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ABSTRACT

Four algorithms for locating an "optimal" new product in a multiattribute product space--Albers and Brockhoff's PROPOSAS; Gavish, Horsky, and Srikanth's Method IV; the author's PRODSRCH; and GRID SEARCH--are compared in terms of relative share of preferences under different simulated market environments. These environments were both ones for which the algorithms were designed as well as other "more realistic" environments. Results indicated that algorithm performance was sensitive to number of segments and segment importance weighting and to the presence of probabilistic choice and less sensitive to differential attribute weights (in the choice models) and the numbers of existing products. Gavish, Horsky, and Srikanth IV and PROPOSAS performed best only under market conditions for which they were designed. PRODSRCH (a general purpose optimizer) was a slightly inferior performer under these special market conditions, but a much better performer overall.

A SIMULATION COMPARISON OF METHODS FOR NEW PRODUCT LOCATION

INTRODUCTION

One of the more widely accepted of new methodologies to assist marketing research and management has been conjoint analysis (Cattin and Wittink 1982). These multiattribute models of preference decision-making have been used extensively to diagnose and predict customer decisions. In this way, they provide management with better understanding of the feature and attribute tradeoffs and objectives sought when customers make decisions among product or service alternatives. Additionally, they assist by predicting reactions to new alternatives introduced into a competitive array or other changes (e.g., product deletions) in the choice set. Since marketing and environmental (e.g., competitive) forces are dynamic, the ability to gain insight into the probable effects of changed circumstance (reaction) as well as identify changes which, if made, are likely to have desirable outcomes (proaction) has opened new possibilities for marketing management.

One of the early applications of this methodology was to the evaluation of potential new product possibilities or concepts prior to their actual introduction. Such concept evaluation permitted the introduction of customer perspectives and viewpoints <u>at an early stage</u> in the product planning process. This could provide management with market feedback in a timely fashion, before support for an arbitrary new product concept could crystallize and perhaps become intransigent. In a recent study, Booz, Allen and Hamilton (1982) credit improved "up front" research with a dramatic increase in the ratio of the number of new product "successes" to the number of ideas introduced into the product development process (one success from 58 ideas in their 1968 survey had changed to one from seven by 1981). These early methodologies have become increasingly more sophisticated over time (Shocker and Srinivasan 1979). A natural outgrowth of such new product evaluation was the suggestion that similar approaches could also be used to generate promising new concepts. For if conjoint analysis is informative regarding the criteria customers use to evaluate competitive product alternatives, then it should be possible to use such insight to design products which would be favorably evaluated by those criteria (Shocker, Gensch, and Simon 1969).

In recent years analytic approaches useful for generating new product ideas or concepts (or aiding the refinement of such ideas) have multiplied. Many, but not all, have benefited from this conjoint analysis heritage. They have made use of a joint space framework wherein products are represented by point locations (benefit bundles, feature combinations, or the like) in a multiattribute perceptual product space and customers are locatable in the same space by their most preferred attribute combinations (termed ideal points). Relative liking of any customer for the products in the competitive array is represented by a multiattribute (conjoint) model measuring "proximity" of each existing alternative to that customer's ideal or target "product." Each customer is presumed to choose the product which is most preferred or located closest to his/her ideal.

There are many variants on this basic framework, although not all such variants have been incorporated or are incorporatable into the several algorithms which now exist for identifying locations for the most promising new product concepts. These variants serve to introduce both greater complexity and realism. Products may be represented as bundles of discrete features (which are either present or absent) or by levels of the continuous attributes which can be presumed to define the product space or by both. Customer decision-making may be modelled by other than the ideal point model. For example, customers may be represented as desiring as much (or as little) of each product attribute as they can obtain and hence their relative liking for each product becomes the weighted sum of attribute levels or the features possessed by the product. Mixed models in which relative liking or preference is represented differently for each product attribute have also been suggested in the literature (Green and Srinivasan 1978). Not all possible combinations of product features or regions of perceptual product space may be feasible for new product concepts. Hence the search process may need to be constrained. All customers may not offer equal purchase potential for products in the competitive array and thus it may prove desirable to weight customers differentially. Finally choice may be modelled probabilistically by permitting each customer to choose from some number of products (possibly all) in relation to his/her relative liking for them. These extensions, and others, could be used to improve the "success rate" of new product concepts identified by the various search algorithms.

The purpose of this paper is to examine and compare several algorithms for identifying promising new product concepts in a joint-space of the type just described. Our approach will involve the creation of a simulated market environment which incorporates many of the variants which we have argued create added realism. Although not all the algorithms compared can deal with these added complexities, it is possible to operationalize them in a market environment they are capable of handling, but evaluate the solution reached (in the simpler environment) in the more complex one. In this way the loss in solution "quality" from using an algorithm which is only operationalizable in a less complex market environment can be estimated. Additionally, the algorithms which can handle these more complex environments can usually be operationalized in less complex ones as well. In this way it is possible also to compare the solutions reached by all algorithms in the most restrictive environments permitted by any.

The algorithms compared in this study are Albers and Brockhoff's (1977) PROPOSAS as extended by Albers (1979), Method IV of Gavish, Horsky and Srikanth (1983) which we have called GHS-IV, and two methods which are operationalizations of suggestions made by Shocker and Srinivasan (1974) for implementing their joint space market simulation, GRID SEARCH and PRODSRCH (a type of gradient procedure).* PROPOSAS was implemented using Albers' PROPOPP computer package (see Albers 1982). Gavish, Horsky and Srikanth supplied the computer program which they had developed for testing their algorithms, and suggested their Method IV as the recommended alternative. GRID SEARCH and PRODSRCH were operationalized by two of the present authors, May and Sudharshan. PRODSRCH depends very heavily upon a general non-linear optimizer QRMNEW which had previously been programmed and tested by May (1979). These four algorithms have not been compared previously. Each author has simply defended his approach as logical and computationally efficient (although computational times can vary significantly with different computers). These algorithms are described below.

*Also compared in results previously reported (May, Shocker, and Sudharshan 1982) was Zufryden's ZIPMAP algorithm. Zufryden (1977) did not report any implementation of his approach. Consequently May and Sudharshan operationalized ZIPMAP using standard integer programming codes as suggested by Zufryden. Albers (1979) has shown that the algorithmic concept of PROPOSAS can be extended to provide solutions to a problem identical to that considered by Zufryden. Albers and Brockhoff (1980) reported extensive numerical results based upon their operationalization which indicate clear superiority (in terms of objective function value) for PROPOSAS. Our results, based upon a different algorithm and a less extensive comparison, indicated that ZIPMAP produced inferior solutions to the other four algorithms. Consequently, any subsequent discussion of Zufryden's approach is presented more in the interest of completeness and no further numerical results are reported here.

GRID SEARCH and PRODSRCH are the more versatile. Specifically, they can readily incorporate the different customer conjoint decision models discussed briefly above (including part-worth function models and mixed models, see Green and Srinivasan 1978), whereas PROPOSAS and GHS-IV assume only an ideal point model. The first two permit differential weighting of individuals to account for different purchasing power as does PROPOSAS, but not GHS-IV. Our previous study (May, Shocker and Sudharshan 1982) considered the effects on algorithm performance of this ability to incorporate differential weighting and these results will only be summarized in this paper. Of particular interest in the present paper is probabilistic choice. GRID SEARCH and PRODSRCH can readily incorporate it, whereas PROPOSAS and GHS-IV can not. In this paper the models will be compared both under probabilistic and single choice conditions. The probabilistic choice condition obviously creates a bias in favor of the algorithms which can consider it explicitly, but our interest here will be in the magnitude of the differences in performance observed when single choice is assumed in what is really a probabilistic choice market. Given the large number of applications where probabilistic models premised upon a deterministic measure of preference or utility have been used (e.g., Punj and Staelin 1978; Srinivasan 1979; Gensch and Recker 1979; Urban and Hauser 1980) and some evidence that aggregating the predictions of single choice models can closely approximate the probabilistic results obtained by aggregating individual-level probabilistic choices (Pessemier, Burger, Teach and Tigert 1971), such a comparison appears warranted.

