



## Product Positioning Using a Self-Organizing Map and the Rings of Influence\*

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### ABSTRACT

In this article, we propose a new product positioning method based on the neural network methodology of a self-organizing map. The method incorporates the concept of rings of influence, where a firm evaluates individual consumers and decides on the intensity to pursue a consumer, based on the probability that this consumer will purchase a competing product. The method has several advantages over earlier work. First, no limitations are imposed on the number of competing products and second, the method can position multiple products in multiple market segments. Using simulations, we compare the new product positioning method with a quasi-Newton method and find that the new method always approaches the best solution obtained by the quasi-Newton method. The quasi-Newton method, however, is dependent on the initial positions of the new products, with the majority of cases ending in a local optimum. Furthermore, the computational time required by the quasi-Newton method increases exponentially, while the time required by the new method is small and remains almost unchanged, when the number of new products positioned increases. We also compute the expected utility that a firm will provide consumers by offering its products. We show that as the intensity with which a firm pursues consumers increases, the new method results in near-optimal solutions in terms of market share, but with higher expected utility provided to consumers when compared to that obtained by a quasi-Newton method. Thus, the new method can serve as a managerial decision-making tool to compare the short-term market share objective with the long-term expected utility that a firm will provide to consumers, when it positions its products and intensifies its effort to attract consumers away from competition. [Submitted: March 28, 2011. Revised: February 1, 2012; June 21, 2012. Accepted: July 3, 2012.]

***Subject Areas: Competition, Kohonen's Self-Organizing Map, Probabilistic Choice Models, Product Design/Planning, and Product Positioning.***

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## INTRODUCTION

The effort to acquire new customers takes many forms, one of which can be the positioning of new products or the repositioning of existing ones. New product introduction is considered in the contemporary business world as an important activity that sustains a firm's competitive advantage and profitability (Bayus, Erickson, & Jacobson, 2003). Kekre and Srinivasan (1990) show that when a firm offers more new products, thus making its product line broader, the result is an increase in its market share. In addition, product repositioning or redesigning a firm's existing products is also considered an activity aimed at maintaining market position.

Introducing a new product or redesigning an existing one implies that a firm must select the product's characteristics or physical features that best meet the needs of consumers in the targeted market segment. Kaul and Rao (1995, p. 299) define product positioning as the problem of "selecting product attribute levels to maximize a firm's objectives." Product attributes are abstract dimensions that characterize the perceptions that consumers have on a product. Shocker and Srinivasan (1974) refer to such attributes as "wants satisfiers." For example, attributes such as sweetness, carbonation level, and taste can be considered for soft drinks (Srinivasan, 1975). Attributes for a yogurt could be color, sweetness, and consistency of texture. Attributes for durable DVDs could be the quality of the picture and sound, versatility, and size or weight. Conjoint analysis and other market research techniques have typically been used to identify these attributes.

Due to its importance, product positioning is an area in the marketing literature that has received a great deal of attention. The origins of the analytical research on product positioning are traced back to Shocker and Srinivasan (1974) who represented products and consumer preferences as points in a joint attribute space (Carroll, 1972). In this framework, the dimensions of the attribute space represent the various product features and each consumer is associated with a vector in the attribute space which represents his/her most preferred product features. This vector is referred to as the consumer *ideal point*. The objective is to position a product in the attribute space so that it is closer to the preferences (ideal points) of a larger number of consumers, or in general, maximizes the firm's objective. Shocker and Srinivasan (1974) modeled the distance between the location of the product and the consumer ideal points as a weighted Euclidean distance. Their framework and all subsequent work that is based on their work, assumes that as the distance between the proposed location of the product in the joint attribute space and the consumer ideal point decreases, the consumer's propensity to buy the product increases.

When more than one product is to be introduced in the market, the problem of identifying the attributes of products is also known as the product line design or product line optimization problem. Whether identifying the attribute levels for a single or multiple products, the problem is characterized as an NP-hard problem (Kohli & Krishnamurthi, 1987) and can not be solved using a polynomial-type algorithm. Hauser (2011) provides a discussion on the complexity of the product line design problem. The primary reason for this complexity stems from the fact that product attributes are often discrete, resulting in an exponential number of

combinations of potential products. The product line design problem becomes more complex when competing products and reactions to entry are incorporated. A number of researchers stress that competition and reactions to entry in product positioning is an area of work that requires further investigation when one or more products are positioned (Belloni, Freund, Selove, & Simester, 2008; Wang, Camm, & Curry, 2009; Hauser, 2011). For example, Belloni et al. (2008) examined a problem with five products, nine product features, and preselected prices that resulted in  $5 \times 10^{15}$  potential products. A complete evaluation of all solutions would require 5,000 years. However, using discrete optimization methods that combine Lagrangian relaxation and branch-and-bound, they solved the problem after 1 week of computation time. This indeed illustrates the complexity of the problem, especially when the number of products in the product line increases. They compared the performance of various solution techniques of the product line design problem for a single product. Simulated annealing and a genetic algorithm obtained near-optimal solutions in reasonable time.

Green and Krieger (1985) classified methods for solving the product line design problem according to two prevalent data collection and consumer preference formation techniques, namely multidimensional scaling and conjoint analysis. Work on product positioning using multidimensional scaling has been carried out by Albers (1979, 1982), Albers and Brockhoff (1977, 1980), Gavish, Horsky, and Srikanth (1983), Sudharshan, May, and Gruca (1988), and Sudharshan, May, and Shocker (1987). Conjoint analysis procedures have been proposed by Zufryden (1977, 1979), Green, Carrol, and Coldberg (1981), Green and Krieger (1985), Dobson and Kalish (1985), Kohli and Krishnamurti (1987), Shi, Olafsson, and Chen, (2001), Camm, Cochran, Curry, and Kannan, (2006), and Wang et al. (2009).

Subsequent work by Bachem and Simon (1981), Moorthy (1988), Choi, Desabro, and Harker (1990), Raman and Chhajer (1995), Hadjinicola (1999), and Tyagi (2000) also incorporated production costs in the product positioning problem. Furthermore, work on product positioning has also been done using economic modeling, which is based on the seminal work by Hotelling (1929). This work provides directional implications on the product positioning problem (Hauser & Shugan, 1983; Hauser, 1988; Carpenter, 1989; Choi, et al. 1990; Hauser & Simmie, 1991; Eliashberg & Manrai, 1992; Ansari, Economides, & Ghosh, 1994; Baier & Gaul, 1999; Kim & Chhajer, 2002; Hadjinicola & Kumar, 2007; Luo, Kannan, & Ratchford, 2007; Sajeesh & Raju, 2010).

Work on product line design has also attempted to link the marketing and engineering functions because the resulting product features selected by the product positioning methodologies are often unrealistic or too costly to produce (Luo, 2011; Michalek, Ebbes, Adiguzel, Feinberg, & Papalambros, 2011). Luo, Kannan, Besharati, and Azarm (2005) presented a framework for new product development that links the marketing and engineering functions when there is variability in consumer preferences and variability in the conditions that the product is used.

Work on product positioning and pricing has also appeared in the literature. Belloni et al. (2008) used seven price levels for the potential products and derived parts—worth for each feature. Michalek et al. (2011) incorporated price and product attributes in the function that captures the probability for a consumer to select the new product offered by a firm. Chen & Hausman (2000) considered a finite set

of candidate products whose attributes are already known. Schon (2010) referred to this problem as the product line selection problem. Consumers declare their utility for these products for a number of price options. Using this information, the optimal product and pricing policy is obtained. This approach reduces the complexity of the product line design problem by making the number of potential product finite. This raises the question as to which products should be the candidate products and what the criteria for their selection should be. This leads back to the problem that the product line design problem tries to address. Another drawback is that asking consumers about their utilities for each candidate product for each price level may not be feasible for large problems. Schon (2010) extended the work by Chen and Hausman (2000) by considering multiple heterogeneous consumer segments.

Despite the presence of applications of product positioning methods (Hauser & Shugan, 1983; Green & Krieger, 1989, 1992; Baier & Gaul, 1999; Rhim & Cooper, 2005; Belloni et al., 2008; Tsafarakis, Marinakis, & Matsatsinis, 2011), some criticism has been exercised by practicing managers. Managers require these methods to serve as decision-making tools to guide them to directions where new products should be positioned rather than focusing on the mathematical accuracy and the algorithmic efficiency. Dodson and Brodsky (1987, p. 203) state that “the power behind using product space maps comes not from generating the precise optimal position of a new product, but from an ability to help define the competitive frame and generate general zones of interest.”

In this article, we present a new product positioning method that is based on the neural network approach of a self-organizing map (SOM) proposed by Kohonen (1990). We also incorporate the concept of rings of influence (ROINF) to capture the intensity with which a firm pursues consumers away from competition. The battleground is staged for consumers whose probability of purchasing a competitor’s product is greater than the probability of purchasing a firm’s product(s). The ROINF are formed from two threshold values. If the probability that a consumer purchases a competitor’s product is greater than the first threshold value, a firm chooses not to adjust its products to meet the needs of this consumer, as this consumer may be considered “locked” by competition. On the other hand, if the probability that a consumer purchases a competitor’s product is less than a second threshold value, a firm chooses to fully consider this consumer’s preferences when positioning its products, as this consumer may be attracted away from competition. Consumers whose probability of purchasing a competitor’s product lies between the two threshold values are pursued by the firm with less intensity. These threshold values are set by the management of a firm and they define the intensity with which a firm wishes to pursue consumers away from competition.

