This document contains the draft version of the following paper:

S.K. Gupta and A.K. Samuel. Integrating the market research with the product development process: A step towards design for profit. *ASME Design for Manufacturing Conference*, Pittsburgh, PA, September 2001.

Readers are encouraged to get the official version from the conference proceedings or by contacting Dr. S.K. Gupta (skgupta@umd.edu).

Integrating Market Research with the Product Development Process: A Step towards Design for Profit

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ABSTRACT

This paper describes a systematic approach for integrating market research with the product development process. The following three problems are addressed in this paper. First, a demand estimation algorithm has been developed based on conjoint measurement techniques. Second, an integrated design decision model has been developed. The main components of this design decision model are representation of available design options using AND/OR tree based representation, and an evaluation procedure for evaluating profit resulting from a design option. Third, a heuristic search technique has been developed that makes use of the design decision model to select the design option that maximizes the profit. Integration of market research with the product development process is expected to result in the following two benefits. First, it will reduce the number of design iterations. Second, it will help the design team in finding the most profitable product designs.

1. INTRODUCTION

Development of consumer products is an activity through which a product development organization attempts to design and manufacture products to realize profit by meeting the customer requirements. This activity usually consists of identifying customer needs and preferences, defining the product functionality, identifying design alternatives, identifying alternative ways of manufacturing/procuring components in various design alternatives, and selecting the optimal design alternative. Usually the goal of most consumer product development organizations is to maximize profit or a closely related financial metric such as net present value or return on investment.

The three major steps in the product development process consist of market research, product design, and procurement and manufacturing. The objective of market research step in product development process is to identify the customer needs and preferences and if possible, convert them into engineering specifications. Usually, market research is performed by conducting market surveys involving potential customers. The output of the market research step is usually engineering specifications (e.g., specifications that describe the desired product functionality). The objective of the design step in the product development is to design a product that meets the engineering specification identified by the marketing department in the market research step. This is usually done by identifying different ways of realizing the desired engineering specifications, evaluating these alternatives, and selecting the most desired alternative based on the preferences of the design team. The objective of procurement and manufacturing step in product development process is to develop and execute a plan for physically realizing the product specifications given by the design department. This step involves generating alternative manufacturing/procurement plans, evaluating these plans, and selecting the plan that minimizes cost.

Iterations between the marketing department and the design department and between the design department and the manufacturing department continue until a profitable product is developed. Concurrent engineering enables the design and manufacturing decision to be made concurrently and therefore eliminate unnecessary iterations between the design department and the manufacturing department. This helps in driving down the cost. Despite the proven success of design and manufacturing integration through concurrent engineering, the marketing department and the design department continue to work sequentially during the product development process. Therefore, iterations between marketing and design continue to be a source of inefficiency in the product development process.

Recently researchers have begun to understand and realize the importance of integrating market research and design steps [1-3]. In the integrated framework, the main role of the design team is to identify various design alternatives. The marketing team develops customer surveys to identify customer preferences and demand estimation algorithms for the design alternatives identified by the design team. Manufacturing team generates plans for physically realizing the design alternatives and develops cost estimation functions for evaluating these alternatives. Finally, an integrated decision-making approach is used to concurrently select engineering specifications, product specifications, and manufacturing/procurement plans. Integrated decision-making process eliminates unnecessary iterations and helps in creating more profitable product designs than the ones attained with the sequential product development process.

This paper addresses the problems of integrating market research with the product development process. In this paper, we cover the following three research problems. First, we describe a new demand estimation algorithm that utilizes the product's performance attributes, customer preferences and the price of the product to estimate demand. Second, we describe an integrated design decision model based on an AND/OR tree-based design option representation and an evaluation procedure for evaluating profit resulting from a design option. Third, we describe a heuristic search technique that makes use of the design decision model to select the design option that maximizes the profit.

2. RELATED WORK

2.1 Using Conjoint Analysis to Conduct Market Research

Conjoint analysis is a multivariate technique utilized to understand customer preferences for products or services [4-9]. According to Hair [9], it is best suited for understanding customer’s preferences. The flexibility and uniqueness of conjoint analysis arise from (1) its ability to accommodate either a metric or nonmetric dependent variable, (2) the use of categorical predictor variables, and (3) the quite general assumptions about the relationships of independent variables with dependant variables.