Comparison of probabilistic choice with single choice models is conducted in this manner (i.e., probabilistic objective function values for those new product locations identified by single choice models are compared with those identified by probabilistic choice models) primarily because we believe probabilistic choice (i.e., an individual consideration set size greater than one) is the more realistic condition. Decision models of the sort considered here are not modelling a single purchase occasion where such a single choice might have been more plausible, but rather a behavioral predisposition (Fishbein and Ajzen 1975). Evidence exists from studies based upon panel data (Massy, Montgomery, and Morrison 1970); the variety-seeking literature (McAlister and Pessemier 1982, McAlister 1982); research dealing with the size of evoked and consideration sets (Urban 1975; Silk and Urban 1978), and other sources (Pessemier, et al. 1971) for the conclusion that for frequently purchased consumer nondurables (and possibly other product categories), consideration sets sizes are typically larger than one. Consequently, if consumers have positive predispositions to purchase more than one product, a probabilistic representation makes sense. (Note that the product planning literature has also commonly modelled individual choice probabilistically (e.g., using logit or probit models) for other reasons.) Differential product availability, temporary price changes, and different point of sale promotion and merchandising, etc., can be treated as stochastic variables affecting choice. Such factors as these are presumed to moderate the behavioral predisposition to purchase predicated on product-specific factors alone. This logic has led us to posit a probabilistic operationalization as the basis for comparing the solutions obtained by the several algorithms. Even though by this assumption the single choice model is strictly wrong, it may still prove a reasonable empirical approximation in the aggregate (as was the case in the laboratory experimentation conducted by Pessemier, et al., 1971).

Other algorithms for new product positioning have appeared in the literature, indicating that the area remains one of active research interest. Pessemier's (1975, 1982) STRATOP; Urban's (1975) PERCEPTOR; Hauser and Simmie's (1981) operationalization and extension of Kelvin Lancaster's (1971) economic theory; Green, Carroll, and Goldberg's (1981) POSSE; and Bachem and Simon's (1981) non-acronym formulation exemplify these other approaches. Aside from reasons of budget and time, they are excluded here because they either suppose a conceptual framework for market structure and decision-making substantially different from the others (Hauser and Simmie), or involve added measurement stages which would bias comparison in the type of simulation carried out here (Urban, Green-Carroll-Goldberg), or make use of algorithms which are insufficiently different from the approaches compared in the present study to warrant separate treatment (Pessemier, Bachem and Simon). Hauser and Simmie, Pessemier, and Bachem and Simon do differ from other approaches in that they incorporate costs and prices explicitly in their framework. This permits the formulation of profit objectives (rather than the sales or share of preference objectives that are more common). However, it is unclear whether cost functions in an attribute space can be readily measured. (Pessemier uses very simplistic functional formsand provides no evidence of validation, Hauser and Simmie also do not provide empirical validation for their measurement approach, and Bachem and Simon ignore measurement issues entirely.) Urban's approach involves multi-stage data collection, resulting in successive refinement of the measures of market structure, whereas the other models we have compared are all single stage. Green, Carroll, and Goldberg's POSSE is a proprietary program whose detail has not been completely published. In addition, it introduces an extra modelling step (a fitted quadratic response surface) not present in the other approaches. There appeared no way to simulate this step without knowledge of an appropriate error function. An arbitrary assumption here could have introduced a major source of bias into any comparison.

THE MARKET SIMULATION

The Market Model

Following Shocker and Srinivasan (1974, 1979), products are conceptualized as bundles of benefits and costs. A product-market consists of those products judged by potential customers to be appropriate for some generic purpose. The competing alternatives and ideal products are represented as point locations in a perceptual space spanned by attribute dimensions determinant of brand preference/choice in that market. Preference behavior is modelled as a linear combination of the different product attribute discrepancies (see Shocker and Srinivasan (1979) for a review of the logical and empirical justification for multi-attribute models generally). Following Pessemier, et al. (1971), choice is modelled probabilistically from among the k-closer competitors, where k can vary between 1 and the number of available brands.

Following the notation in Shocker and Srinivasan (1974) and May, Shocker, and Sudharshan (1982), let n_B be the number of existing brands in the product market, n_M be the number of market segments, n_A be the number of determinant product attributes,

$Y_j = \{y_{jp}\}$ = the modal perception of the j^{th} product on the p^{th} dimension.

$W_i = \{w_{ip}\}$ = the attribute weights for the i^{th} segment.

$I_i = \{I_{ip}\}$ = the ideal point for the i^{th} market segment. It is assumed finite, but need not lie in the region where feasible products might be located.

d_{ij} = the weighted Euclidean distance from the j^{th} product to the i^{th} segment's ideal point.

S_i = the i^{th} segment's demand.

π_{ij} = the share of the i^{th} segment's demand allocated to the j^{th} product alternative. $\pi_{ij} = f(d_{ij}^{-1})$ and

$$\sum_{j=1}^{n_B} \pi_{ij} = 1 \text{ for all } i = 1, 2, \ldots, n$$

Following Bachem and Simon (1981) and Shocker and Srinivasan (1974), several forms for π_{ij} (i.e., decision rules) can be considered:

Case 1. Every available alternative could have some non-zero likelihood of purchase, e.g., $\pi_{ij} = a_i/d_{ij}^b$ where $a_i = 1/\sum_{j=1}^{n_B} (1/d_{ij}^b)$ and b is a parameter which varies with the product class (Pessemier, et al. 1971). Whether or not a segment actually purchases a brand, there is the potential to do so. As a model of segment behavior, it is more credible than as a model of individual behavior, where individuals often are observed to restrict their purchases to many fewer than all available brands (Urban 1975; Silk and Urban 1978).

Case 2. Individuals are assumed more likely to become familiar with products which come reasonably close to meeting their objectives, due to self-interest (Aaker and Myers 1974). A parameter k, (possibly k_i which varies with each individual) restricts choice to the k "closer" alternatives. $\pi_{ij} = a_i/d_{ij}^b$ for $d_{ij} < d_i^{(k)}$, where $d_i^{(k)}$ is the distance from the i^{th} segment's ideal point to its k^{th} closer product, and $\pi_{ij} = 0$ otherwise.

Case 3. Individuals purchase only their most preferred brand, i.e., k = 1. Support for this approach was described in the Introduction.

Assume that the firm's single objective is to maximize total incremental demand, or preference share, from the new product introduction. This means that we must account for any demand for the new product which is cannibalized from the firm's existing brands. Let

$\Psi_i(\Psi_i^*)$ = the set of k closer products before (after) introduction.

$\chi_i(\chi_i^*)$ = the i^{th} firm's self products before (after) introduction.

$\pi_{ij}(\pi_{ij}^*)$ = product likelihoods of purchase before (after) new product introduction,

$x = \{x_p\}$ = the new product location,

and

L = an arbitrarily large number.