Our article makes several contributions. First, in the new product positioning method we combine the algorithmic steps of a SOM with the ROINF, which guide the updating process. Second, the method can position multiple products in multiple market segments in the presence of multiple competing products. Third, the method obtains near-optimal solutions at all times, as compared with a quasi-Newton method that in the majority of cases gets trapped in local maxima. The computational time required by the new method is small and remains almost unchanged when the number of new products positioned increases, whereas the

time required by a quasi-Newton method increases exponentially. Fourth, we also compute the expected utility that a firm will provide consumers by offering its products. We show that as the intensity with which a firm pursues consumers increases, the new product positioning method results in near-optimal solutions, in terms of market share, but with higher expected utility provided to consumers than a quasi-Newton method. Thus, the new method can serve as a managerial decision-making tool to compare the short-term market share objective with the long-term expected utility that a firm will provide consumers, when it positions its products and intensifies its effort to attract consumers away from competition.

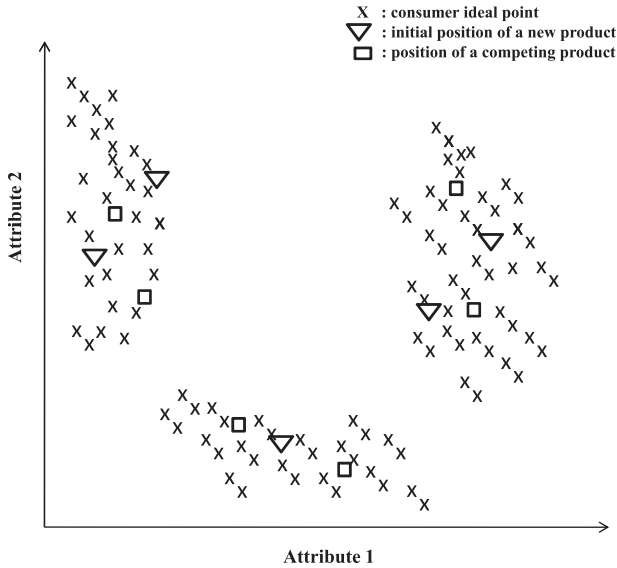
The organization of the article is as follows. We present the product positioning method, followed by numerical examples of the new method and comparisons of the solutions obtained by the method and those obtained by a quasi-Newton method. Finally, we make concluding remarks and provide directions for future research.

## PRODUCT POSITIONING METHOD

The product positioning method presented in this article is based on the artificial neural network architecture of a SOM, which was proposed by Kohonen (1981). The logic behind a SOM is based on the fact that specific parts of the brain respond to various stimuli or sensory signals. In a way, the part of the brain responding to the specific stimulus stores the *map* of the stimulus. For example, in the area of the brain responsible for a person's vision, there are line orientation and color maps, whereas in the auditory area there are maps associated with various pitches of tones (Kohonen, 1990). When the stimulus of a particular color is observed, specific cell areas of the brain respond and exhibit activity. This way, neighboring cells in the brain develop adaptively into specific detectors of different signal patterns. An SOM tries to imitate this localization of the brain functions by having specific artificial neurons tuned to various input signal patterns or classes of patterns through a competitive learning process (also called an unsupervised or self-organizing learning process). More information on the topic can be found in Kohonen (1990, 1995). SOM has been used as a decision-making tool in business-related problems such as market segmentation (Hanafizadeh & Mirzazadeh, 2011) and group technology (Kiang, Kulkarni, & Tam, 1995; Chattopadhyay, Dan, & Majumdar, 2012).

To apply the SOM algorithm in product positioning, we need to introduce in the steps of the algorithm a number of elements to accommodate marketing concepts and objectives, as well as the presence of competition. To better illustrate the intuition behind an SOM and how it is related to the product positioning problem, consider Figure 1. The figure shows a two-dimensional attribute space that includes the coordinates of consumer ideal points, the positions of competing products in the attribute space as perceived by consumers, and the initial positions of the new products to be introduced in the market by a firm. The new products to be introduced in the market would correspond to the neurons of an SOM and the consumer ideal points would correspond to the input signals. The objective of the product positioning method is to locate the new products in the attribute space

**Figure 1:** A two-dimensional attribute space that includes consumer ideal points, competitor products, and the initial positions of the new products to be positioned by a firm.



in order to maximize an objective function, for example, the market share derived from positioning the new products.

The product positioning method consists of two major phases. During Phase 1, the initial positions of the new products are extracted and serve as a seed for Phase 2, during which the final positions of the new products are obtained. Phase 1 of the method follows exactly the algorithmic steps of an SOM proposed by Kohonen (1981). During the first step in Phase 1 the new products are given random positions/coordinates in the attribute space. Furthermore, for each new product we define its neighborhood, which includes a set of other neighboring new products. This is the most important characteristic of competitive learning, where during the learning or updating process, products are not updated independently from one another, but are updated in topologically related subsets. In other words, during the learning process, products that are “close” to each other are updated according to some predefined rule. This way, we emulate the phenomenon occurring in the brain where neighboring cells are activated when a specific stimulus is observed.

During the second step of Phase 1, we randomly select a consumer ideal point and compute its distance from the new products. The winner product or best matching product is the new product that has the minimum distance from this consumer ideal point. This winner product and all products in its neighborhood are moved/updated to match even more closely the consumer’s ideal point. New products outside the neighborhood are not moved. Then, the next random consumer

ideal point is selected and the process is repeated until all consumer ideal points have been used. When all consumer ideal points have been used, the method has gone through an epoch. During the third step of Phase 1, we check the stopping criterion, which, for example, can be a specified number of epochs. Finally, in the fourth step of Phase 1, the neighborhood size is decreased in order to fine-tune the positions of the new products. Note that in this phase, the initial positions are obtained without considering the positions of competing products.

During Phase 2 of the product positioning method, we use the seed positions of the new products obtained earlier in Phase 1 to extract the final new product positions. The steps of Phase 2 follow the algorithmic steps of an SOM, with the updating process complemented with the concept of ROINF to handle the presence of competition. However, during Phase 2, we do not use the concept of a neighborhood in the updating process.

### Definitions and Objective Function

We define  $\mathbf{x}_i = [x_{i1}, x_{i2}, \dots, x_{iL}]^T \in R^L, i = 1, 2, \dots, K$ , to be the ideal point of consumer  $i$ . Note that there are  $K$  consumers in the market and that the products have  $L$  attributes. We assume that in the short-term, consumer ideal points remain unchanged. In addition, we define  $\mathbf{m}_j(t) = [m_{j1}(t), m_{j2}(t), \dots, m_{jL}(t)]^T \in R^L$ , where  $j = 1, 2, \dots, M$ , to be the coordinates of new product  $j$  in the attribute space at period  $t$  of the iterative product positioning method ( $t = 0, 1, 2, \dots, t_{\max}$ ).

We also define  $\mathbf{c}_q = [c_{q1}, c_{q2}, \dots, c_{qL}]^T \in R^L, q = 1, 2, \dots, Q$ , to be the perceived position of competitor product  $q$  in the attribute space. Every consumer forms his/her perception on each dimension of the attribute space for every product available. This results in vectors of perceptions for each consumer for each competing product. In our analysis, we represent the perceptual position that consumers have for a competing product with the vector containing the means of the consumers' perceptions on each dimension of the attribute space. The same assumption has been used in the majority of the product positioning studies, whether approaching the problem from the modeling or algorithmic point of view.

Let  $U_{ij}(t) = g(\|\mathbf{x}_i - \mathbf{m}_j(t)\|)$  represent the utility derived by consumer  $i$  from new product  $j$  at time  $t$  of the method. The utility is a function of a distance norm between the consumer's ideal point  $\mathbf{x}_i$  and new product  $\mathbf{m}_j(t)$ . Following the principles of classic economic theory, it is implied that  $U_{ij}$  increases when  $\|\mathbf{x}_i - \mathbf{m}_j(t)\|$  decreases. Let  $P_{ij}(t) = f(U_{ij}(t))$  be the probability that consumer  $i$  purchases new product  $j$  at point in time  $t$  of the method. Similarly, let  $U_{iq}(t) = g(\|\mathbf{x}_i - \mathbf{c}_q\|)$  represent the utility derived by consumer  $i$  from competitor product  $q$  and  $P_{iq}(t) = f(U_{iq}(t))$  be the probability that consumer  $i$  purchases competing product  $q$ .

Single-choice or deterministic models and multichoice or probabilistic models (Corstjens & Gautschi, 1983; McFadden, 1986; Sudharshan et al., 1988) have been used to capture the probability that a consumer purchases a product. Under the single-choice model, consumers buy the product which is closest to their most preferred product (their ideal point) or in general, they buy the product that maximizes their utility. In probabilistic choice models, each consumer assigns a probability of being purchased to each product belonging to his/her set of known

products. In general, this probability increases when the distance between the consumer ideal point and the position of the product in the joint attribute space decreases. Aggregation over all consumers of these probabilities for a particular product, results in the expected number of units of this product to be sold by a firm.