Conjoint analysis is based on the assumption that customers assign values to each attribute and the total value will be considered while buying a product. The market researcher presents a hypothetical set of product/services to the customers, who provide their overall evaluations. The main advantage of conjoint analysis is that the customers have to only provide their preferences on the given set of choices. They don't have to pick the attributes that they like. The market researcher extracts the importance of each attribute and value of the each attribute from the customer's overall ratings. A product or service should be described in terms of its attributes and the relevant values for each attribute. The possible values for each attribute are usually called levels. When a set of attribute and its corresponding levels are described to portray a product, it is called a product configuration.

The customers would be asked to rank the given set of product configurations on a preference scale. For example, preference scale can be defined to be in the range of one to ten, with ten representing the most preferred value. The preference of a product for a customer can be expressed in terms of the partworths for each performance attribute. Partworth is the estimate from conjoint analysis of the overall preference associated with each value of each attribute used to define product [9]. Many times a simple additive model is sufficient for capturing a customer’s preferences.

Green and Sreenivasan [10] discuss various issues involved in implementing conjoint analysis. They used the term conjoint analysis broadly to refer to any decomposition method that estimates the structure of a consumer's preferences. There are several different alternative approaches and formulations to carry out each step in the conjoint analysis. In our work, partworth function model will be utilized for selection of a model of preference step. For data collection step, full profile method will be utilized. For construction of feasible product configurations, fractional factorial design method will be utilized. For presenting product configurations to the customer, textual description will be utilized. For the measurement of attribute effects, rating scales will be utilized. For estimating partworths, single regression method will be utilized.

2.2 Estimating Demand

Several previous approaches for estimating demand utilized aggregates of the preferences of a group of customers [11, 12]. Hazelrigg [11] points out that all the customer preference information is lost when one aggregates the preferences of a group of customers and utilizes arrows impossibility theorem to prove this. His proposal was that customer makes a decision to buy or not to buy based upon his or her own preferences. Hazelrigg proposed a framework for decision based engineering design [12]. An important component of Hazelrigg's framework is the formulation of demand function.

Li and Azarm [3] extended and implemented Hazelrigg's framework accounting for both customer preferences and market competitions. They assume that the market analysis has been performed and partworths for all the attribute levels have been computed for each customer in the sample. Demand for every configuration in a given set of product configurations is computed in the following manner. For each customer in the sample, total partworth is computed for every product in the given set. Demand for a configuration is computed by counting the number of times the configuration appears as the most preferred configuration for various customers in the sample, and multiplying this number by the ratio of the population and the sample size. Their approach for estimating demand assumes that the market size is independent of available product choices. This means that each customer will definitely buy one of the products that are available in the market.

2.3 Solution Methodologies for Selecting the Most Preferred Design Option

Li and Azarm [3] developed a methodology that accounts for designer’s preferences, customer’s preferences, and market competition. The model also considers uncertainties in the product design life, market size and its yearly change, cost and its yearly change, price, and discount rate, among others. An iterative two-stage approach consisting of design alternative generation and design alternative evaluation was developed. In design alternative generation stage, for alternatives that are handled in the performance model, multi-objective optimization is performed to generate a set of Pareto design solution. For generating Pareto optimal solutions, multi-objective genetic algorithms are used [13]. For attributes that are not handled by multiobjective optimization a permutation of their levels over all Pareto solutions is performed to generate design alternatives. The design alternative evaluation model evaluated design alternatives based on business goals such as net present value of profit and market share. Customer preferences, competitor products, cost, and the generated design alternative were used as an input to the design evaluation model. Uncertainty was accounted for various factors using Monte Carlo simulation. This approach has limited ability to handle problems where a diverse set of design concepts will need to be used because a common set of design variables cannot be always identified when considering diverse design concepts. It is assumed that cost estimation function is defined in terms of design attributes. In many cases, estimating cost based on assemblies or components cost can provide more accurate cost estimates than the ones based on design attributes.

Trichur and Ball [14] suggested multiobjective integer programming models for product design. They suggested representing the design alternatives available at product design stage as an AND/OR tree using functional decomposition. Integer programming model was applied to find the optimal product design represented using AND/OR tree. The multiple objectives of the product design for example can be to minimize cost and to maximize manufacturing yield.

3. PROBLEM FORMULATION

3.1 Definitions

Performance Attributes: Product attributes that affect a potential customer's decision to buy a given product configuration are called performance attributes. For example, for an exercise machine that aims to build abdominal muscles, the performance attributes can be: (1) position of exercise, (2) adjustment of equipment resistance, (3) daily time required for burning 100 calories, and (4) portability. Performance attributes can be assigned (1) integer values, (2) real values, or (3) predefined types (e.g., the performance attribute *position of exercise* takes values from the following predefined types: *{"sitting", "standing", "lying down"}*.