Then, as in Albers (1979) and Gavish, Horsky and Srikanth (1983), we can identify an optimal new product location be solving the mixed integer nonlinear programming problem

$$\text{Maximize} \sum_{i=1}^{n_M} u_i \left[\frac{\sum_{j \varepsilon \chi_i^*} \pi_{ij}^*}{\sum_{j \varepsilon \Psi_i^*} \pi_{ij}^*} - \frac{\sum_{j \varepsilon \chi_i} \pi_{ij}}{\sum_{j \varepsilon \Psi_i} \pi_{ij}} \right] S_i$$

subject to

$$d_i^{(k)}\,(1 - u_i) < [\sum_{p=1}^{n_A} (I_{ij} - x_p)^2 w_{ij}]^{1/2} < d_i^{(k)} + L(1 - u_i)$$

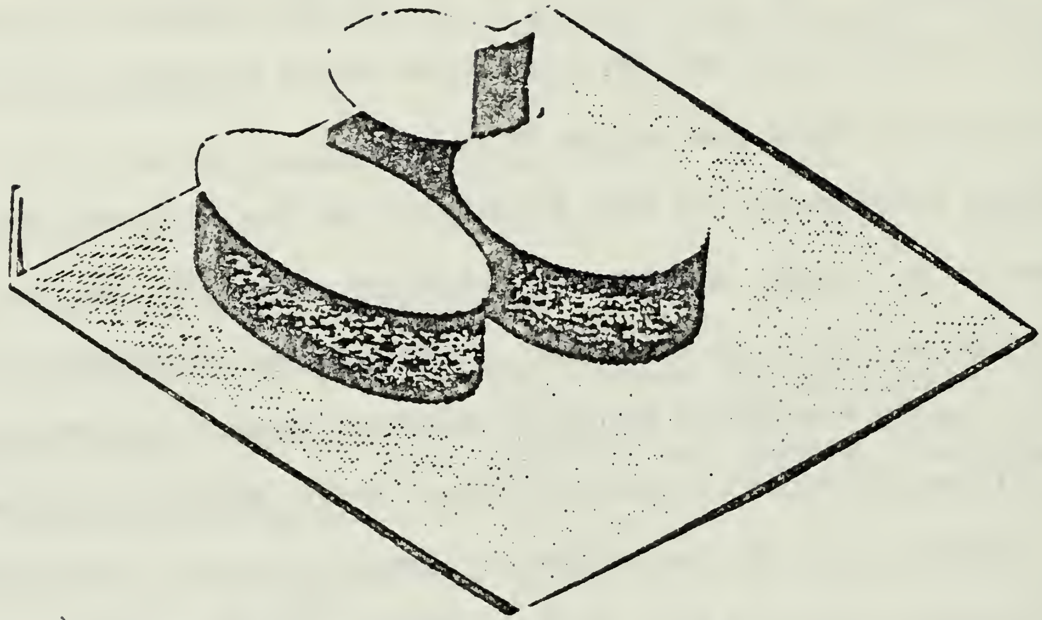
for all x ε R, and i ε M, where u_i is zero or one depending on whether (1) or not (0) the new product is among the k closer for the i-th segment.

This formulation assumes that the attribute axes are continuous, and that a market segment may alter its probabilities of purchase with even a miniscule change in product location. Nominal attributes, or those which could be fixed at only a finite number of levels, would introduce additional integer variables into the formulation. Zufryden (1979) allowed for such attributes with a linear objective function determined by conjoint analysis and linear constraints. Green <u>et al.</u> (1981), also using a conjoint framework, allow for a quadratic objective function.

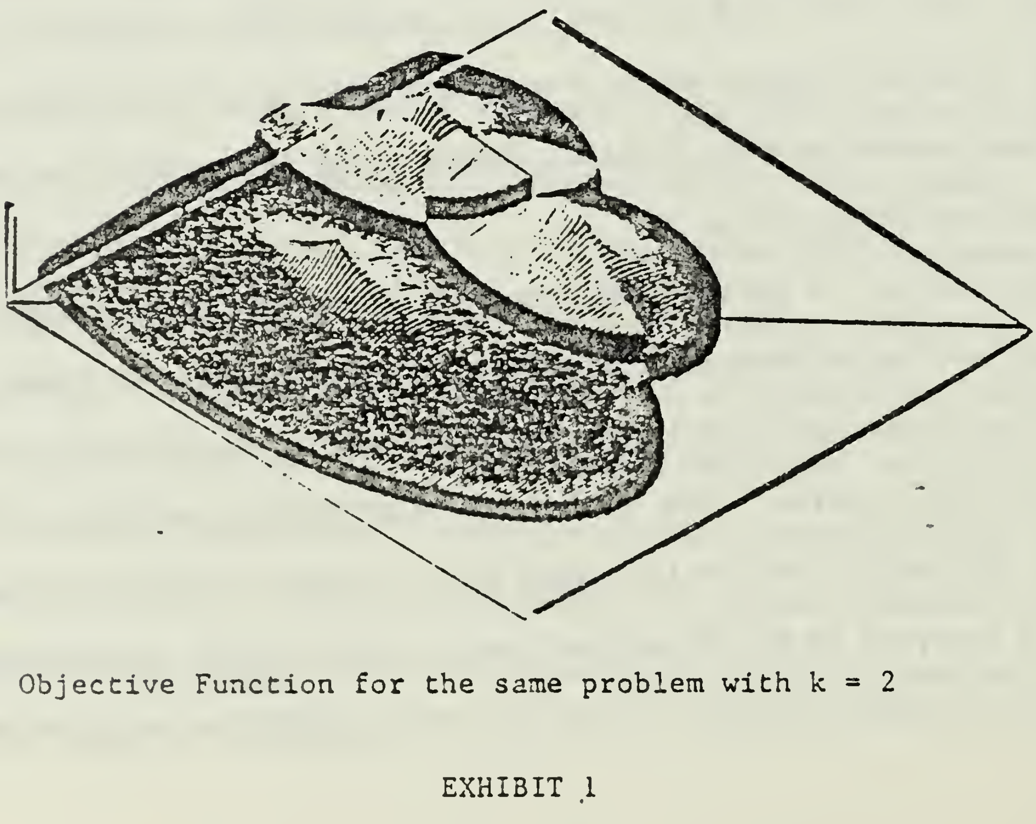
For Case 1, the quadratic constraints never become binding (u_i = 1 for all i) and the problem reduces to an unconstrained maximization of the objective function. If $1 < k < n_s + 1$, we must consider the quadratic constraints, but the x_{ij}'s will be continuous except when the X_i's change, so that gradient-based techniques may be of value.

The major complication in this formulation is the nonlinear constraints, which serve as a linkage between the location variables and the X_i^* sets. Consider the geometry of the situation (as represented by Exhibit 1a for the case of k=1), using a weighted Euclidean distance measure for the d_{ij}. There is a hyperellipsoidic region around each ideal point, where any product placed within it captures all of that segment's demand, and any one outside that region will capture none of it. Each hyperellipsoid is centered at an ideal point, has its axes parallel to the attribute (coordinate) axes; its boundary just touches the existing product k-closest to the ideal point, and its eccentricity is determined by the relative attribute weightings--if the weights are equal, it is a hypersphere, and the more unequal the weights are, the "flatter" and more oval it is. The optimization problem is then to examine the feasible places where these hyperellipsoids intersect, and to locate the new product in that feasible intersection region which captures the greatest quantity of new sales.

The case when k = 2 gets somewhat more complex. As shown in Exhibit 1b, for a similar problem situation, the ellipsoidic regions may be larger and of different sizes since the second closer product may be farther away from some ideal points than others. The preference distribution defined over each individual's ellipsoidic region is peaked with its mode at the ideal point and exponentially decaying in all directions away. If a product is simultaneously either first or second closest to two (or more) customers, section of these



A. Objective Function for a k = 1 Problem (with equal sales potentials)



B. Objective Function for the same problem with k = 2

EXHIBIT 1

preference distributions are added, producing the unusual terrain (objective function) shown in the Exhibit.

