means a line of substitute products.

In today's highly competitive environment the share of choices criterion is very important for the enterprises. The market share plays a crucial role in the survival of an enterprise and it has a significant influence on the profit [21]. In section 2 the product line design problem using the share of choices criterion is presented.

In the last decades there is a growing interest in the application of the Evolutionary Algorithms (EAs) in different fields. EAs were inspired by the natural evolution and have shown their ability to solve complex optimization problems. The present paper proposes an EA based technique for the product line design using the share of choices criterion. The proposed EA solution method is presented in detail in section 3.

In order to see whether there exists any computational advantage of the proposed EA, we compared it with the Beam Search (BS) method. The results of the computational study are very encouraging for the proposed method with respect to the computational time and the quality of the solutions. The computational results are presented in section 4.

Finally, the conclusions of the present paper are summarized in section 5.

2. Problem Description

Before the engineering and manufacture of products a design using customer preference data is necessary. It is assumed that individuals choose the product from a set of available alternatives that gives them maximum utility. Product design is one of the more important managerial decisions in the area of product policy.

The principal stages of product design are the following [10]:

1. *Defining the product market.* The product market can be defined as “the set of products judged to be substitutes within those usage situations in which similar patterns of benefits are sought by group customers” [20].
2. *Identifying the important product attributes.* It is important to distinguish between product characteristics and product attributes. The term product characteristic is used for the various physical features that define the product. Product attributes tend to be abstract and fewer in number than product characteristics. The product characteristics influence the formation of product attributes. Consumer compare products based on the product attributes. Consequently, product attributes are used in the description of the consumer choice process.
3. *Modeling the consumer’s product choice decision process.* There are two basic approaches for modelling the single product or product line design problem: the multidimensional scaling approach (MDS) and the conjoint analysis (CA) approach. CA has superior analytical capabilities and MDS has superior graphics and data display features [8]. CA is a very popular method, which has had several thousand commercial applications [24]. CA can estimate the value that individuals associate with particular product attributes [12]. The data used by the proposed EA can be estimated using the CA.
4. *Designing the products.* By the term product design we mean the selection of product attribute levels in order to optimize a firm’s objective. The present paper focuses on this stage.

In the present paper the problem is formulated within the CA framework. Products are described using attributes and attribute levels. For example, in printers an attribute may be ‘printing quality’ with levels ‘high’, medium’ and ‘low’. The problem is to select a specific level for each attribute in order to optimize an objective. In the present paper we deal with the product line design problem, that means that several products have to be determined to optimize an objective. The proposed EA selects the product attribute levels in order to maximize the share of choices.

A representative sample of the population of buyers is used to estimate the part worth utility of each individual for each attribute level. Each individual has to choose only one of the products offered in the market. Individuals usually differ in their choice, because in the most cases they derive different utilities from the same product. The consumer decision making process is represented through a multi-attribute utility approach in which an individual's utility derived from a product can be computed by adding the part-worth utilities of the selected attribute levels. Each individual selects the product that maximizes his utility.

As markets become more crowded and competitive, so the importance of the share of choices criterion increases. The share of choices criterion takes directly into account competitors' products. The product that a buyer prefers before the introduction of the new product line is called the status quo product. An individual switches from his status quo product, only if a new product offers to him more utility. To account for cannibalization the share of choices is maximized over the subset of buyers whose status quo product is offered by a competitor.

The product line design problem within the above framework has been formulated as a 0-1 integer program [11]. A dynamic programming heuristic method [11] and a BS heuristic method [17] have been proposed for designing the items of a product line. A computational study comparing the above two heuristic methods has shown that the BS method is superior with respect to the CPU time and the quality of the solutions. BS methods have been developed in the 1970s for Artificial Intelligence search problems. It is a breadth-first search process with no backtracking. At any level of BS the b most promising nodes are explored further in the search tree, where b is called the beam width [17]. In the present paper the proposed EA is compared to the BS method developed for the product line design problem using the share of choices criterion.

3. The Evolutionary Algorithm for the Product Line Design Problem using the Share of Choices Criterion

The early pioneers of computer science expressed their interest in biology and psychology. EAs were inspired by the natural evolution. EAs are iterative procedures. In each iteration they consider populations of candidate solutions rather than a single candidate solution at a time. Each iteration of an EA is called a generation. An EA works by repeatedly modifying a population of candidate solutions using the natural genetic operations of reproduction, crossover and mutation. The candidate solutions can be coded in different ways depending on the underlying problem. The initial population can be generated randomly or by using prior information [16].