Design Attributes: Product attributes that are directly specified by the designers are called design attributes. In general, performance attributes are functions of design attributes. Sometimes, there is a one-to-one mapping between a design and a performance attribute. For example, color of the car is both a design attribute and a performance attribute. In some other cases a more complex mapping may be needed. Mapping function estimates the performance attributes from a given set of design attributes for a design option. Design attributes can be assigned integer values, real values, or predefined types. For example, length of a support rod is a design attribute that can be assigned a positive real value. On the other hand, a design attribute such as color takes a value from a predefined set of colors.

Product Configuration**:** A product configuration is defined by assigning all performance attributes for the product to certain values or types. Table 1 shows an example of product configuration for an exercise machine that builds abdominal muscles.

Table 1: An Example of Product Configuration

Performance Attributes	*Performance Attribute Value*
Position of Exercise	Sitting
Adjustment of Resistance	Beginner to Average Level
Daily time to be spend for burning 100 calories	15mts
Portability	Fits Underneath Bed

Demand: Demand refers to the number of customers willing to buy a given product configuration for a given price.

AND/OR Tree Based Design Representation**:** Our approach utilizes a hierarchical design representation based on functional decomposition for all the subdesigns considered during the product development process. We use *AND/OR* tree to represent all possible design options. Alternative design concepts are the OR nodes in the representation while functional decomposition are the AND nodes. Leaf nodes in the *AND/OR* tree are the physical components/assemblies that make up the product design.

Design Options*:* A design option is a complete subtree of AND/OR tree. In our framework, the AND/OR tree represents all possible design options. A subtree (a subset of the given AND/OR tree) is considered *complete*, if and only if:

- It includes all children of every AND node in the subtree
- It includes only one children of every OR node in the subtree

Node Interactions in AND/OR Tree**:** Nodes in an AND/OR tree may interact with each other and may reduce design options. A typical situation can be that the selection of one node dictates the selection of the other or vice versa. Rules between nodes that dictate the conditions under which a node or a collection of nodes should be selected are called node interactions. The simple node interaction can be "must select" interaction and "must not select" interactions. Rules that are more complicated can be defined for node interactions, with many nested structures.

Profit*:* Profit for a given product configuration at a given price is given by demand times the difference of price and cost i.e., $P = D(R-C)$. (Where, P is the profit, D is the demand, R is the price for which the product will be sold, C is the cost).

3.2 Problem Statement

The input to the integrated decision support system consists of:

1. ***AND/OR Tree Based Design Representations:*** AND/OR tree based design representation encompasses all the design options that will be considered at the product development process. Node interactions among the design options are also defined to make sure that only a feasible design option is selected.
2. ***Customer Preferences:*** We are given customer preferences for a set of customers who are representative of the population to whom the product will be marketed. For each customer, we get preferences of the customer for a small number of pre-selected product configurations by conducting market surveys.
3. ***Mapping Functions:*** Mapping functions provide a framework for mapping design attributes into performance attributes. Mapping functions are crucial for estimating demand for a design option under consideration.
4. ***Supplier Options:*** Supplier options describe the supplier pool from which suppliers will be selected to realize physical components of the AND/OR tree based design representation.

Our objective is to select a design option that maximizes profit. The output of the decision support system will be:

1. A design option that maximizes profit.
2. A supplier for each component in the design option.
3. Recommended price for selling the product.

3.3 Assumptions on the Input and Output

The following assumptions are imposed on the design problems that can be handled by the approach described in this paper:

1. Product design can be hierarchically decomposed into subdesigns, with an explicitly enumerable set of design options.
2. Design options can be characterized as sets of design attributes.
3. Only pre-specified discrete price levels will be considered.
4. Performance attributes are only assigned discrete values.
5. Mapping between design and performance attributes is possible.
6. All parts/components that comprise the product are assumed to be procured from outside suppliers. Therefore, manufacturing planning issues are not considered.
7. Only supplier cost is considered for the supplier decision-making process.
8. Volume discount in processing large number of parts is not considered for estimating the cost for the product design. In addition, assembly costs is not considered.
9. Time value of money is not considered.
10. During design process, the sizing problem is not considered.
11. The effect of time-to-market on profit is not considered.
12. Only linear models are used in conjoint analysis.
13. The aspects of competitors in the market was not considered for demand estimation algorithm.
14. The dependent/coupled effects of performance attributes were not considered for heuristic search technique.