Positioning Algorithms

The several positioning algorithms which are compared in the current simulation are very briefly discussed below. A more complete description of each is contained in the originals and in May, Shocker, and Sudharshan (1982).

1. Grid Search, a modification of explicit enumeration, tries to locate an optimum by imposing successively finer grids on smaller and smaller regions in n_A-dimensional space. As described below, in the simulation, we assume that all attributes are restricted to 1.0, 1.1, 1.2, 1.3, ..., 9.8, 9.9, 10.0 . For n_A salient attributes, there are then 91^{n_A} lattice points as possible product concept locations. As illustrated in Exhibit 1, parts a and b for the cases where $k = 1$ and $k = 2$, respectively, local optima will exist. The only guaranteed method of finding the global optimum is explicit enumeration of all points, which is not a practical approach. At 0.01 seconds per objective function evaluation, 1.38 minutes would be required to evaluate all 91^2 points. But for a three dimensional problem, 2 hours would be required for the 91^3 points in three attributes, and so on.

The search strategy we use for GRID SEARCH is a simple one. A grid of nine equally spaced values per attribute is imposed on the feasible region, and the objective function is evaluated at the centroid of each resulting parallelotope. The region with the highest value is retained. A second grid with the same number of divisions as the original is imposed over it, and the best point from this second grid is retained. This process is repeated until the best point found at an iteration yields less than a 5% improvement over the incumbent.

2. <u>PRODSRCH</u> is our implementation of the "gradient search" idea suggested by Shocker and Srinivasan (1974). As noted after the problem formulation in the previous section, and illustrated in Exhibit 1b, for $k > 2$ the derivatives of the objective function should be smooth almost everywhere. Iterative methods which choose a search direction strategy using the gradient might tend to work well in these cases.

To our knowledge, there are no special purpose algorithms for solving the nonlinear mixed integer new product location problem for $k > 2$. A good survey of the state of the art for nonlinear mixed integer problems is given in Gupta (1980). Given current technology, a general purpose nonlinear optimizer, while not strictly appropriate for the $k = 1$ case, was thought to provide a balance between efficiency and robustness.

The frequent changes in the set of k-closer products, as illustrated in Exhibit 1b, precludes our computation of analytical derivatives for $k > 2$. The step-like nature of the objective function for $k = 1$, as shown in Exhibit 1a, argues for a method with a local search capability, to prevent premature termination. A local search would provide for the explicit evaluation of points in the neighborhood of a presumed optimum, in addition to the use of derivative-based information. Reliable mathematical convergence properties and our familiarity with the algorithmic parameters involved were also significant considerations. We chose QRNMEW (May 1979) as the underlying optimizer because it satisfied these criteria.

QRNMEW combines the method of local variations with an approximate projected Newton method. The former provides the local search; the latter the rapid convergence. The algorithm incorporates a sophisticated method for dealing with local non-concavity. A method not requiring analytical derivatives might be expected to use more computer time than one requiring them, trading off the extra computer time for the savings in human time. Numerical results for a standard set of nonlinear test problems do not show such an increase for QRMNEW.

It should be noted that the complexity of the next two algorithms discussed, PROPOSAS and GHS-IV, is dependent upon the number of market segments, since each segment generates another hyperellipsoid, and so many more potential intersections. The complexity of PRODSRCH is chiefly dependent on the number of attributes, since it treats that space directly.

3. The general approach of PROPOSAS (Albers and Brockhoff 1977; Albers 1979) is that of branch-and-bound. PROPOSAS selects sets of segments to investigate, in decreasing order of weighted potential incremental revenue, and stops when the incumbent best new location found is superior to that which could be obtained from any of the remaining sets. PROPOSAS consists of two parts--ENUSOS and INTSEA. ENUSOS generates a list of segments whose hyperellipsoids intersect pairwise and INTSEA tries to find a point of intersection for any given set of segments. The largest weighted (by sales potential) set of hyperellipsoids, all of which intersect pairwise, is then selected and a point in that intersection is found heuristically.

4. Gavish, Horsky, and Srikanth (GHS) (1983) propose a basic approach which incorporates certain ideas similar to those of PROPOSAS. They assume k = 1 and equal sales potentials. Attribute weights are allowed to be idiosyncratic. A key notion is the restriction of search to points on the surfaces of hyperellipsoids. While the set of optimal locations is in reality a region, and a conservative estimation approach might seek an interior point, there is a substantial gain in efficiency by this assumption.

To overcome the computational complexity of their basic approach, GHS propose four variations within the same algorithmic structure. Line search-based heuristics are their recommended approach. Because it is possible to verify if a line passes through a hyperellipsoid, and where its entry and exit points are, it is possible to find good intersection regions if one generates good lines. Note that the probability of a random line intersecting the optimal region will be a function of the region's size. As the number of existing products grows, one would expect that region to have an increasingly smaller n_A-dimensional volume.

We restrict our consideration to their Method IV, the version they judge superior. It selects a starting solution by generating a large number of random points, and choosing the best one. A line is then drawn from the incumbent solution z to the point nearest it on the surface of the hyperellipsoid of each segment not captured by z. Each of these lines is searched, and, if a part of any one of them yields an improvement, an end point of such a line segment replaces the incumbent and the process repeats.

The Simulation

The problems of meaningfully comparing the several frameworks above (in terms of estimates of market behavior toward the new concepts generated) are not trivial, given the paucity of published work reporting relevant empirical findings regarding market structure and behavior. Most applications of similar frameworks have been proprietary (Wind 1973, Green, Carroll, and Goldberg 1981) and, at best, report summarized results. We made reasonable assumptions to construct a market environment which comprised, approximately, the union of features suggested in the market models assumed by the other authors. For each market, we not only specified various structural characteristics, (e.g., number of customers, number of existing products, number of attributes, sales potentials of each customer segment, customer segment ideal point locations and attribute weights), but we also specified the form of the consumer behavior model believed to be the true one for it.

Based on this construction existing products were located using a crude GRID SEARCH in a sequential fashion. Exhibit 2 provides a flow chart describing the various steps used in the simulation.

The simulation involved 180 possible design combinations of existing products, number of ideal points, attribute space dimensionality, attribute weighting, and the form of the "true" consumer behavior model (the parameter k). Reasons for the selection of the particular levels of each of the above characteristics used are described in May, Shocker, Sudharshan (1982), and Sudharshan (1982) and are not repeated here.

Each search algorithm was implemented, insofar as feasible, within each design configuration. Five replications of each design combination were performed. The solutions reached by the various algorithms were compared based on the estimates of consumer preference obtained using the "true" preference model prespecified for a given market.