In the product positioning literature, single-choice models capturing consumer choice have been used by Shocker and Srinivasan (1974), Albers (1979, 1982), Zufryden (1979), Gavish et al. (1983), Camm et al. (2006), Wang et al. (2009), and Michalek et al. (2011). Kaul and Rao (1995, p. 307) state that single-choice models “fail to account for variation in choices made by consumers in the actual marketplace (e.g., choosing different brands on different choice occasions).” Other studies by Pessemier, Burger, Teach, and Tigert (1971), Shocker and Srinivasan (1974, 1979), and Sudharshan et al. (1987, 1988) also argue that probabilistic choice models are more realistic.

In this article, we use the probabilistic choice framework, where each product carries some probability of being purchased by a consumer. Subsequently in the article we present typical functions of such probabilities that have been used in the literature. The method presented in this article can also accommodate single-choice models.

The probability that consumer  $i$  will purchase any of the  $M$  new products to be offered by a firm is equal to  $\sum_{j=1}^M P_{ij}(U_{ij}(t))$ . Aggregating over all consumers, we obtain the total number of new products to be purchased. This is equivalent to the share-of-choice objective function that is frequently used in product line design methods (Wang et al., 2009; Tsafarakis et al., 2011). The mathematical formulation of this product positioning problem is as follows:

$$\max_{\mathbf{m}_j(t)} \sum_{i=1}^K \sum_{j=1}^M P_{ij}(U_{ij}(t)). \quad (1)$$

A profit maximization can also be used, however, a number of factors need to be taken into account. First, the dynamic gaming nature of product positioning must be considered. That is, are competing firms allowed to change product positions and prices upon entry? This points to the literature of defensive marketing strategies (Hauser & Shugan, 1983). Hadjinicola and Kumar (2007) show that when the number of firms and products in the market increase, the new static Nash equilibrium forces firms to reposition their products closer to the mean ideal point of the market segment and reduce their prices. In addition, in these models we have variations such as allowing only prices to change to establish a new Nash equilibrium. Second, the cost of the new product needs to be considered as a function of its attributes (Hadjinicola, 1999). These issues highlight the challenges of the product positioning problem in a dynamic setting and provide directions for further research.

## Product Positioning and Competition

In the formulation presented in this article, we assume that each product carries a probability of being purchased by a consumer. As a result, in the presence of competition, a consumer may choose to purchase a competitor’s product



or purchase a new product offered by a firm, or not purchase any product. In conjoint-based product positioning approaches, competition is represented by the so called “status quo” products, which are products that consumers benchmark their choices for the new products (Zufryden, 1977).

In cases where the most preferred or winner product for a consumer is a competitor’s product, we incorporate the concept of ROINF to govern the new product updating process and determine the intensity with which a firm pursues consumers. The ROINF are formed from two threshold probability values exogenously set by a firm introducing the new products in the attribute space. These threshold values are  $\gamma$  and  $\delta$  with  $\gamma \geq \delta$ . If the probability for a consumer to purchase a competitor’s product is greater than the probability that he/she purchases any of the new products introduced by a firm, then the following three cases emerge.

In the first case, if the probability for a consumer to purchase a competitor’s product is greater than the threshold value  $\gamma$ , then no updating of the new products is performed. The logic behind this step is that the positioning method will not move the new products closer to consumers that are in a way locked by a competing product. In other words, no effort is exerted to capture consumers that are more likely to buy an existing product offered by a competitor.

In the second case, if the probability for a consumer to purchase a competitor’s product is between the two threshold values  $\delta$  and  $\gamma$ , the method identifies a new winning product only among the new products introduced by a firm. Then, updating of the winning product and all other new products is performed using a factor  $\beta$ , where  $0 < \beta \leq 1$ , which represents the intensity with which a firm pursues consumers. In other words, some effort is made to move the new products closer to this consumer, however, given that this consumer has a high probability of purchasing a competing product, the effort exerted is discounted by the factor  $\beta$ . As factor  $\beta$  approaches 1, a firm introducing new products in the attribute space exerts more effort to capture this consumer from competition.

Finally, in the third case, if the probability for a consumer to purchase a competitor’s product is less than the threshold value  $\delta$ , the method again identifies a new winning product only among the new products introduced by a firm. Then, the winning product and all the other new products are moved closer to the consumer ideal point without using any discount factor. In this case, a firm, through the updating process, exerts the maximum effort to satisfy this consumer by moving all new products closer to his/her ideal point. In other words, a firm is very interested in this consumer.

The concept of ROINF can be traced in consumer choice models. Bachem and Simon (1981) describe a consumer buying behavior framework in which they hypothesize that during the product evaluation process, consumers will behave in one of three ways, depending on the distance of their ideal point to the position of the product in the attribute space. Under the first case, a consumer purchases a product with probability 1 if the distance is less than some lower threshold value. In the second case, a consumer will not purchase a product if the distance is greater than an upper threshold value. Finally, in the third case, products whose distance from the consumer ideal point lies between the lower and the upper threshold values carry some probability of being purchased. This decision-making rule was later used in studies by Sudharshan et al. (1987, 1988).

## Phases of the Product Positioning Method

We will now present the two phases and the algorithmic steps of the new product positioning method. Let  $C$  denote the set of products belonging to competitors and  $F$  denote the set of new products to be positioned in the attribute space by a firm.

**Phase 1:** Perform steps 1.1–1.4.

**Step 1.1:** Perform steps 1.1.1–1.1.4.

- 1.1.1 Set the initial values of  $\mathbf{m}_j(t)$ ,  $j = 1, 2, \dots, M$ , that is, set  $\mathbf{m}_j(0)$ .
- 1.1.2 Set the initial radius of the neighborhood  $N_j(t)$  of new product  $j$ , that is, set  $N_j(0)$ .
- 1.1.3 Set the initial learning rate  $\alpha(t)$ , that is, set  $\alpha(0)$ .
- 1.1.4 Randomize the order of the vectors of consumer ideal points and assign an index to them to create the random sequence of  $\mathbf{x}_i$ ,  $i = 1, \dots, K$ .

**Step 1.2:** While the stopping condition is false, perform steps 1.3 and 1.4, otherwise set  $\mathbf{ini}_j = \mathbf{m}_j(t)$ , for  $j = 1, \dots, M$ , and go to Phase 2.

**Step 1.3:** For each consumer ideal point  $\mathbf{x}_i$ ,  $i = 1, 2, \dots, K$ , perform the steps below:

- 1.3.1 Determine the winner product  $\mathbf{w}_i^*(t)$  from  $F$  for consumer ideal point  $\mathbf{x}_i$ , such that  $\|\mathbf{x}_i - \mathbf{w}_i^*(t)\| = \min_{j=1, \dots, M} \{\|\mathbf{x}_i - \mathbf{m}_j(t)\|\}$ .
- 1.3.2 Identify all products that belong in the neighborhood  $N_i^*(t)$  of winner product  $\mathbf{w}_i^*(t)$ .
- 1.3.3 Update the new product vectors as follows:

$$\mathbf{m}_j(t+1) = \begin{cases} \mathbf{m}_j(t) + \alpha(t)[\mathbf{x}_i - \mathbf{m}_j(t)] & \text{if } j \in N_i^*(t), \\ \mathbf{m}_j(t) & \text{if } j \notin N_i^*(t). \end{cases}$$

**Step 1.4:** Perform steps 1.4.1–1.4.3.

- 1.4.1 Compute the new value of the learning rate for  $t + 1$ , that is, compute  $\alpha(t + 1)$ .
- 1.4.2 Reduce the size of the neighborhood radius.
- 1.4.3 Go to step 1.2.

**Phase 2:** Perform steps 2.1–2.4.

**Step 2.1:** Perform steps 2.1.1–2.1.2.

- 2.1.1 Set the initial values of  $\mathbf{m}_j(0) = \mathbf{ini}_j$ ,  $j = 1, 2, \dots, M$ .
- 2.1.2 Set the initial learning rate  $\alpha(t)$ , that is, set  $\alpha(0)$ .

**Step 2.2:** While the stopping condition is false, perform steps 2.3 and 2.4, otherwise stop.

**Step 2.3:** For each consumer ideal point  $\mathbf{x}_i$ ,  $i = 1, 2, \dots, K$ , perform steps 2.3.1–2.3.4.

- 2.3.1 Determine the winner product  $\mathbf{w}_i^*(t)$  from  $F \cup C$  for consumer ideal point  $\mathbf{x}_i$ , such that  $P_i^*(U(\|\mathbf{x}_i - \mathbf{w}_i^*(t)\|)) = \max\{\max_{j=1, \dots, M} \{P_{ij}(U(\|\mathbf{x}_i - \mathbf{m}_j(t)\|))\}, \max_{q=1, \dots, Q} \{P_{iq}(U(\|\mathbf{x}_i - \mathbf{c}_q\|))\}\}$ .
- 2.3.2 If the winning product belongs to  $F$ , set  $W$  equal to the index of the winning product and go to step 2.3.4, otherwise go to step 2.3.3.
- 2.3.3 Perform steps 2.3.3.1–2.3.3.5.
  - 2.3.3.1 If  $P_i^*(t) > \gamma$ , go to step 2.3, otherwise go to step 2.3.3.2.