A fitness function is used to assign a measure of quality to each population element. A selection method reproduces population elements according to their fitness. Several selection methods are available, like roulette selection, tournament selection and rank-based selection. The crossover operator mimics the sexual reproduction and generates new population elements by combining selected pairs of elements. From a pair of parents two children are created that are partly equal to their mother and partly to their father. Several forms of crossover are available, like one-point crossover, two-point crossover, multi-point crossover and uniform crossover. The mutation operator is applied to slightly modify some population elements. It is the occasional random alteration of the value at a string position of a candidate solution. An EA creates new generations until a predefined stopping criterion is met [1], [6], [16], [19].

EAs have gained wide popularity in the last decades. They can solve some extremely difficult problems. Exact algorithms guarantee the optimal solution. However, exact algorithms can not solve many real world optimization problems in a realistic computation time. In these cases we are forced to use heuristic methods. Correctly applied EAs are very promising for the solution of such problems. EAs have been proposed for many integer programming problems. For example, EAs have been developed for the well known traveling salesman problem [13], the knapsack problem [4], [7], the set partitioning problem [5], etc. In the last years some researchers expressed their interest in using EAs in marketing problems, e.g. market segmentation, pricing, site location problem, learning models of consumer choice [9], [18]. An EA based method has been developed for the single product design problem [2].

An EA for the product line design problem using the share of choices criterion is presented. In the formal description of the proposed EA based method $\Omega = \{1, 2, \dots, K\}$ denotes the set of K attributes and $\Phi_k = \{1, 2, \dots, J_k\}$ denotes the set of J_k levels of attribute $k \in \Omega$. Also let $\Psi = \{1, 2, \dots, PN\}$ denote the set of PN items to be selected, where the multi-attribute description of each item is to be determined by solving the share of choices problem. Let $\Theta = \{1, 2, \dots, I\}$ denote the set of individuals. Let w_{ijk} denote the part worth of level $j \in \Phi_k$ of attribute $k \in \Omega$ for individual $i \in \Theta$. As mentioned earlier, the part worths can be estimated using the CA. Matrix $STATUTIL_I$ maintains the utilities of the status quo product of each individual $i \in \Theta$.

It follows the description of the proposed EA.

Representation of the solutions

Let P denote the set of the candidate product lines and $M=|P|$ denote the population size. The population is maintained in a matrix POP_{M*PN*K}. The elements POP_{pmk}, where $p \in P$, $m \in \Psi$ and $k \in \Omega$, denote the selected level of each attribute. That is, if level $j \in \Phi_k$ of attribute $k \in \Omega$ is assigned to product $m \in \Psi$ of product line $p \in P$, then $POP_{pmk}=j$.

Initial population.

The initial population of candidate product lines is randomly generated and stored in matrix $POP_{M*PN*K.}$

Fitness evaluation.

The fitness of the population is evaluated according to the share of choices criterion. Matrices $PRODUTIL_{M*I*PN}$, SOC_{M*I} and $TOTAL\_SOC_M$ are computed in order to evaluate the expected share of choices.

Matrix $PRODUTIL_{M*I*PN}$ maintains the utilities of the PN different products of each candidate product line which are derived by each buyer. It can be computed as follows: $PRODUTIL_{pim} = \sum_{k \in \Omega} w_{i(POP_{pmk})k}$ where $p \in P$, $i \in \Theta$, $m \in \Psi$.

SOC_{pi} indicates whether buyer $i \in \Theta$ would buy one of the items of the product line $p \in P$. In particular, if buyer $i \in \Theta$ would buy one of the items of the product line $p \in P$ then $SOC_{pi}=1$, else $SOC_{pi}=0$. Each buyer chooses the product that gives him maximum utility. Moreover, a buyer switches from his status-quo product to a new product, only if it offers him higher utility. Let m' denote the index m such as $PRODUTIL_{pim'} = \max_{m \in \Psi} PRODUTIL_{pim}$, where $p \in P$ and $i \in \Theta$.

$$\text{If } PRODUTIL_{pim'} > STATUTIL_i, \text{ then } SOC_{pi} = 1,$$

else $SOC_{pi} = 0$, $p \in P$, $i \in \Theta$.

The number of customers of each candidate product line is stored in matrix $TOTAL\_SOC_M$, that can be computed as follows:

$$TOTAL\_SOC_p = \sum_{i \in \Theta} SOC_{pi}, \text{ where } p \in P.$$

The expected share of choices that is maintained in matrix $TOTAL\_SOC_M$ is used for the fitness evaluation of the population elements.