Analysis and Results

To assess the relative performance of the different algorithms under the different market environments simulated, we performed our analysis in two parts. In the first part we studied their relative performance in segmented (unequally weighted customer) markets, and, in the second, in unsegmented (equally weighted customer) markets. We investigated both segmented and non-segmented (sample-weighted) markets for several reasons. If an external criterion exists for defining segments (e.g., benefit segmentation based upon similarity of preference orderings of the existing products (Ginter and Pessemier 1978) or of the parameters of individual decision models (Lehmann 1971), then more reliable estimation of the model of segment decision-making should result from a pooling of individual judgments. Further, the importance

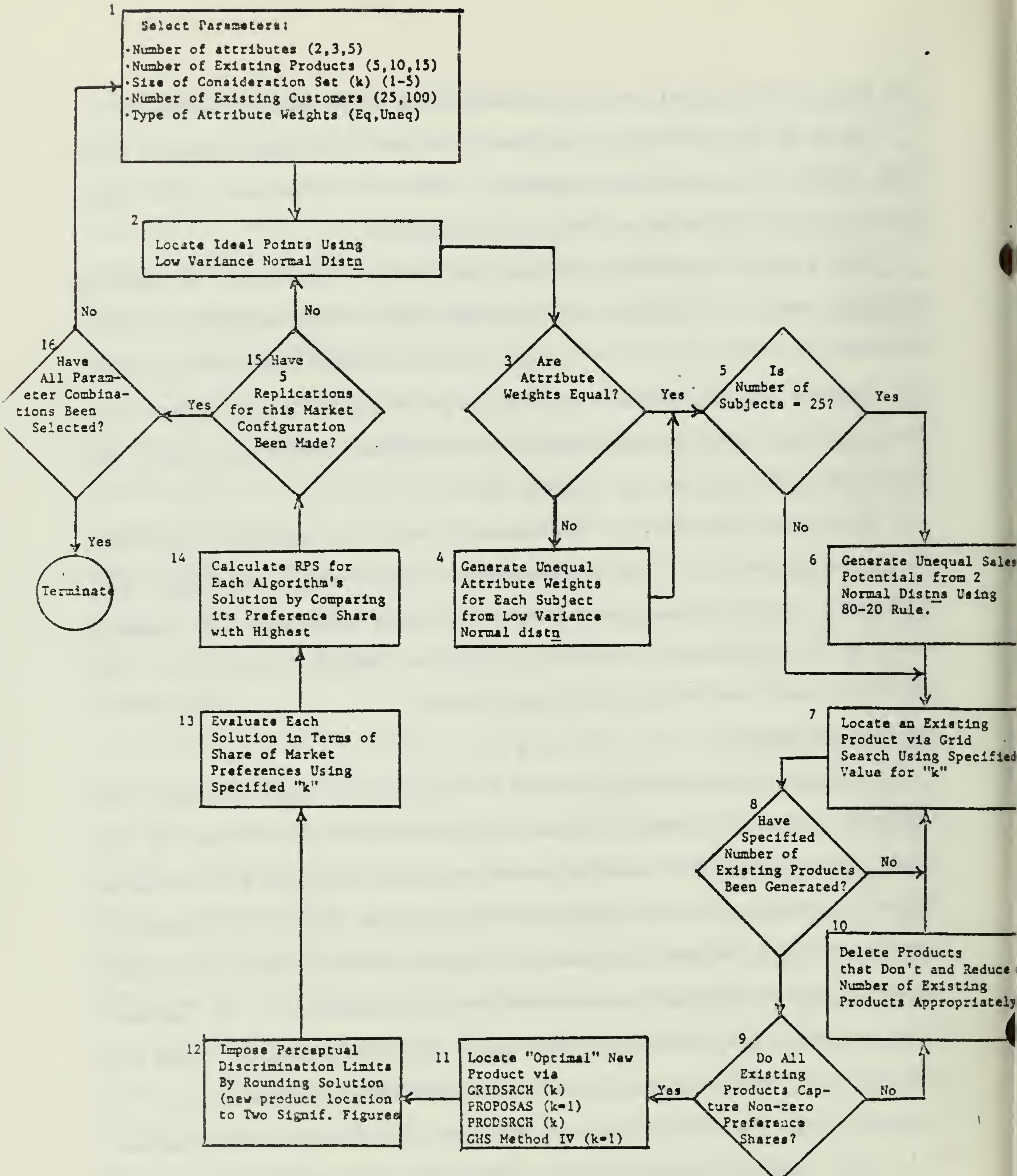


EXHIBIT 2

Flowchart of Simulation

of each segment to market purchasing can be incorporated through differential segment weights. Otherwise, the analyst is dependent upon the representation of each segment in the sample of customers modelled for implicit weighting of segment importance. The explicit formation of segments also reduced computation time, which could be a factor in some applications. Which approach (external a priori or internal sample-weighted segmentation) produces the more valid predictive results is, of course, an empirical question. But it was deemed useful to consider both approaches because each could find application in practice.

Our focus was on determining the effects of using algorithms especially formulated for the single choice ($k = 1$) case in markets where $k > 1$, and of using methods expected to perform better in $k > 1$ cases in $k = 1$ market environments. We also wished to study if variations in other simulated market characteristics affected the relative algorithm performances.

To explore the effects of the different search algorithms, we regressed the design characteristics of each simulated market and the search algorithm used (all coded as dummy variables) on the dependent variable relative preference share (RPS). Although the total demand available for capture by all competing brands (existing and new) was identical in each simulated market, the fraction of that demand available for capture by a new product differed across these markets, because demand potential depends upon the specific "positions" of the existing brands relative to market desires (ideal points). Specific values for existing product and ideal point locations, specific attribute effects, and different segment sales potentials could not easily be incorporated into the analysis, thus it was deemed desirable to express the results of each simulation run in relative terms. None of the algorithms compared here can guarantee a globally optimal solution, so that the solution (share of demand) obtained by any algorithm (for the new product it located), was expressed relative to the highest value obtained by <u>any</u> algorithm. This dependent variable (relative preference share or RPS), consequently, is positive valued at unity or less.

Ordinary Least Squares (OLS) dummy variables regression (with intercept), was used as the principal means of analysis. Strictly speaking, OLS is inappropriate when the dependent variable is constrained. Given the large number of degrees of freedom involved in each analysis (which permits reference to the asymptotic properties of the estimates) and the well-known robustness of the OLS procedure, the conclusions drawn from such analysis appear reasonable. This assertion is further supported by results from the pooled regressions (discussed below) where fewer than 8 percent (segmented markets) and 0.3% (non-segmented markets) of predicted values lay "out of range."

The results of our comparison for the segmented (unequally weighted customers) environments is presented in detail in May, Shocker, and Sudharshan (1982) and in Sudharshan (1982). Therefore we only provide a summary of those results here. Exhibit 3 indicates statistically significant regression coefficients for the unsegmented market cases. The data from the simulation runs have been analyzed two ways, one in which the effects of all the explanatory variables are accounted for statistically (the so-called "pooled regression" model) and one in which the effects of each independent predictor (other than the search algorithm used) are mechanically held constant while the statistical relation between the remaining variables is examined (so called "subset regression" models). By holding constant the effects of each explanatory variable we can see more clearly how the performance of the different search algorithms varies with changes in each market specification parameter. Plots of t-statistic variation for the subset regressions associated with different levels of each parameter (in both segmented and unsegmented market simulations) are shown in Exhibit 4. The overall regression has an R^2 of 0.16. All regression equations (overall and subset) are statistically significant.

Referring to Exhibit 3, the magnitudes of the regression coefficients are more or less directly comparable since the factorial design used to generate "market conditions" is balanced. They are interpretable much as beta weights, since all predicters are dummy variables. Overall, the search algorithm used has the greatest effect on RPS followed by the number of products and size of consideration set (value of k). (Whether "attribute weights were equal or unequal" and the "dimensionality of the attribute space" do not appear to have significant effects upon quality of solution obtained.) *Ex post*, this result seems plausible since the effect of different attribute weights is to emphasize discrepancies on specific attribute dimensions. Random determination of such attribute weights for respondents whose ideal points are randomly distributed through the space should not tend to produce a systematic effect. One would expect all algorithms to perform less well in spaces of higher dimensionality, especially PRODSRCH, GRID SEARCH, and the method of Gavish, Horsky, and Srikanth (GHS-IV), where difficulty in optimization is directly related to the dimensionality of the space.