2.3.3.2 Determine the winner product  $\mathbf{w}_i^*(t)$  from  $F$  for consumer ideal point  $\mathbf{x}_i$  such that  $P_i^*(U[\|\mathbf{x}_i - \mathbf{w}_i^*(t)\|]) = \max_{j=1, \dots, M} \{P_{ij}(U[\|\mathbf{x}_i - \mathbf{m}_j(t)\|])\}$ .

2.3.3.3 Set  $W$  equal to the index of the winner product.

2.3.3.4 If  $\delta < P_i^*(t) \leq \gamma$ , perform steps 2.3.3.4.1–2.3.3.4.2, otherwise go to step 2.3.3.5.

2.3.3.4.1 For all  $j$ , update the new product vectors as follows:

$$\mathbf{m}_j(t + 1) = \begin{cases} \mathbf{m}_j(t) + \alpha(t)\beta P_{ij}(t)[1 - P_{ij}(t)][\mathbf{x}_i - \mathbf{m}_j(t)] & \text{if } j = W, \\ \mathbf{m}_j(t) - \alpha(t)\beta P_{ij}(t)P_{iW}(t)[\mathbf{x}_i - \mathbf{m}_j(t)] & \text{if } j \neq W. \end{cases}$$

2.3.3.4.2 Go to step 2.3.

2.3.3.5 If  $P_{ij}(t) \leq \delta$ , go to step 2.3.4.

2.3.4 Perform 2.3.4.1–2.3.4.2.

2.3.4.1 Update the new product vectors as follows:

$$\mathbf{m}_j(t + 1) = \begin{cases} \mathbf{m}_j(t) + \alpha(t)P_{ij}(t)[1 - P_{ij}(t)][\mathbf{x}_i - \mathbf{m}_j(t)] & \text{if } j = W, \\ \mathbf{m}_j(t) - \alpha(t)P_{ij}(t)P_{iW}(t)[\mathbf{x}_i - \mathbf{m}_j(t)] & \text{if } j \neq W. \end{cases}$$

2.3.4.2 Go to step 2.3.

**Step 2.4:** Perform steps 2.4.1–2.4.2.

2.4.1 Compute the new value of the learning rate for  $t + 1$ , that is, compute  $\alpha(t + 1)$ .

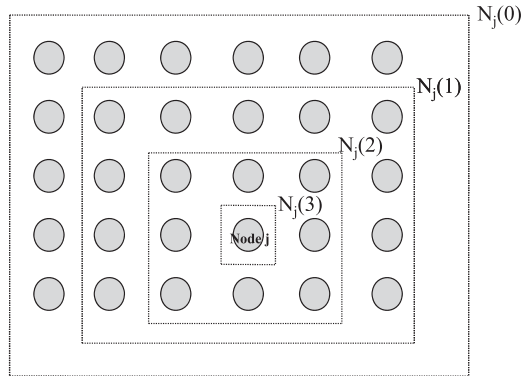
2.4.2 Go to step 2.2.

Steps 1.1.1–1.1.4 are nonrepetitive steps and are performed at the beginning of Phase 1. Step 1.1.1 provides an initial position to the new products that are represented in the joint attribute space by their vectors  $\mathbf{m}_j(t)$ . The initial positions are set within the range of the various dimensions of the joint attribute space. Setting the initial reference vector  $\mathbf{m}_j(0)$  associated with each new product  $j$  in a random way is an initialization method frequently used in an SOM (Kohonen, 1981).

Step 1.1.2 sets the initial radius of the topological neighborhood  $N_j(0)$  for new product  $j$ . The length of the radius of the neighborhood is usually time-varying; in fact, it has been shown using simulations that it is better for the radius of the neighborhood to be very wide in the beginning of the learning process and decrease monotonically with time. It is even suggested that the initial radius of the neighborhood should be more than half the diameter of the network (Kohonen, 1990). This ensures that during the initial steps of the learning process, a rough global ordering is performed which considers all consumer ideal points in the attribute space. Subsequently, as the method progresses, the radius of the neighborhood is decreased (step 1.4.2). This is done in order to make the updating process, which moves the new products closer to consumer ideal points, ignore consumers that are too far away from the new product. As such, the method refines the resolution of the new product position by considering the ideal points of consumers that are closer to the new product. Figure 2 demonstrates the rectangular time-varying topological neighborhood used in this article.

Step 1.1.3 sets the initial learning rate. Typical functions of  $\alpha(t)$  found in the SOM literature include  $\alpha(t) = \alpha(0)[1 - (t/t_{\max})]$ ,  $\alpha(t + 1) = c\alpha(t)$ , where  $0 < c < 1$ ,  $t = 1, 2, \dots, t_{\max}$ , and  $\alpha(0)$  represents the initial value of  $\alpha(t)$  at  $t = 0$ . Another function for  $\alpha(t)$  can be the geometric decreasing function  $\alpha(t) = \alpha(0)[\alpha_f/\alpha(0)]^{t/t_{\max}}$  with  $\alpha_f$  being the final value of the learning factor. The choice

**Figure 2:** Time-varying topological neighborhoods  $N_j(t)$  of new product  $j$  at times 0, 1, 2, and 3 in Phase 1 of the product positioning method.



of functions that make the learning rate smaller as the method progresses, ensures that the updating of new products toward consumer ideal points is done in smaller steps, thus refining the position of the new products.

Step 1.1.4 plays an important role in the successful application of an SOM and the product positioning method presented in this article. The order of the consumer ideal points is randomized and each ideal point in the randomized sequence is assigned an index  $i$ . The method updates the positions of the new products by using one consumer ideal point at a time. If the consumer ideal points are not randomized, the method may create patterns of new products or accumulate the new products in one segment of the market.

Steps 1.2 and 2.2 describe the stopping rule of the approach. The following two stopping rules are frequently used to terminate the method's operation: (i) reaching a prespecified number of iterations and (ii) the change in value of all elements of the vectors of the new products is less than some small value  $\epsilon$ .

Step 1.3 includes the updating process of the winner product and the products in its neighborhood. The updating process moves the products closer, in a spatial way, to the consumer ideal point under consideration. The updating process during Phase 1 of the method does not consider the presence of competing products. In other words, Phase 1 positions new products as if a firm was the only one offering products in the market. These positions serve as the seed for Phase 2 (step 2.1.1) where the final product positions are obtained.

Step 2.3 in Phase 2 includes the updating of the new product positions according to the ROINF described earlier. Step 2.3.3.1 shows the case where the new product is not moved closer to the consumer ideal point if his/her probability of purchasing a competing product is the highest and this probability is greater than threshold value  $\gamma$ . Step 2.3.3.4 shows how the new product is moved closer to the consumer ideal point if his/her probability of purchasing a competing product is the highest and this probability is between the threshold values  $\delta$  and  $\gamma$ . This is the case where a firm exerts some effort to position its products closer to the

ideal point of a consumer that prefers a competing product. The level of effort is depicted by the factor  $\beta$  in the updating step 2.3.3.4.1, where higher values of  $\beta$  indicate that a firm is moving its products closer to the consumer ideal point with a bigger step size.

In step 2.3.3.4.1, we see how the method moves the new products closer to the consumer ideal point. If we update a new product which is the winner product for the consumer under consideration, then the movement toward his/her ideal point is  $\alpha(t)\beta P_{ij}(t)[1 - P_{ij}(t)][\mathbf{x}_i - \mathbf{m}_j(t)]$ . For the rest of the new products, the movement toward his/her ideal point is  $\alpha(t)\beta P_{ij}(t)P_{iw}(t)[\mathbf{x}_i - \mathbf{m}_j(t)]$ . These movements are proportional to the first order derivatives of the multinomial logit model with respect to the position of the winner product being updated. The multinomial logit model computes the probability that a consumer will purchase a particular product. Choosing such movements (i.e., proportional to the first order derivative) is common in numerical optimization methods, such as Quasi-Newton methods.

Step 2.3.4 presents the updating of the new product when a firm exerts the maximum effort to position its product closer to a consumer ideal point. This occurs in two cases. First, when the consumer prefers a firm's new product, and second, if his/her probability of purchasing a competing product is the highest and this probability is less than the threshold value  $\delta$  (step 2.3.3.5). We use the same concept of moving the new products closer to the consumer ideal point as in step 2.3.3.4.1, but we set  $\beta = 1$  to exert the maximum effort in approaching the consumer ideal point under consideration.

The product positioning method presented in this article can also accommodate the case where a consumer considers only the closest products (Green & Krieger, 1989) or considers only products within some predefined radius. This is based on the fact that "individuals become familiar with products which are reasonably close to meeting their objectives, due to self-interest" (Sudharshan et al., 1988, p. 55).

The method presented in this article has several advantages over existing methods. First, the product preference of each individual consumer is taken into consideration during each step of the product positioning process. This allows us to consider the heterogeneity of each consumer and its impact on product positioning. Second, no limitations are imposed on the number of competing products present in the market. Third, the method can position multiple products in multiple market segments. Often, due to the complexity of the product positioning problem, existing methods examine cases with a small number of products and consumers. Fourth, the method uses probabilistic choice models where each product, including competing products, carries some probability of being purchased. Finally, the method can operate both in discrete and continuous joint attribute spaces.