3.4 Overview

This paper describes the following three main component of our approach:

1. ***Demand Estimation:*** We need a systematic approach to estimating demand for various design alternatives being considered during the product development process and will need to extend the existing conjoint analysis methods for estimating demand. Furthermore, we will need to develop market survey techniques to gather the relevant customer preference information to facilitate demand estimation. Section 4 describes in detail our market survey methodology and demand estimation algorithm.
2. ***Representing and Evaluating Design Alternatives:*** In an integrated decision-making framework, design alternatives need to be considered and evaluated for several sets of engineering specifications as opposed to a single set of engineering specifications. In order to facilitate use of computer aided tools in decision-making, the design alternatives should be represented in a computer-interpretable form. Furthermore, usually a design is a collection of large number of subsystems or devices. In many cases selecting one subsystem or device may affect whether or not some other subsystem or device can be used in the design or not. Section 5 describes our approach for design representation based on the hierarchical decomposition and how to estimate profit for a given design option.
3. ***Selecting the Design Option:*** The design problem consisting of the large number of design alternatives generated in the integrated decision-making approach has to be solved to select the best possible design. Section 6 describes a heuristic search method for selecting a design option in an integrated framework.

4. MARKET SURVEY AND DEMAND ESTIMATION

Figure 1 shows an overview of demand estimation methodology. This methodology enables us to estimate demand for a given product configuration at a given price using the customer survey data. The three major steps in our approach consists of designing and conducting market survey, using conjoint analysis to compute partworths for each surveyed customer, and an algorithm for using the computed partworths for various customers to estimate demand for a new product configuration.

4.1 Designing and Conducting Market Survey

A preliminary market survey is conducted to identify the performance attributes for the product design under consideration. The levels of performance attributes are also identified at this time.

Depending on the number of performance attribute levels, partial product configuration consisting of two attributes at a time, full factorial design or fractional factorial design can be utilized [10]. Full factorial design can be utilized when the number of performance attributes levels is not large. Fractional factorial designs are used for product designs with large number of performance attribute levels for deciding what is to be included in the sample.

The product of the levels for all the performance attributes gives the total number of product configuration. Some of the product configurations given by the combination of performance attribute levels may not be realistic and can be removed. The survey should now be checked to see if the levels for all the performance attributes are distributed equally for ensuring that the effects for all the levels can be measured from the market survey. Also in order to measure the effects of the combination of the levels, the survey should be checked to see that the product configurations to be utilized for the survey is representative to measure the effects of the combination of the levels. Usually 10 to 25 product configuration are used for the market survey. In this survey twenty different product configurations were used.

The sample size for the market survey is also decided at this stage. The size of the sample to be selected from the population depends on the desired confidence level and error allowed for the statistic under consideration [15]. Usually 95% confidence level is considered and an appropriate value of error is chosen as per the desired accuracy to select the appropriate sample size.

The data collection procedure used is described in the following steps. A set of cards each representing a product configuration is given to each customer. The respondents are then asked to do the following:

- Divide the set of cards into two sets, one set representing the products that the respondents are willing to buy termed, as “Acceptable Products” and the other set representing the products that the respondents will certainly not buy termed as “Unacceptable Products”.
- The respondents are then asked to give a score in the range of 0 to 10 with 10 representing the most preferred product configuration and 0 representing the least preferred from the “Acceptable Products” set.
- “Unacceptable Products” set is then marked with the reduced prices for which the respondents will consider buying it. We did not use ranking system in this case, because respondents had difficulty in expressing their degree of dislikeness through giving ranks. The respondents also can specify certain level of the attribute that motivated them to consider the product as “Unacceptable Products”. This capability is provided, since the respondent in some cases may be following a simple rule of not buying a product since he dislikes certain performance attribute levels completely.