Overall, PRODSRCH is the better performing algorithm, due in large measure to its flexibility (it and GRID SEARCH are the only techniques which can accommodate all parameter specifications). The method of Gavish, Horsky and Srikanth is generally second best followed by GRID SEARCH and PROPOSAS. GRID SEARCH might well have performed better had we incorporated a more sophisticated grid strategy for it, but at the expense of additional computer

Exhibit 3

Non-Segmented Markets

Regression Coefficients

(by Type of Simulated Market)

Regression Corresponding to Market Type	SAMPLE SIZE	P10	P15	K2	K3	K4	K5	DPROP (PROPOSAS)	DPROD (PRODSRCH)	DGHS (GHS-IV)
		Coefficients Corresponding to Dummy Variables								
Overall	1800	0.046 (7.131)	0.039 (5.988)	0.035 (4.259)	0.031 (3.7)	*	*	-0.02 (-2.719)	0.081 (10.865)	0.029 (3.847)
k = 1	360	*	*	-	-	-	-	0.068 (4.141)	*	0.179 (10.862)
k = 2 (K2)	360	*	*	-	-	-	-	*	0.05 (3.817)	0.056 (4.24)
k = 3 (K3)	360	*	*	-	-	-	-	*	0.087 (6.668)	*
k = 4 (K4)	360	0.14 (10.623)	0.119 (9.017)	-	-	-	-	-0.046 (-3.005)	0.134 (8.8)	*
k = 5 (K5)	360	*	*	-	-	-	-	-0.081 (-6.136)	0.109 (8.32)	-0.076 (-5.818)
Equal Att. Wt.	900	0.05 (5.408)	0.033 (3.596)	0.039 (3.272)	*	*	*	*	0.089 (8.351)	0.028 (2.63)
Unequal Att. Wt.	900	0.042 (4.659)	0.044 (4.892)	0.032 (2.739)	-0.031 (2.676)	*	*	*	0.0719 (6.982)	0.029 (2.811)
No. of Prod = 5	600	-	-	*	*	0.102 (-6.823)	-0.082 (-5.478)	-0.05 (-3.708)	0.113 (8.411)	*
No. of Prod = 10 (P10)	600	-	-	0.034 (2.791)	*	0.037 (3.027)	*	*	0.073 (6.741)	0.036 (3.33)
No. of Prod = 15 (P15)	600	-	-	0.036 (2.614)	0.052 (3.8)	*	0.04 (2.914)	*	0.057 (4.603)	0.056 (4.555)
No. of Att. = 2	600	0.053 (4.803)	*	*	*	-0.042 (-2.899)	*	*	0.095 (7.435)	0.038 (2.959)
No. of Att. = 3	600	0.035 (3.112)	0.04 (3.586)	*	*	*	-0.04 (-2.725)	*	0.092 (7.132)	0.033 (2.562)
No. of Att. = 5	600	0.05 (4.657)	0.054 (5.009)	0.061 (4.405)	0.075 (5.431)	0.037 (2.694)	*	-0.078 (-6.457)	0.055 (4.474)	*

Notes:

1. Coefficients for Equal and Unequal Attribute Weights and for Number of Attributes were included in the regressions, but were generally not significant ($\alpha \geq .01$)
2. (*)Coefficient not significant at the 0.01 level.
3. (-)not defined for this subset regression.
4. t-statistics are in parentheses.
5. All regression equations were significant at the 0.01 level.

time. Exhibit 5 shows the average RPS for each algorithm, which, of course, confirms the regression results. Average RPS for PRODSRCH was 6 percentage points higher than GHS-IV and 10 percentage points higher than PROPOSAS.

While these overall orderings of methods are informative, there are specific conditions where different results obtained. Exhibit 4 plots t-statistics associated with dummy variables representing each algorithm versus the parameter value held constant in each of the subset regressions. Results for both segmented and non-segmented markets are reported. (The effect of plotting t-statistics rather than dummy variable coefficients is to emphasize differences in statistical significance.) Let us consider these results:

Number of attributes. PRODSRCH remains the superior algorithm (relative to GRID SEARCH) as the dimensionality of the market increases (Exhibit 4a, b). PROPOSAS is second in the case of segmented markets while GHS-IV performs second best in the unsegmented cases. All algorithms are significantly different from GRID SEARCH (and each other) except in the case of PROPOSAS in two-dimensional markets. The algorithms tend to worsen relative to GRID SEARCH as the number of attributes increases, but their relative ordering remains unchanged. PRODSRCH is less affected relatively, a point in its favor since it is the algorithm most strongly affected by the number of attributes. PROPOSAS is statistically indistinguishable from GRID SEARCH in attribute spaces of low dimensionality (n_A F 3) in the case of non-segmented markets, but becomes significantly inferior as the dimensionality increases. (GHS-IV performs similarly in the segmented market cases.)

Number of Products. All algorithms appear to improve relative to GRID SEARCH as the number of existing products increases with the exception of PRODSRCH (non-segmented markets). Exhibits 4c, d show that PRODSRCH is again consistently the better performing algorithm. As before, GHS-IV is second