## DEMONSTRATION OF THE PRODUCT POSITIONING METHOD

To demonstrate the method and obtain a visual understanding of the positioning of new products, we use examples from a two-dimensional joint attribute space. In fact, joint attribute spaces of small dimensionality are not uncommon as the number of attributes is smaller than the number of product characteristics (Kaul &

Rao, 1995). The following frequently used utility function is employed

$$U_{ij} = - \sum_{n=1}^L w_{in} [x_{in} - m_{jn}]^2, \quad (2)$$

where  $w_{in}$  represents the weight that consumer  $i$  places on product attribute  $n$ ,  $x_{in}$  is consumer's  $i$  ideal point on the  $n^{\text{th}}$  attribute dimension, and  $m_{jn}$  is the location of new product  $j$  on attribute dimension  $n$ . For the case where a consumer evaluates a competing product, we replace  $m_{jn}$  with  $c_{qn}$ , which represents the mean of the distribution of the consumer perceptions for competing product  $q$  on attribute dimension  $n$ . Kaul and Rao (1995, p. 307) point out that "product positioning models either ignore consumer heterogeneity or account for it by devising different statistical ways." The utility function presented in Equation (2) captures consumer heterogeneity at the individual level in two ways. First, through the presence of consumer ideal points and second, through the different weights consumers assign on each attribute dimension.

The multinomial logit model (Corstjens & Cautschi, 1983; McFadden, 1986) is a common modeling framework relating the utility derived by a consumer and the probability of this consumer purchasing the product. It has been widely used in estimating market shares (Cooper & Nakanishi, 1988) and also in the product positioning literature (Choi et al., 1990). Using the multinomial logit model, the probability that consumer  $i$  purchases product  $p$  is given by

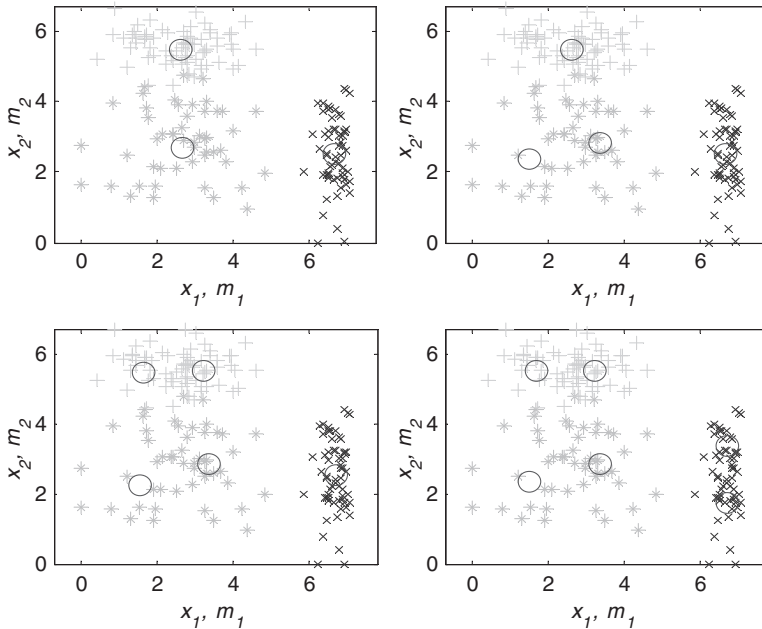
$$P_{ip} = \frac{e^{U_{ip}}}{\sum_{j=1}^M e^{U_{ij}} + \sum_{q=1}^Q e^{U_{iq}}} \quad (3)$$

The multinomial logit model is based on Luce's (1959) choice axiom postulating that the probability of a product being chosen is equal to the ratio of its utility to the sum of utilities of products in the available choice set. More discussion and extensions of the axiom can be found in Lilien, Kotler, and Moorthy (1992). Multinomial logit models have been characterized by Cooper and Nakanishi (1988) as "logically consistent" implying that the sum of all derived probabilities is equal to one. Finally, these models can also consider the no-purchase case where a consumer does not purchase a product. This is achieved by adding a constant in the denominator of Equation (3), thus making the no-purchase probability nonzero.

### Demonstration of Phase 1 of the Product Positioning Method

The new product positioning method was implemented using the software MATLAB. The learning rate function used is  $\alpha(t) = 0.1(1 - t/(t_{\max}))$ , where  $t_{\max}$  is the maximum number of iterations performed by the method. In the examples presented in this article, we set  $t_{\max} = 80$ . For Phase 1, the initial neighborhoods were chosen to have a rectangular shape and to include all new products in the topological space. The radius was decreased by one unit in each dimension of the topological space in every iteration until the neighborhood comprised only of the winning product. The initial positions of the products in Phase 1 were randomly chosen from a two-dimensional uniform distribution. The ranges of the dimensions of the uniform two-dimensional distribution are the same with the ranges of the

**Figure 3:** Applying Phase 1 of the method by positioning three, four, five, and six products in a market consisting of three market segments and in the absence of competition. Asterisks and crosses indicate consumer ideal points and circles indicate new products.



product attribute space. Furthermore, all weights  $w_{in}$  that consumer  $i$  places on product attribute  $n$  were set to one.

In Figure 3, we demonstrate the application of Phase 1 of the new product positioning method, which basically applies Kohonen’s SOM algorithm. The figure presents the positioning of three, four, five, and six products, respectively, in a market without competing products and consisting of consumers that can be grouped in three distinct segments. The function used to obtain the winner product in step 1.3.1 of the method was the absolute value of Equation (2), that is  $|U_{ij}(t)| = \sum_{n=1}^L w_{in}[x_{in} - m_{jn}(t)]^2$ . The range in which the two attributes assume their values is  $[0, 7]$ . The asterisks and crosses in these four examples, and in all subsequent examples, represent consumer ideal points, whereas the circles represent the new product(s) positioned by the product positioning method. From Figure 3, we observe that when the number of new products positioned in a market segment is increased, the positions of the new products in this segment are different from the positions of the products in the case where a smaller number of products was positioned. This occurs because as the number of new products positioned in the attribute space increases, the products are dispersed to capture as closely as possible the distribution of consumer ideal points.

This observation has also been reported by Sudharshan et al. (1988) who found that the positions of the product concepts generated sequentially are different

from those generated simultaneously. This observation has repercussions on the product policy of firms that introduce products in a sequential manner. As such, every time a new product is introduced by a firm, it causes a change in the position of existing products in the same segment, whereas the positions of products in other segments remain unchanged or are only slightly changed. This suggests that firms must carefully plan the entry of new products by analyzing the number of products they plan to introduce in the long term. The new product positioning method presented in this article can serve as a tool in that direction.

### Testing the Performance of the Product Positioning Method

In the analysis that follows, we demonstrate the product positioning method in the presence of competing products, and at the same time we investigate the effect on market share when a firm intensifies its effort to attract consumers away from competition. We also compare the solution obtained by the product positioning method with the solution obtained by the quasi-Newton method developed by Broyden, Fletcher, Goldfarb, and Shanno (BFGS method). Fletcher (1987) provides more information on this nonlinear optimization method which can obtain the optimal solution. However, depending on the initial product positions, this quasi-Newton method frequently gets trapped in local optima. The two methods are compared on a number of common market problems. Comparison of the new product positioning method with a technique that can obtain the optimal solution was considered essential because the new method does not guarantee that the solution obtained will be the optimal one. We compare the market share obtained by the two methods for each problem tested. We also compare the two methods using a utility function which is computed after the termination of the methods.

The utility function is obtained as follows. Customer  $i$  will purchase a firm's new product  $j$  with probability  $P_{ij}(U_{ij}(t))$ , and in doing so, he/she will derive utility  $U_{ij}(t)$ . Therefore, the expected utility that a firm will provide consumer  $i$  by offering its  $M$  new products is given by  $\sum_{j=1}^M P_{ij}(U_{ij}(t))U_{ij}(t)$ . Aggregating over all consumers, we obtain the total expected utility that a firm will provide consumers by offerings  $M$  new products. If a firm wishes to position its products and maximize this function, the mathematical program is given by

$$\max_{\mathbf{m}_j(t)} \sum_{i=1}^K \sum_{j=1}^M P_{ij}(U_{ij}(t))U_{ij}(t). \quad (4)$$

The objective function in Equation (4) is not commonly used in product positioning, as it is a market-centered objective instead of a firm-centered one. One may argue that, if a firm tries to position its products in order to maximize the expected utility that it provides to consumers, this will make a firm more long-term oriented. As such, we make the reasonable assumption that offering products that are more appealing to consumers will eventually have a positive impact on a firm and ensure that it remains sustainable in the long term. Furthermore, product positioning is an activity characterized by longer time horizons, and should not be used in conjunction with short-term economic objectives.

Intensification of the effort to attract consumers away from competition can be achieved in two ways. The first way is to increase the lower ROINF threshold value



$\delta$  toward the upper value  $\gamma$ . In cases where a consumer has a higher probability of purchasing a competing product and this probability is less than the threshold value  $\delta$ , a firm finds its product that is most preferred by this consumer. Then, it updates the winner product and all other new products by exerting the maximum possible effort (Steps 2.3.3.3 and 2.3.4). In other words, a firm moves its products closer to this consumer, as if his/her most preferred product belonged to the firm. As a result, increasing the minimum threshold value  $\delta$  implies that a firm tries to move its products closer to the ideal points of a larger number of consumers who prefer competing products.