Selection method

40% of the elements of the new population are reproduced using the selection method described next. The selection method reproduces candidate solutions according to their expected share of choices. The elitist strategy is used in order ensure that the best population element will survive from the current generation to the next generation. In particular, the (4/10)M best candidate product lines are chosen to survive in the next population. The selection method strives to remain population diversity. For this reason, if there are similar population elements, only one of them can be reproduced.

Crossover operator

40% of the elements of the new population are generated using the uniform crossover operator. From the population elements reproduced using the above selection method (2/10)M pairs of parents are randomly selected. The selected pairs of parents are combined to produce (4/10)M children. Consider two population elements that are selected to be a pair of parents to produce two children. The uniform crossover operator decides randomly for each attribute of each item of the product line which parent contributes its attribute level to which child.

Mutation operator

20% of the elements of the new population are generated using mutation. The mutation operator picks randomly (2/10)M population elements from the set of the (8/10)M elements which were reproduced using the selection method and created using the crossover operator. The value at a random string position of each product line is randomly alterated.

Stopping condition

The EA terminates when the best candidate solution doesn't improve in the last 20 consecutive generations.

It follows a formal description of the proposed EA based method.
Initial population generation
Repeat
Fitness evaluation using the share of choices criterion
Selection using an elitist strategy and maintaining the population diversity
Uniform crossover
Mutation
Until the stopping condition is satisfied.

4. Computational Results

A computational study has been performed in order to compare the proposed EA based method to the BS heuristic method. Neither the proposed EA based method nor the BS method guarantees the optimal solution. The purpose of the computational study is to compare the quality of the solutions found by the different methods. Also, it aims to compare the computational time of the above solution methods.

Computational results for 12 different problem sizes are presented. In order to generate the 12 different problem sizes different values were given to the number of items of the product line (PN=2, 3), the number of attributes (K=8, 9) and the number of attribute levels (J=2, 3, 4). The number of consumers was set equal to 100, that is I=100. For each problem size the number of possible products and the number of possible product lines are presented in table 1.

Table 1. The number of the possible products and the number of the possible product lines of the different problem sizes

PN	K	J	Number of possible products	Number of possible product lines
2	8	2	256	32640
2	8	3	6561	21520080
2	8	4	65536	2147450880
2	9	2	512	130816
2	9	3	19683	193700403
2	9	4	262144	34359607296
3	8	2	256	2763520
3	8	3	6561	47050068240
3	8	4	65536	46910348656640
3	9	2	512	22238720
3	9	3	19683	1270739210481
3	9	4	262144	3002365391929340

In the implementation of the EA the population size was set equal to 150, that is M=150. The EA terminates, when in 20 consecutive generations the best candidate solution doesn't improve. In some cases the results of the EA can be improved by increasing the population size or by setting a more strict stopping condition. However, the population size and the stopping condition, that have been used in the computational study, seem to perform good for the problem sizes examined.

For each problem size 10 problem instances are randomly generated. The 120 test problem instances have been solved using the BS heuristic method and the proposed EA based method. In the test problem instances the part-worths were generated randomly from a uniform distribution and normalized within respondent. The normalized part worths are assumed interpersonally comparable. It is assumed that before the introduction of the new product line three products offered by competitors are available in the market.

The complete enumeration method guarantees the optimal solution. However, it is impossible to use the complete enumeration method to solve large sized problems, because the product line design problem is NP-Hard. For that reason, in the computational study only relative small problems have been solved using the complete enumeration method.

The implementation was done using the programming language Borland C++ 5.02. The computational tests were carried out on a PC with a Pentium Processor (64 MB RAM, 350 MHz, using Windows 95).

The researchers, who developed the BS heuristic method, suggest computing the beam width by $b = \min(14, 4\left\lceil \frac{K}{4} \right\rceil + \left\lfloor \frac{j^2}{2} \right\rfloor)$, *where* $j = \frac{\sum_{k \in \Theta} J_k}{K}$. This suggestion has been followed in the computational study performed in the present paper.

Table 2. Computational results of the Enumeration method, the BS method and the proposed EA

PN	K	J	Mean CPU time of the Enumeration method (sec)	Mean CPU time of the BS method (sec)	Mean CPU time of the EA (sec)	Average number of generations of the EA
2	8	2	2,75	0,52	1,12	29,10
2	8	3	1757,53	0,84	1,41	41,20
2	8	4	*	2,35	1,57	46,40
2	9	2	10,51	1,15	1,22	31,60
2	9	3	*	1,25	1,46	42,50
2	9	4	*	2,38	1,72	46,20
3	8	2	287,27	0,67	1,52	37,60
3	8	3	*	1,12	2,12	58,90
3	8	4	*	4,04	2,31	62,20
3	9	2	2557,33	1,71	1,93	50,10
3	9	3	*	1,91	2,29	59,90
3	9	4	*	4,10	2,46	64,80