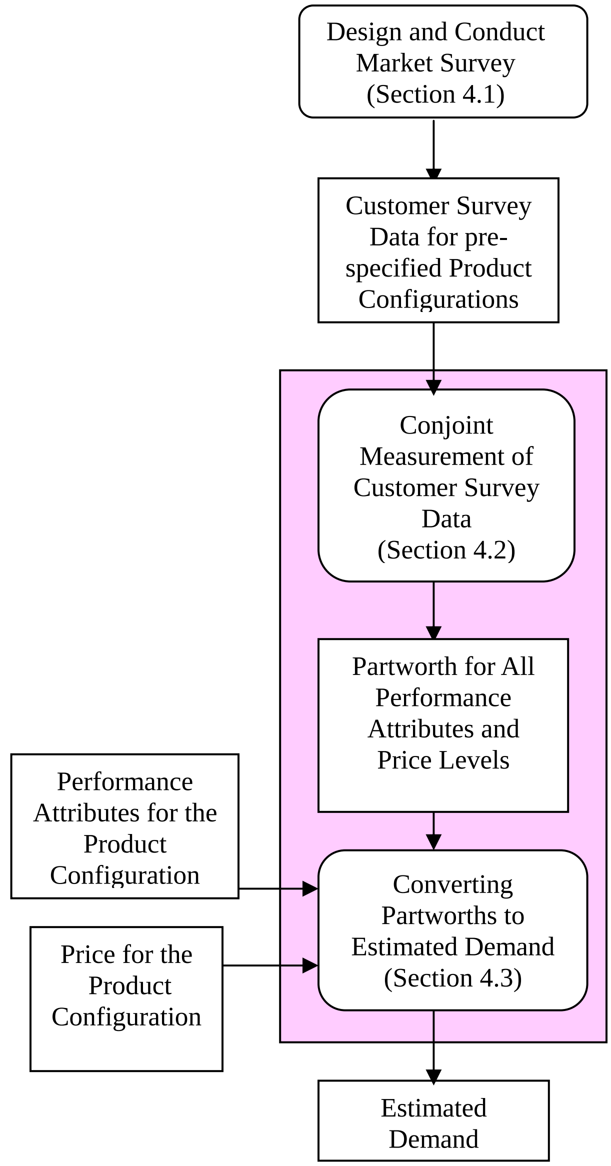

Figure 1: Overview of Demand Estimation

At the end of the data collection procedure administered to each respondent, there will be two sets of cards namely “Acceptable Products” cards and the “Unacceptable Products” cards.

4.2 Conjoint Analysis of Customer Survey Data

The cardinal scores from the set of cards for “Acceptable Products” and the desired reduction in price levels from the set of cards for the “Unacceptable Products” are converted to ordinal ranks for computing partworths. The procedure utilized for this is described below:

- Based on the scores assigned by respondent to each of the “Acceptable Products”, ordinal ranks are assigned. For the “Unacceptable Products”, the difference between the absolute value of the original price and the preferred price of the respondent is computed. The desired reduction in prices are then normalized using the function *N=d/R* (Where, *N* is the normalized value obtained for a product configuration in the "Unacceptable Products' set, *d* is desired price reduction and *R* is the price level assigned to the product configuration).

  The normalized values are then used to assign ordinal ranks to products in “Unacceptable Products” set. At the end of the data processing step, two sets of ordinal ranks, one for “Acceptable Products” and one for “Unacceptable Products” are obtained. These two ranks are then concatenated into a single ordered set (all "Acceptable Products" have higher ranks than the all "Unacceptable Products"). For each respondent we also record the transition rank interval, where customer's preference changes from acceptable to unacceptable (i.e., the lowest ranked acceptable configuration and highest ranked unacceptable configuration define this interval).
- Conjoint analysis is used on the ordinal ranks given by each respondent to find the partworths. Linear models are applied to the rank data if no second or higher order interactions are present. Linear models assume that the value or utility of a product configuration is the sum of the part worth of the performance attributes levels. The total partworth for a product configuration can be obtained as shown below:

$$T = \sum_{j=1}^{m} \sum_{i=1}^{n} x_{ij} W_{ij}$$

  where,

  T is the total part worth for a product configuration with m performance attributes each at one or more levels with the maximum number of levels being n.

  x_{ij} is equal to one, if jth performance attribute is set to level i and is equal to zero otherwise.

  W_{ij} is the part worth of the j attribute at the i performance attribute level.
- The average ranks for each level of a performance attribute are found by summing the ranks for the levels in the survey data and dividing it by its total number of occurrences. The part worth of a performance attribute level is then calculated as W= (A-S)/ *(M-S) (W*here, *W* is the part worth for the performance attribute level, *A* is the average rank for the performance attribute level, *S* is the minimum average rank for the set of performance attribute levels, *M* is the maximum average rank for the set of performance attribute levels). These values are computed for each respondent separately.
- If the respondent has simple rules by which a product configuration is marked as “Unacceptable Products”, the rules are noted and the corresponding product configurations from the list are removed. If the linear model does not fit the market survey data, non-linear models have to be utilized. Usually, this will instigate a new market survey for considering performance attribute interactions.

At the end of part-worth analysis, we will have part worth and transition rank interval for each respondent separately.