Second, intensification of the effort to attract consumers away from competition can also be achieved by increasing the factor  $\beta$  toward 1. In cases where a consumer has a higher probability of purchasing a competing product and this probability is between the ROINF threshold values  $\delta$  and  $\gamma$ , a firm again identifies its product that is most preferred by this consumer. Then, it updates the winner product and all other new products by exerting some effort proportional to  $\beta$ . When  $\beta$  increases, a firm moves its products even closer to the ideal points of consumers who prefer competing products (step 2.3.3.2).

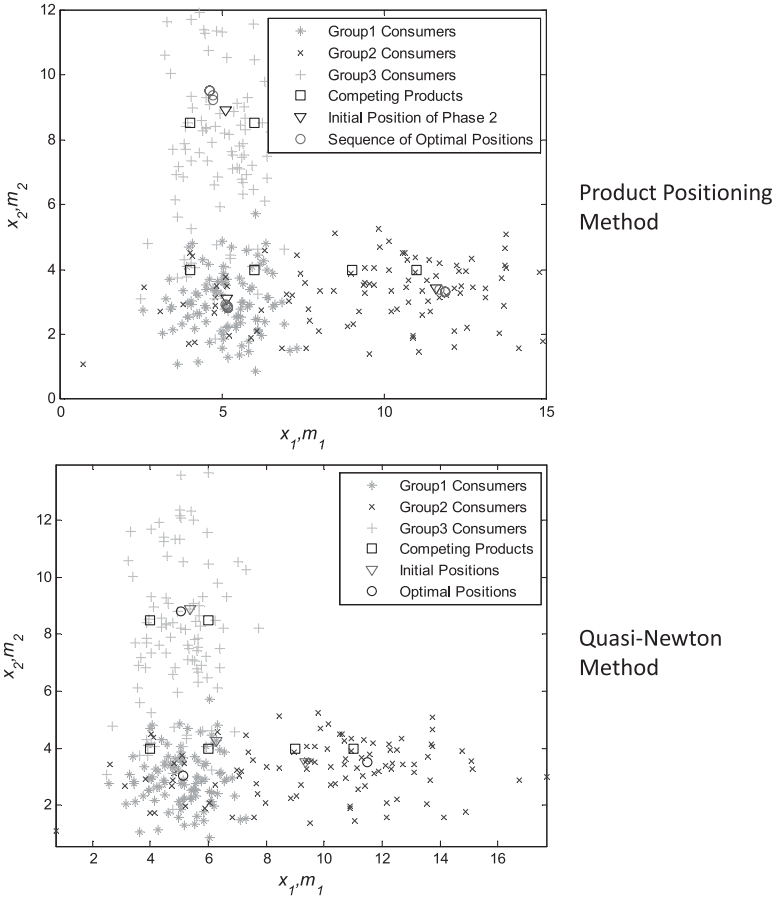
Figure 4 shows a market scenario consisting of consumer ideal points (indicated with asterisks and crosses) that can be grouped in three market segments. Each segment consists of 100 consumers, thus the maximum market share that can be obtained is 300. The market has also six competing products whose positions can be seen in the figure. The first graph in Figure 4 includes the initial product positions obtained in Phase 1 (indicated with triangles) and the final product positions of the three new products that a firm is introducing (indicated with circles). In this example we allow the minimum threshold value  $\delta$  to move toward  $\gamma$ , which indicates that a firm intensifies its effort to attract consumers away from competition.

For the creation of the first graph in Figure 4, we have set  $\gamma = 0.7$ ,  $\beta = 0.2$ , and allowed  $\delta$  to vary between 0.2 and 0.7 with increments of 0.1. For each value of  $\delta$ , the method positioned the new products which are represented by the circles. From the first graph of Figure 4, we note that as the value of  $\delta$  increases, the final positions of the new products move closer to the positions obtained in Phase 1. Note that product positions in Phase 1 were obtained without considering the presence of competition. This result is intuitive because a firm tries to approach the dominant product positions when positioning its products (Hotelling, 1929).

The second graph in Figure 4 presents the best solution obtained by the quasi-Newton method. Even though the quasi-Newton method can obtain the optimal solution, it may get trapped in local maxima, depending on the starting positions of the new products. In fact, we ran the technique with 10 different initial product positions and selected the best solution shown in the second graph. The initial product positions were randomly selected from the coordinates of the consumer ideal points. A comparison of the final product positions of the three new products obtained by the two methods shows that they have similar coordinates in the attribute space.

Figure 5 includes two graphs. The first graph shows the resulting market share of a firm when the lower threshold value  $\delta$  of the ROINF increases toward  $\gamma$ . The second graph shows the computed expected utility that a firm will provide

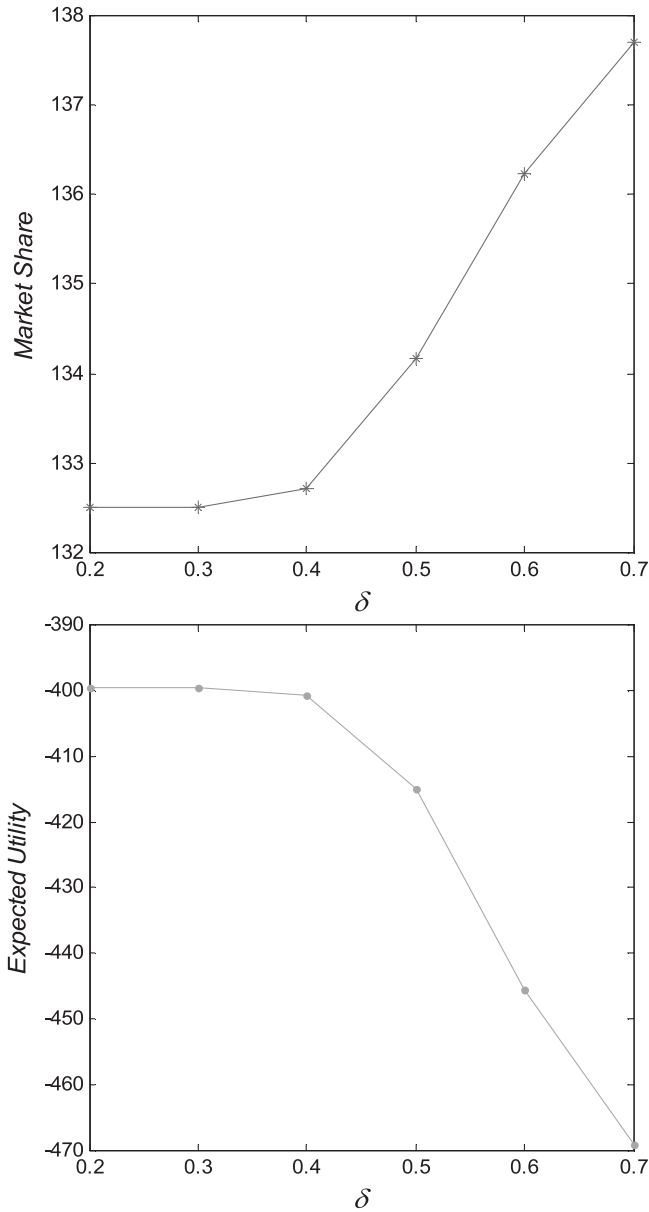
**Figure 4:** Positioning of three new products in a market with six competing products using the new product positioning method and a quasi-Newton method. For the new product method, we allow  $\delta$  to increase and for each value we obtain the new product positions.



consumers by offering its three new products when  $\delta$  changes. We observe that as a firm intensifies its effort to pursue consumers away from competition by increasing the value of  $\delta$ , its market share increases, but the expected utility a firm will provide consumers deteriorates. Given that the expected utility function in Equation (4) is negative, values closer to zero imply that a firm offers products from which consumers derive high utilities. This is an interesting result because it indicates that a firm chooses product positions that maximize its market share or its chances of capturing consumers but do not fully meet their preferences.

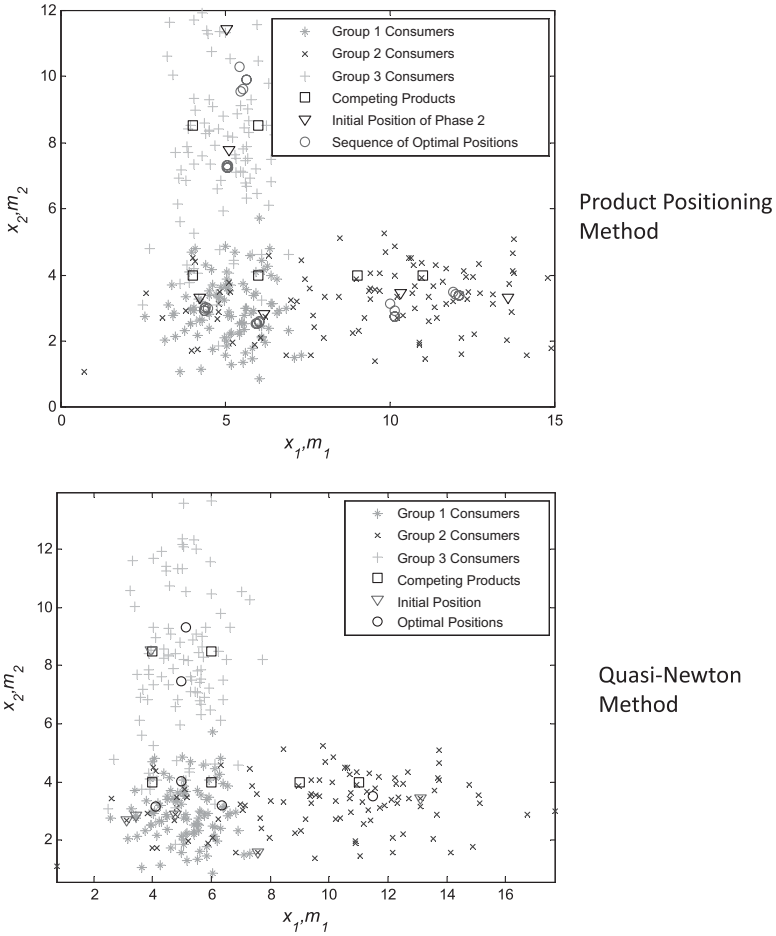
As a firm intensifies its effort to attract consumers away from competition, it is expected that its market share would increase. Therefore, why should a rationally acting firm impose constraints on its effort toward maximizing its market share,