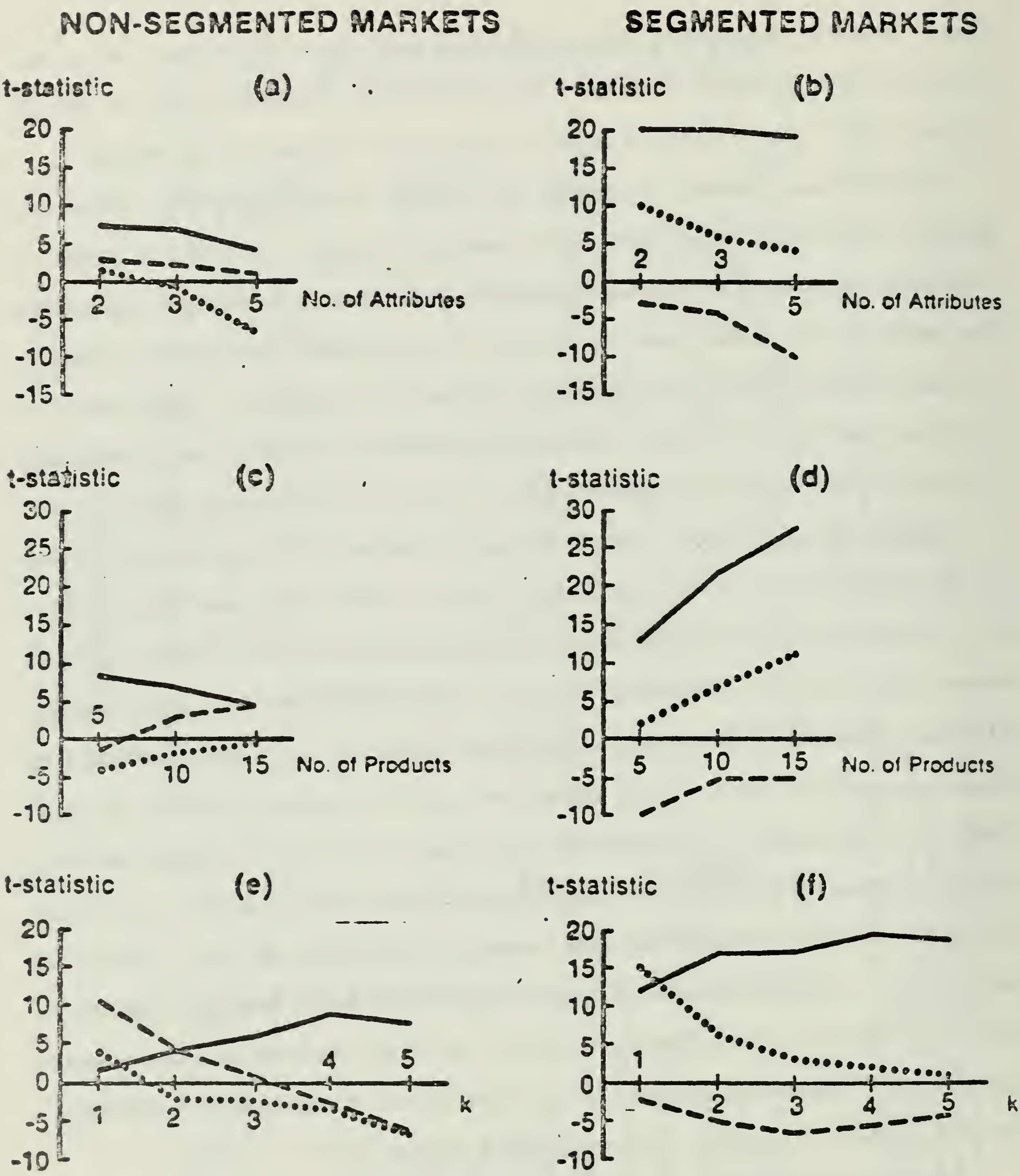


Exhibit 4
Plot t-statistic (relative to Grid Search)
versus attribute level
(based upon subset regressions)

KEY:
PRODSRCH
GHS IV
PROPOSAS

best performing in the non-segmented cases while PROPOSAS is second in the case of segmented markets. GRID SEARCH and PROPOSAS are virtually indistinguishable in (non-segmented) markets with large number of products (n_B = 15). Interestingly, PRODSRCH and GHS-IV are statistically indistinguishable (non-segmented markets) also in the case of $n_B = 15$. There is no obvious explanation for either result.

<u>Size of Consideration Set</u>. Perhaps the more interesting distinctions occur in relation to differences in size of consideration set (Exhibits 4e, f). When $k = 1$ both PROPOSAS and GHS-IV outperform PRODSRCH (in the non-segmented markets (and PROPOSAS alone does so in the segmented markets). Both algorithms were, of course, specifically developed for the $k = 1$ case (and PROPOSAS explicitly allows for differential segment weights), whereas PRODSRCH is a general purpose algorithm (attested to by its generally superior performance in the $k > 1$ cases). All algorithms appear to worsen relative to PRODSRCH as k increases. An exception to this generalization is the parity of GHS-IV with PRODSRCH in the $k = 2$ condition for the non-segmented markets.

A more detailed way of examining the simulation output is to note the dominant algorithm for each possible micro-market. Exhibit 5 indicates which algorithm provided the highest average RPS and which others provided an average RPS in excess of 0.90. Unlike the preceding analyses, "purified" algorithm effects are not isolated statistically (i.e., no regression is used to control for the other variable effects). Exhibit 5, of course, confirms the conclusions drawn previously, but provides more detail. Consider the non-segmented market configurations:

PRODSRCH is the better performing algorithm in all but the $k = 1$ cases (in first place 57/72 = 79.2% of these cases versus 11/72 = 15.3% for GHS and 3/72 = 4.2% for PROPOSAS and 1/72 = 1.4% for GRID SEARCH). When PRODSRCH was

Exhibit 5

A. The Better Algorithms in Specific Market Configurations - Non-Segmented Markets
(Avg. RPS $\geq$ 0.90, listed in decreasing order, left to right)

No. of Attributes:	2		3		5	
Attributes Wts.:	EQUAL	UNEQUAL	EQUAL	UNEQUAL	EQUAL	UNEQUAL
Number of Products = 5						
k = 1	GH/PP	GH/PP/PS	GH/PP/PS	GH/PS	GH	GH
k = 2	PS/GH/PP/GS	GH/PS	GH/PS	PS/GH	GH/PS/PP	GH/PS
k = 3	PS/GH/PP/GS	PS/GH/PP	PS	PS/GH/PP	PS/GH/PP	PS
k = 4	PS	PS	PS	PS	PS	PS
k = 5	PS/GS	PS	PS	PS/GS	PS	PS
Number of Products = 10						
k = 1	GH/PP	GH/PP	PP/GH	GH/PP/PS	GH	GH
k = 2	PS/GH/PP/GS	PP/PS/GH	GH/PS	PS/GS	PS/GS/GH	GH/PS/GS
k = 3	PS/GS	PS	PS/GS/GH	PS	PS/GH	PS/GH
k = 4	PS/GH	PS/GH/PP/GS	PS/GS/GH	PS/GS/GH	PS	GS/GH/PS
k = 5	PS/GS	PS/GH/GS/PP	PS	PS	PS/PP	PS
Number of Products = 15						
k = 1	GH/PP	GH/PP	PP/GH	PP/GH	GH	GH
k = 2	PS/GH	GH/PP	PS/GH/GS/PP	GH/PP/GS	GH/PS	GH/GS/PS
k = 3	PS/GS	PP/PS/GH	PS/GH	PP/GH/PS/GS	GH/PS/GS	GS/PS/GH
k = 4	PS	PS	PS	PS/GH	PS/GS/GH	PS/GS
k = 5	PS	PS/GH/PP/GS	PS	PS/GS/PP/GH	PS/GH/GS	PS/GS/GH

Summary

Algorithm	All Markets			k = 1 Markets		
	Mean RPS	Range	Rank	Mean RPS	Range	Rank
PRODSRCH	.95	(.73 - 1.0)	1	.83	(.73 - .92)	3
GHS-IV	.89	(.61 - 1.0)	2	.99	(.97 - 1.0)	1
GRID SEARCH	.87	(.66 - .99)	3	.81	(.66 - .89)	4
PROPOSAS	.85	(.58 - 1.0)	4	.88	(.61 - 1.0)	2

B. The Better Algorithms in Specific Market Configurations - Segmented Markets

Summary

Algorithm	All Markets			k = 1 Markets		
	Mean RPS	Range	Rank	Mean RPS	Range	Rank
PRODSRCH	.96	(.72 - 1.0)	1	.86	(.72 - .98)	2
PROPOSAS	.64	(.29 - 1.0)	2	.98	(.87 - 1.0)	1
GRID SEARCH	.47	(.07 - .89)	3	.47	(.07 - .76)	3
GHS-IV	.33	(.09 - .72)	4	.42	(.16 - .72)	4

Legend: GH - Gavish, Horsky, Srikanth, Method IV
GS - GRID SEARCH
PP - PROPOSAS
PS - PRODSRCH

not first, it was almost always a close second. In the k = 1 cases, PRODSRCH was never the best performing and rarely second; but it performed on average within 17% of the best.

GHS IV was the best performing method for the k = 1 cases (15/18 = 83.3%) and was either first (10) or second (5) best performing in the k = 2 cases (83.3%). It gave good results in k > 2 markets, especially when the number of products in the market was large and the number of attributes was also large. PROPOSAS was generally second to GHS-IV in the k = 1 market configuration but otherwise did not perform consistently well. It appeared more likely to perform better in spaces of lower dimensionality. GRID SEARCH generally was second to PRODSRCH in those conditions (k > 2, larger dimensional spaces, larger number of existing products) where PRODSRCH was also superior.

In the case of the segmented market simulations, the relative performance of the different algorithms was more clear cut. PROPOSAS was the dominant algorithm in those instances where k = 1, but PRODSRCH was generally a close second. PRODSRCH was substantially the better performing algorithm in all other cases.