4.3 Converting Partworths to Estimated Demand

The procedure for converting partworths to estimated demand is described below:

1. The input to this procedure are product configuration and a price level for which the demand needs to be estimated.
2. For each respondent, the total partworth for the new product configuration is computed using the partworths for that respondent. The total computed partworth for the new product configuration is compared with the computed total partworths of every surveyed product configuration. If the computed partworth lies in the range of acceptable product configurations, the new configuration is considered acceptable to the respondent. If computed partworth value lies in the range of unacceptable product configurations, then we consider the product to be unacceptable to the respondent. If the computed partworth value lies in the transition interval range, then we cannot determine whether this product configuration is acceptable for the respondent or not.
3. We count the total number of respondents for whom the new product configuration is acceptable at the given price. We also count the total number of respondents for whom this product configuration is unacceptable at the given price.
4. The demand fraction *f* for the new product configuration is the ratio of the number of respondents for which the product configuration is acceptable divided by the sum of the number of respondents for which product configuration is acceptable and the number of respondents for which the product is unacceptable.
5. The demand for the new product configuration at the given price is given by the product of its demand fraction and the target population i.e., *D=fm* (Where, *D* is the demand for a product configuration at the given price, *f* is the demand fraction, and *m* is the target population).

5. DESIGN DECISION MODEL

The objective of design decision models is to provide an integrated framework for decision making during the product development process. The main components of design decision model developed in our approach is described below:

1. ***Representing Available Design Options*:** Design options are realized by the functional decomposition of the design requirements and by including all the design alternatives at each stage as an AND/OR tree. By this scheme, the function of the product is mapped to the physical components. The lowest level in the AND/OR tree for the design options will have the physical components necessary to realize a product design. The AND/OR tree based design representation is given by:

   N_A is the set of AND nodes
   N_O is the set of OR nodes
   $N = N_A \cup N_O$
   n_r is the root node of the tree,
   CHILD(n_i) is the set of nodes that are children of node n_i
   x_I is the selection variable defined as equal to one, if n_i node is selected in a design option, $i \in N$ and is equal to zero otherwise.

   The constraints for the AND/OR tree are as following:
   $x_r = 1$ implies that root node should always be selected.

   For AND nodes, the constraints are as following.
   $x_j = x_i \quad \forall i \in N_A, j \in$ CHILD(n_i)
   The constraints ensure that all the children of AND nodes are selected.

   For OR nodes, the constraints are as following:

   $$\sum_{j \in \text{CHILD}(n_i)} x_j = x_i \quad \forall i \in N_O$$

   These constraints ensure that exactly one of the children is selected for the *OR* node. Let x_1, x_2, x_3 are selection variables associated with three nodes, n_1, n_2, n_3 selected from the subtree of an AND/OR tree based design representation. If "must select" condition is applied between n_1 and n_2, n_1 and n_3, then if n_1 is selected, n_2 and n_3 should also be selected, then the constraints are $x_1 = x_2$ and $x_1 = x_3$.

   If "must not select" condition is applied, such that if n_1 is selected, n_2 and n_3 should never be selected, then the constraints are $x_1 + x_2 \leq 1$ and $x_1 + x_3 \leq 1$.
2. ***Design Option Selection Criteria:*** The objective function of the design decision model will be to select the most profitable product design.
3. ***Evaluating a Design Option*:** Figure 2 shows how a given design option at a given price can be evaluated using various components of the design decision model to estimate the profit. Design attributes are extracted from the design options. Utilizing the user defined mapping functions (described below), performance attributes are estimated from the design attributes. Customer preferences realized from the market survey, estimated performance attributes and the given product price is used to estimate the demand using the demand estimation algorithm (described in Section 4). Cost estimation function (described below) uses design attributes to estimate product cost. Utilizing the product price, estimated demand and product cost, profit for the given design option is estimated. Therefore conceptually, our decision model provided us a framework for comparing different design option and help in selecting the most profitable design option.

   Mapping function captures the mapping between design attributes and performance attributes. Mapping functions can be procedural in nature. In our approach, only "and" or "or" relations are considered for predefined types of design attributes and "add" or "multiply" relations are considered for real or integer valued design attributes. "and" relation for predefined type of design attributes