**Figure 5:** Market share and expected utility a firm will provide consumers when the value of  $\delta$  increases for the market shown in Figure 4.



such as the ROINF, when positioning its products? The answer lies in the trade-off between the market share obtained and the expected utility a firm will provide consumers by offering its products. Figure 5 clearly shows this trade-off. A simple maximization of the market share results in product positions that satisfy the broader market, whereas the product positioning method using the ROINF allows

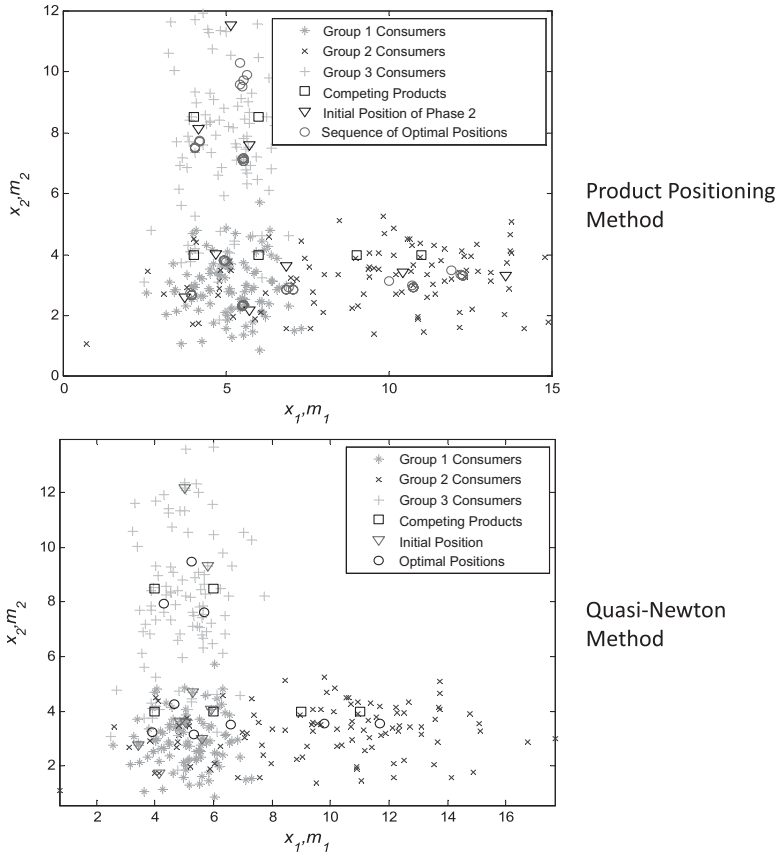
**Figure 6:** Positioning of six new products in a market with six competing products, using the new product positioning method and a quasi-Newton method. For the new product method, we allow  $\delta$  to increase and for each value we obtain the new product positions.



a firm to exploit local preferences in segments or subsegments of the market. Thus, the new product positioning method can serve as a managerial decision-making tool to compare the short-term market share objective with the long-term expected utility provided to consumers, when a firm positions its products and intensifies its effort to attract consumers from competition.

Figures 6 and 7 include the same analysis as Figure 4, when six and nine new products are positioned in the market, respectively. The market conditions are the same as in the example in Figure 4, allowing again the value of  $\delta$  to increase toward  $\gamma$ . Once again, the market share of a firm increases and the expected utility provided to consumers decreases. We also observe in the examples shown

**Figure 7:** Positioning of nine new products in a market with six competing products using the new product positioning method and a quasi-Newton method. For the new product method, we allow  $\delta$  to increase and for each value we obtain the new product positions.



in Figures 6 and 7, that the positions of the new products obtained by the new product positioning method and the quasi-Newton method are not the same, even though in Figure 8 we observe that the market share obtained by the two methods is about the same. This points to the existence of multiple optimal or near-optimal solutions.

Using the market conditions shown in the examples in Figures 4, 6, and 7, additional simulations were performed when the value of  $\beta$  was gradually increased toward 1, thus again pursuing consumers away from competition with higher intensity. In these simulations we also observe that the new product positions lead to an increase in market share and a decrease in the resulting expected utility that a firm will provide consumers.

To further investigate the accuracy of the new product positioning method and the trade-off between the market share and the expected utility that a firm will

**Figure 8:** Comparisons of the new product positioning method using various values of the ROINF with a quasi-Newton method. Comparisons were performed when positioning products with two and three attributes.

Method	Objective Function		Computed Expected Utility		Computational	
	$\sum_{i=1}^K \sum_{j=1}^M P_{ij}(U_{ij}(t))$		$\sum_{i=1}^K \sum_{j=1}^M P_{ij}(U_{ij}(t))U_{ij}(t)$		Time (sec)	
	2 Attr.	3 Attr.	2 Attr.	3 Attr.	2 Attr.	3 Attr.
3 New Products						
Quasi-Newton	139.07	171.78	-495.77	-1207.70	30.34	36.40
ROINF: $\beta = 1,$ $\delta = \gamma = 1$	139.05	164.98	-495.60	-1178.00	3.93	4.06
ROINF: $\beta = 0.2,$ $\delta = \gamma = 0.7$	137.50	152.39	-470.25	-915.80	6.90	7.64
ROINF: $\beta = 0.2,$ $\delta = 0.2, \gamma = 0.7$	132.34	151.09	-400.35	-885.40	6.95	7.62
6 New Products						
Quasi-Newton	195.35	243.99	-551.61	-1750.20	130.51	155.23
ROINF: $\beta = 1,$ $\delta = \gamma = 1$	194.39	231.37	-547.69	-1210.80	7.56	8.89
ROINF: $\beta = 0.2,$ $\delta = \gamma = 0.7$	190.52	230.60	-510.49	-1185.00	7.73	9.02
ROINF: $\beta = 0.2,$ $\delta = 0.2, \gamma = 0.7$	185.19	227.06	-420.37	-1080.90	7.74	9.04
9 New Products						
Quasi-Newton	220.29	259.92	-547.32	-1822.60	570.23	678.81
ROINF: $\beta = 1,$ $\delta = \gamma = 1$	218.02	250.50	-527.68	-1122.60	9.42	10.26
ROINF: $\beta = 0.2,$ $\delta = \gamma = 0.7$	217.91	248.65	-520.19	-1112.40	9.45	10.38
ROINF: $\beta = 0.2,$ $\delta = 0.2, \gamma = 0.7$	211.52	246.54	-419.44	-1051.90	9.52	10.40

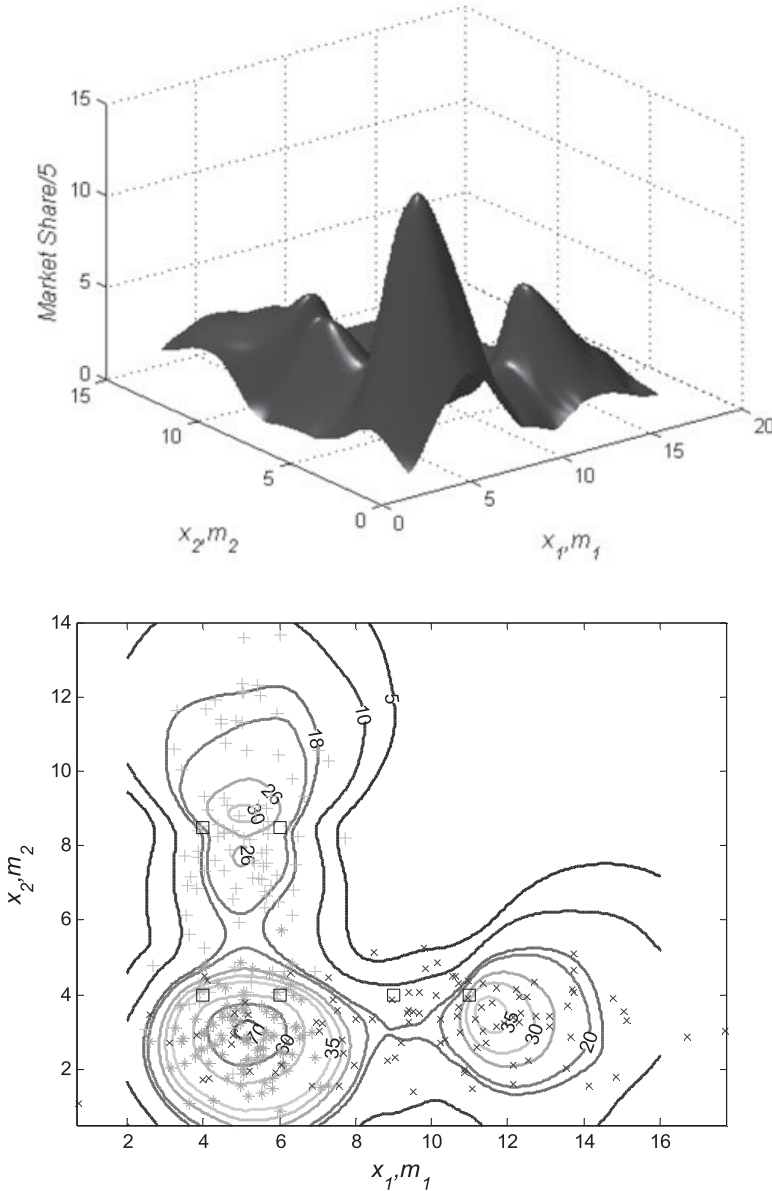
provide consumers, we run two simulation experiments. In the first simulation, shown in Figure 8, we obtain the solution of the new product positioning method for three cases. In the first case, we set the ROINF values to  $\delta = 0.2, \gamma = 0.7,$  and  $\beta = 0.2$ . In the second case we set the ROINF values to  $\delta = \gamma = 0.7$  and  $\beta = 0.2,$  thus increasing the intensity with which a firm pursues consumers away from competition. Finally, in the third case, we set the ROINF values to  $\delta = \gamma = 1$  and