DISCUSSION

The market characteristics which seemed to have the greater effect on algorithm performances were unequal segment weights and size of the consideration set. Both these changes are related to statistically significant differences in the performances of GHS-IV and PROPOSAS, particularly. Segmentation vs. non-segmentation is, of course, confounded in our simulation with the number of customers (25 and 100) and thus attribution should logically await further research where, say, number of customers is varied under controlled conditions. We concluded that PROPOSAS was vastly superior to GHS under the segmented market conditions, but GHS was only somewhat superior to PROPOSAS under the non-segmented market conditions (although its superiority appears to increase as the number of existing products and k increase). The complexity of both PROPOSAS and GHS increases, of course, with the number of segments and given the superiority okf GHS with the non-segmented cases, it seems plausible to presume that the superiority of PROPOSAS in the segmented cases is due to its ability to incorporate differential segment weights. Sonke Albers (personal communication) has challenged this interpretation, however.

Correct specification of the size of consideration set (and the related concept of probabilistic choice) seems important. Algorithms which assume k = 1 in a k > 1 world perform significantly less well in this study. Surprisingly, GRID SEARCH (which could explicitly consider the correct value of k as well as incorporate segment weights) was markedly inferior (by 50%) to PRODSRCH in solution quality in segmented markets, but not substantially so (by 8%) in the non-segmented cases. GRID SEARCH was also outperformed by GHS-IV (non-segmented markets) and PROPOSAS (segmented markets), algorithms which could not incorporate values of k different from unity. These observations may, of course, say more about our operationalization of GRID SEARCH, since by a suitable choice of fineness of grid one should always be able to obtain a global optimum, albeit at a substantial cost in computational efficiency. Exhibit 4, in addition to providing plots of t-statistics versus parameter level, mirrors the direct effect of changes in RPS due to parameter changes. (This is so because the regression coefficient is interpretable as change in RPS in the presence of each algorithm and the specific algorithm accounts for most of the explained variance.) Exhibits 4e, f show declines for all algorithms (other than PRODSRCH) with increasing k. (A fact also confirmed by examination of average RPS directly, although these data are not reported here. GRID SEARCH remains approximately constant in average RPS for all values of k.) Sudharshan (1982) discusses several empirical methods for estimating the "correct" value of k and, using small samples, demonstrates the superior performance of PRODSRCH over GHS-IV empirically.

PRODSRCH performs well in virtually all simulations. It is most often the better performer and rarely worse than second. It is statistically inferior to GHS-IV and PROPOSAS generally only under the conditions for which those algorithms were specifically designed. Even when it is the second performer, its RPS is not substantially below the leader (Exhibits 4, 5) a fact which was not always true for the other algorithms. Additionally, PRODSRCH offers considerable flexibility to the modeling process. We have already noted that only it and GRID SEARCH are able to consider probabilistic choice. It is also easily able to be used with multiattribute decision models different from the ideal point model (e.g., vector, conjoint, mixed models), whereas the other algorithms (but again with the exception of GRID SEARCH) cannot. Nominally-scaled attributes can also be incorporated into the PRODSRCH framework.

FINAL REMARKS

The study has, despite some limitations, provided useful and needed comparisons of several of the more prominent algorithms for identifying promising new product possibilities. We have varied certain parameter specifications in an attempt to discover which elements of our market model are more critical to the performance of these different search algorithms. The more fundamental question which we have not answered is with respect to the realism and usefulness of the market model itself. Further research, particularly empirical, is necessary to determine the adequacy of such models.

Particularly critical is the assumption that one can predict preferences toward any arbitrary product location in perceptual space using comparatively simple models. There are several reasons for believing that such may not always be more than approximately possible. Some locations in perceptual space invariably lie outside the range of attribute values which characterize the products used to calibrate customer decision-models. The ability of such models to reliably forecast behavior toward potential products which are different from those used for calibration must be suspect on logical grounds. Further, perceptual product spaces may consist of some number of loosely connected or discrete regions in each of which clusters of products are located rather than a space in which preferences are continuously variable with distance. This seems plausible when one considers that perceptual attributes need not be continuously variable with changes in product characteristics, possibly leading to discrete jumps in preference as one moves from one region to another. This possibility becomes even more plausible when one realizes that most perceptual mapping methods merely lead to representation of the positioning of known products. The products are all that are known from the perceptual mapping exercise; the underlying perceptual dimensions must be interpreted using clues from these product locations (Shocker and Stewart 1983).

Even were we to ignore the possibility that perceptual space is discrete and that simple customer models may not be able reliably to predict customer preferences for arbitrary locations in perceptual space, there may be other problems. Products are represented as points in a common space spanned by determinant attributes. This assertion of a common space is made for operational simplicity, since, otherwise, a single new product possibility would have to be identified simultaneously in some potentially large number of idiosyncratic market structures. Such structures may vary across individuals because marketing actions by competing firms can be differentially perceived. Customers can have different familiarities or experiences with the existing product alternatives which can lead to variability in their perceptions. Perceptual measurement can introduce another source of error (Shocker and Stewart 1983). Each of the product point locations in some hypothesized common perceptual space might better be considered as the centroid of some underlying perceptual distribution (determined by pooling individual judgments). High variance in such distributions may limit the usefulness of models of the sort we have been considering. A further complication is introduced by the fact that any new product discovered this way is also identified by its single point location. Actualizing such a location into a tangible product and marketing program remains the major problem for all approaches to new product development. Algorithms which permit sensitivity analyses of their "optimal" solutions may offer a practical advantage.

The ideal point model can be criticized as too limiting a multiattribute model. Ideal points imply that some finite level of an attribute is optimal and greater or lesser quantities than this are less preferred, *ceteris paribus*. Some attributes may be better regarded as features which are either present or absent and hence nominally-scaled (e.g., conjoint analysis, see Green, Carroll, and Goldberg (1981)). Such complexities pose problems for several of the search algorithms considered here. Decision-modelling flexibility would appear to be a very desirable characteristic since the nature of relevant attributes and models of the preference/choice decision process should rightfully be an empirical question. The choices should vary with the product category and, perhaps, the skill and insight of the analyst.

Searches for "optimal" new product concepts may result in trivial or obvious possibilities (Paul Green, personal communication) if such search is unconstrained. (Although the imposition of arbitrary constraints could potentially preclude desirable feasible alternatives resulting in suboptimization.) A high quality, low price alternative may be everyone's dream, but may be impractical. Models which must ignore differential costs of development, manufacturing, and marketing may lead to less profitable real world solutions. If vector (infinite ideal point) models of decision-making are incorporated into the objective function, an unconstrained model may also produce results which are not useful. Technical or economic logic may or may not be enough to enable unaided managerial judgment (about things the manager has not experienced) to provide reasonable constraints. There are admittedly pragmatic problems in eliciting realistic constraints which do not preclude desirable solutions. There will also be limitations on the types of constraints (e.g., linear versus non-linear, continuous versus discontinuous) which can be considered by a given search algorithm. But the superior algorithm may well be the one with the greater flexibility in this regard.

Flexible algorithms such as the PRODSRCH or GRID SEARCH tested here and the POSSE package of programs (Green, Carroll, and Goldberg (1981)) would seem to afford the better opportunity for moving closer to solutions that prove desirable in that more complex reality we call real world markets. Such algorithms can better accommodate such reality while retaining their all important tractability. We do not mean to be alarmist. Models such as those reviewed here simply are not panaceas. Rather we would urge further empirical testing of these frameworks and comparison with more conventional/traditional methods for generating new product ideas. Such research can only help to provide better understanding of the limits of their usefulness and of the possibilities they afford for improving implementation of the marketing concept.

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