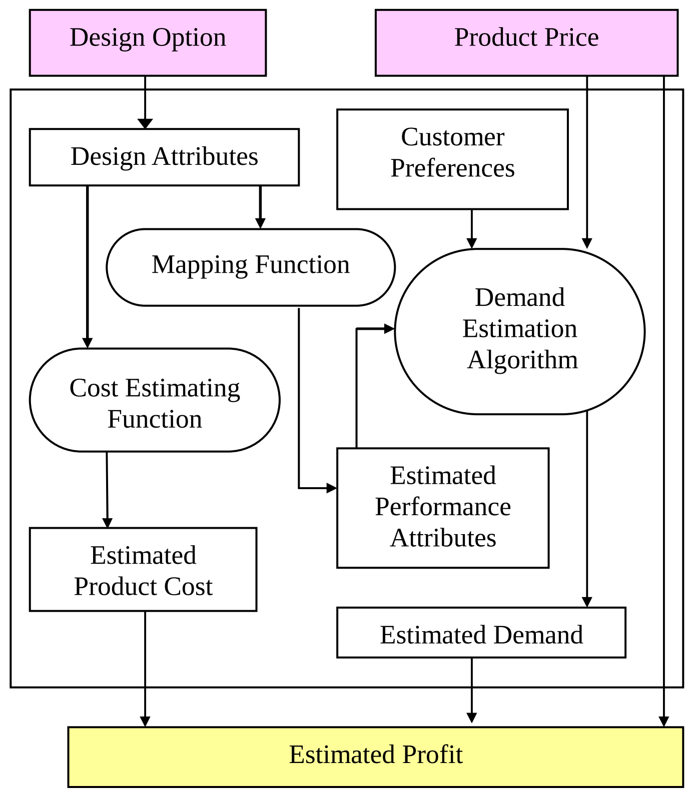

Figure 2: Evaluating a Design Option

means that a single performance attribute level is given by the collection of the design attributes from the design options. "or" relation for predefined type of design attributes means that a single performance attribute level is given by one of the design attributes in the collection selected. "add" relation for real or integer valued design attributes means that addition relations can be assigned between the design attributes defined. "multiply" relation for real or integer valued design attributes mean that multiply relations can be assigned between the design attributes defined. After the mapping procedure is completed, the mapping function should estimate the performance attributes given the set of design attributes that constitute the product design.

The cost associated with the design alternatives depicted in the design options is given by the cost estimation function. The inputs to the cost estimation function are the design attributes extracted from the design options. To estimate cost we add costs of individual components in the design.

6. HEURISTIC SEARCH TECHNIQUES FOR SELECTING THE DESIGN OPTION

6.1 State Space Search Formulation for the Design Problem

All possible design options form the search space for the design problem. The search procedure that can enumerate and evaluate various nodes searched for solving the design problem is listed below:

1. At the beginning of the procedure, three variables namely Current Best Profit (P_b), Current Best Design (D_b) and Current Price Level (R_b) are initialized to zero, null and zero values respectively.
2. A previously unexplored design option D_{cr} is generated from the AND/OR tree based representation considering the node interactions. Heuristics described in Section 6.2 are used to avoid generation of unpromising design options (i.e., design options for which estimated upper bound on profits is smaller than the current best design)
3. The cost associated with the design option is calculated using the cost estimation function.
4. Mapping function defined by the designer is then used to map the design attributes from the design options to performance attributes.
5. A new price level is selected from the set of predefined price levels for the product. Any price level for which estimated upper bound on profits is smaller than the current best design is not explored.
6. Demand is estimated using the demand estimation algorithm.
7. The estimated profit P_{cr} for the design option is computed as estimated demand times the difference between price and estimated cost.
8. If P_{cr} is more than P_b then P_b is assigned P_{cr}, D_b is assigned D_{cr} and R_b is assigned R. If all price levels have not been considered (either evaluated or pruned) for the current design option, then go to Step 5.
9. If a design option exists that has not been considered (either evaluated or pruned), then go to Step 2.
10. At the end of the search procedure, the P_b, D_b, and R_b will give the "best possible profit", "best possible profitable product design" and the “recommended price level for the product design” respectively.

6.1 Search Heuristics

The heuristics developed for pruning unpromising design option during the search process are described below:

- *Heuristic A:* If a performance attribute is identified such that increasing/decreasing its level monotonically decreases demand, then we call such attribute as monotonic effect attribute. During the conjoint measurement process, monotonic effect attributes can be identified. For monotonic effect attributes, selection of the smaller/higher level of a performance attribute will monotonically decrease the demand. For example, the performance attribute for the exercise machine namely, daily time required to burn 100 calories has three levels: 15mts, 30mts, 60mts. If all other performance attributes remain the same and if the level of this performance attribute alone is increased, the demand value decreases (most people want to get the same results namely firmer stomach in the lowest possible time). Therefore this is a monotonic effect attribute.