For each problem size the mean CPU time of the complete enumeration method, the BS method and the EA were computed. Also the average number of generations of the EA were computed. These computational results are presented in table 2. As mentioned earlier, only some problems have been solved using the complete enumeration method. For the other problem sizes in the columns referring to the complete enumeration method the symbol “*” is used. As expected, the results show that the CPU time of the complete enumeration method increases with problem size dramatically. On the contrary, the CPU time of the EA increases with problem size in a reasonable manner. For example, for the problem size PN=3, K=9 and J=4, the complete enumeration method needs some thousand of years to solve a problem instance, while the proposed EA needs only some seconds. It is obvious, that the EA can solve within reasonable CPU time real sized problems. Also, the CPU time of the BS method is reasonable.

It is very important to compare the solutions found by the BS method and the EA based method. For the relative small problem sizes the number of cases, where the BS method and the EA find the optimal solution have been computed. Also, the number of cases, where the solution found by the BS method and the EA is greater than the 95% of the optimal solution have been computed. Moreover, for each problem size the number of cases, where one of the methods finds a better solution than that found by the other is computed. These results are shown in table 3. It is obvious, that the EA finds better solutions than that found by the BS method in comparable times. In the 62% of the cases examined, the EA finds the optimal solution, while only in the 32% of the cases the BS method finds the optimal solution. Also, in the 98% of the cases examined the solution found by the EA is greater than the 95% of the optimal solution, while the respective percent for the BS method is 88%. As shown in the last two columns of table 3, in the 65% of the cases examined, the EA finds a better solution than that found by the BS method, while only in the 12,5% of the cases the BS method finds a better solution.

Table 3. Comparative results of the solutions of the BS method and the proposed EA

PN	K	J	BS=OPT.	BS>95% OPT.	EA=OPT.	EA>95% OPT.	BS>EA	EA>BS
2	8	2	6	10	9	10	1	4
2	8	3	3	7	4	9	1	6
2	8	4	*	*	*	*	3	7
2	9	2	6	10	8	10	1	3
2	9	3	*	*	*	*	2	6
2	9	4	*	*	*	*	2	6
3	8	2	1	9	5	10	0	6
3	8	3	*	*	*	*	0	8
3	8	4	*	*	*	*	1	9
3	9	2	0	8	5	10	0	9
3	9	3	*	*	*	*	1	7
3	9	4	*	*	*	*	3	7
AVERAGE			32%	88%	62%	98%	12,5%	65%

It is obvious, that the EA presented in the current paper is superior to the BS method concerning the solution quality. Also, the EA can find good solutions for real sized problems within reasonable computation time. Consequently, the proposed EA is an applicable solution method for the product line design problem using the share of choices criterion.

5. Conclusions

The current paper proposed the use and presented the advantages of an EA based method for solving the product line design problem using the share of choices criterion.

Today's managers are faced with a rapidly changing and highly competitive marketing environment. Many efforts have been made in marketing to take advantage of the opportunities offered by modern information technology and information systems. Information systems offer new ways for improving the effectiveness of marketing. In the last three decades many authors proposed models for marketing information systems [22]. Marketing Decision Support Systems (MDSSs) are a very important category of the marketing information systems. MDSSs act as consultants for marketing managers. An MDSS can be defined as "a coordinated collection of data, models, analytic tools and computing power by which an organization gathers information from the environment and turns it into a basis for action" [19].

Many problems in marketing can not be solved by using exact algorithms and we are forced to use heuristic methods. By definition heuristic methods can not guarantee optimal solutions. Also, in marketing the available computational methods can not replace the individuals insights, which play a key role in creative marketing decisions, but they can assist the manager's decision making process. For these reasons, it is very helpful for a marketing manager to use an MDSS that provides to him more than one different heuristic methods.

Because the product line design problem is NP-hard, we are forced to use heuristic methods. The proposed EA does not guarantee optimality. However, the results of the computational study show, that the proposed EA can find near optimal solutions within reasonable computation time. Also, the EA outperforms the BS method concerning the solution quality. Furthermore, the first population of the EA based method can be generated by using solutions obtained by other heuristic methods.

It is obvious, that the proposed EA can be used in the model base of an MDSS for the product line design problem. The parameters of the EA used in the computational study seem to perform well for real-sized problems. Consequently, they can be used as default parameters in an MDSS. However, an MDSS can allow the users, which are familiar with EA models, to adjust the parameters.

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