$\beta = 1$ , which implies that a firm tries to position its products with the new product positioning method and exerts the maximum possible effort to capture consumers away from competition. This is equivalent to maximizing the market share objective without imposing any constraints. We also present the best solution obtained by the quasi-Newton method, after running the method 10 times with different starting product positions. The market share and the computed expected utility that a firm will provide consumers are reported in Figure 8, when three, six, and nine new products are positioned in the market, respectively. The market conditions were exactly the same as those used in the example shown in Figures 4, 6, and 7 and the simulation experiment was performed when the products positioned have two and three attributes. Figure 8 also reports the computational time required to obtain the solution by the quasi-Newton method and the new product positioning method.

From Figure 8, we see that the quasi-Newton method always obtains the highest market share. In all three scenarios of positioning three, six, and nine products, the new product positioning method, when used without imposing the ROINF constraint, achieves market shares that deviate less than 1% and 5.2% from the market share obtained by the quasi-Newton method for the cases where the products have two and three attributes, respectively. Note that the new product positioning method was run once, whereas the quasi-Newton method was run 10 times in order to find the best solution. From Figure 8 we also observe that the new product positioning method is more computationally efficient than the quasi-Newton method. This computational advantage of the new method over the quasi-Newton method is more evident when the number of new products positioned increases. For example, when positioning nine new products having three attributes, the new method requires about 10 seconds to reach the solution where as the quasi-Newton method requires close to 680 seconds. We observe that the computation time required by the quasi-Newton method increases exponentially with the number of new product to be positioned. To further demonstrate this, we ran a simulation in which 15 new products with 3 attributes were positioned in a market consisting of 3 segments with 300 ideal points each. In this simulation, the quasi-Newton method required approximately 2 hours to yield the solution, where as the new method required only 11 seconds. The deviation in the market share was approximately 5%. Therefore, in problems dealing with the positioning of a large number of new products, the quasi-Newton method will not be able to provide a solution in a finite time, whereas the new product positioning method does so in a computational efficient way.

More importantly, Figure 8 shows the trade-off of a reduction in the market share for an increase in the expected utility a firm will provide consumers. This trade-off can be seen when comparing the results of the quasi-Newton method with those obtained by the new product positioning method when the ROINF values are set to  $\delta = 0.2$ ,  $\gamma = 0.7$ , and  $\beta = 0.2$ . When positioning three new products with two attributes, the quasi-Newton method results in a market share of 139.07 and an expected utility provided to consumers of  $-495.77$ . The respective values of the product positioning method using the above ROINF are 132.34 and  $-400.35$ . Thus, the quasi-Newton method provides solutions with better market shares and the new product positioning method with the ROINF provides solutions with better expected utilities provided to consumers. This poses the following

**Figure 9:** Surface plot and contours of the market share objective function for the market shown in Figure 4, when one new product is positioned.



dilemma to a manager: Is a firm willing to accept a reduction of 4.83%  $[(139.07 - 132.34)/139.07]$  in market share in order to enjoy an increase of 19.24%  $[( -495.77 - (-400.35))/(-495.77)]$  in expected utility by positioning its products using the ROINF method? When positioning six products with two attributes, these trade-off proportions are 5.20% and 21.97%, respectively. For the example where nine new products with two attributes are positioned, the trade-off proportions are 3.98%



and 23.36%, respectively. This dilemma is even more evident when positioning products with three attributes. For example, when positioning nine new products with three attributes, the trade-off proportions are 5.14% and 42.28%. The answer to this dilemma rests entirely on the managers of a firm and their short-term and long-term objectives. This clearly shows that the new product positioning method using the ROINF can be a useful tool in the hands of marketing professionals.

In the second simulation, we test the accuracy of the solution of the new product positioning method by comparing it to the solution obtained by the quasi-Newton method. We simulated 500 different market scenarios and allowed the positioning of one, three, six, and nine products in a two-dimensional attribute space. The new product positioning method was run by setting  $\delta = \gamma = 1$  and  $\beta = 1$ , which implies that a firm exerts the maximum possible effort to attract consumers. For each scenario, the quasi-Newton method was run 10 times and the best solution was selected. The ROINF method was run once. In all 500 cases, the market share of the new product positioning method deviated less than 1.2% from the solution obtained by the quasi-Newton method. We repeated this experiment 500 times with products having 3 attributes, with the market share of the new product positioning method deviating less than 5.2% from the solution obtained by the quasi-Newton method.

To illustrate the complexity of the product positioning problem in a continuous attribute space, Figure 9 shows the surface plot of the market share function in Equation (1) and the contours of this function, for the market scenario used in Figures 4, 6, and 7 when only one new product is positioned. The graphs clearly show the presence of multiple local maxima. The product positioning problem becomes more difficult to solve in higher dimensionality attribute spaces with larger number of consumers. Numerical optimization techniques may not yield the optimal solutions and require high computational times. The simulation experiments show that the new product positioning method obtains near-optimal solutions in a time-efficient way, especially in high dimensionality problems. The method also allows managers to assess the trade-offs between market share and the expected utility a firm will provide consumers.

## CONCLUSION

As stressed in the literature, the product positioning problem remains a challenge for both academics and practitioners. On one hand, positioning products in a discrete attribute space, results in an NP-hard problem. On the other hand, positioning products in a continuous attribute space may result in solutions trapped in local maxima. In small dimensionality problems, the optimal solution can be obtained using optimization techniques. However, as the problem becomes larger in terms of the number of attribute dimensions, consumers, and competitors, and thus become more realistic, new methods are required to find good solutions.

In this article, we propose a product positioning method which is based on the neural network methodology of an SOM. The method incorporates the concept of ROINF where a firm evaluates individual consumers and decides on the intensity with which to pursue a consumer, based on the probability that this consumer will purchase a competing product. The method has several advantages. First, the

product preference of each individual consumer is taken into consideration during each step of the product positioning process. Second, no limitations are imposed on the number of competing products present in the market, and third, the method can position multiple products in multiple market segments. Using simulation, we compare the new product positioning method with the BFGS method which belongs to the class of quasi-Newton methods. We find that new product positioning method always approaches the best solution obtained by the quasi-Newton method in significantly less computational time than the quasi-Newton method. We also compute the expected consumer utility that a firm will provide consumers by offering its products. We show that as the intensity with which a firm pursues consumers increases, the new product positioning method obtains near-optimal solutions, in terms of market share, but with higher expected consumer utilities compared to those obtained by the quasi-Newton method. Thus, the new method can serve as a managerial decision-making tool to compare the short-term market share objective with the long-term expected utility that a firm will provide consumers, when it positions its products and intensifies its effort to attract consumers away from competition.

The method is certainly not without limitations. The method positions new products in attribute spaces whose dimensions are known. It is not a method that generates new attribute dimensions or radically new or novel products (Shocker & Srinivasan, 1974, p. 923). In addition, because the method solves the product positioning problem with an iterative numerical approach, there is no guarantee that the optimal positions will be reached. Optimality of the product position remains a problem that all existing positioning methods face.

Research can be extended in various ways. First, the method can be used to examine the effect of other factors on the decision to pursue consumers away from competitors. Such factors may include the intensity of competition, which can be reflected in the density of competing products present in the market, and the number of market segments present. The cost of product positioning could also be incorporated in the analysis. Second, the cost of pursuing consumers with higher intensity can also be used to examine its effect on new product positions and market share. Third, the product positioning method presented in this article can be used to extract the Nash equilibrium when competition is present. This could be achieved by applying the updating process in a game theoretic approach, where competitors and a firm, update their product positions in an alternate manner. Fourth, a comparative study can be carried out to compare the performance of existing product positioning methodologies. The difficulty of this study lies in the plurality of objective functions and inputs used by each method. Fifth, more work is required in product positioning for products with new attributes that consumers do not have any experience with.

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