  Let L be the value of a monotonic effect attribute that gives the highest demand. After considering L, considering other levels of this attribute that require same or higher cost to realize will not give a better solution while all other performance attributes remain the same. Therefore, such nodes can be pruned.
- *Heuristic B:* During the search process, if the upper bound on profit from selecting a node is expected to be smaller than the current best solution, then the product configuration should be pruned. Upper bound on profit is estimated by estimating the upper bound on the demand for various price levels.

  A preprocessing step is necessary to apply this heuristic. The upper bound on demand for every price level is estimated by selecting the most preferred product configuration for each surveyed customer and using the demand estimation algorithm described in Section 4.
- *Heuristic C:* If the cost for the selected product configuration is higher than the current price level, the selected product configuration will not be profitable for any lower price levels. Hence, discard the price level considered and every lower price level.
- *Heuristic D:* If the profit for a product configuration for maximum demand is lower than the current best profit, then the product configuration will not give higher profit than the current best profit. Let D is the estimated demand for the given product configuration, m is the target population, P_b is the current best profit, R is the price level considered, C is the cost for the selected product configuration

The maximum possible demand for the product configuration is equal to the target population. (i.e., $D = m$). Therefore if $P_b > m\ (R\text{-}C)$, then discard price level R.

- *Heuristic E:* If the demand for the selected product configuration for the current price level is zero, if other factors remaining the same, the selected product configuration will never be profitable for higher price levels. Hence, discard the price level considered and every higher price level.

7. DESIGN EXAMPLE

Let us assume that "Tummy Cruncher" is the generic name for the exercise machine to be designed, which with regular use will help users to have a flat stomach and firmer abdominal muscles. There are many different ways to attain a flat stomach and firmer abdominal muscles. Our goal is to design an exercise machine that provides this intended functionality by offering resistance to the abdominal muscles, thus burning calories in the exercise process. The following sections show an example of a design problem solved using the framework described in this paper.

7.1 Market Research

The four steps in market research are:

1. ***Conduct Preliminary Market Survey:*** A preliminary market survey is conducted to understand the attributes that are pertinent from the customer's point of view. The preliminary market survey conducted helped in identifying the following performance attributes for exercise machine design example: {Position of Exercise, Daily time required to burn 100 calories, Adjustment of Resistance, Portability}
2. ***Design Detailed Survey:*** The performance attributes along with their possible values for "Tummy Cruncher" is listed below:

   Position of Exercise: {Sitting, Standing, Lying down}
   Daily time required to burn 100 calories: {15 Mts., 30 Mts., 60 Mts.}
   Adjustment of Resistance: {Beginner to Average Level, Average to Professional Level, Professional Level Only}
   Portability: {Fits underneath bed, Fits in a closet, Not portable}

   The total number of product configurations that can be formed is equal to the product of the number of levels of performance attributes. For the exercise machine design example, total number of product configurations = 3 x 3 x 3 x 3 = 81. For the market survey step in market research, prices are also considered. Four price levels considered are: {$29.99, $49.99, $99.99, $199.99}. Hence the total number of combinations possible = 81 x 4 = 324. Twenty product configurations were selected for the market survey using the fractional factorial design.
3. ***Conduct Market Survey:*** The number of customers to be surveyed or the sample size is to be decided at this step. Since the resources were limited for this study, it was assumed that confidence level required is 95% and the error allowed is 20%. Therefore we selected 21 customers. Out of the 21 surveyed customers, linear conjoint analysis model fits well for 15 customers. Since we did not perform non-linear analysis, we only used the data for 15 customers for the conjoint measurement technique in subsequent analysis.
4. ***Analyze Market Data to Extract Partworth:*** The market data is processed using conjoint analysis to estimate partworths for all performance attribute levels for all customers.

7.2 Define Design Options

The three major steps in this process are:

a. ***Create AND/OR Tree Representing Design Options:*** The objective of this step is to do recursive functional decomposition until physical components that realize product designs are reached. This information is utilized to create AND/OR tree based design representation. We assume that "Tummy Cruncher" is functionally decoupled.

   The functional requirement at the highest level is the flat stomach and firmer abdominal muscles that the user wants to attain by exercising his abdominal muscles. The functional requirement at the next level is {Isolate abdominal muscles, Provide muscle movements for exercise, Provide resistance/load for muscle movements, Adjustment of exercise resistance}. There may be several alternative design concepts to meet a functional requirement. So at next level we enumerate these alternative concepts. For example, for isolation of abdominal muscles for the exercise machine, three design concepts are available namely positioning head and shoulders, positioning hands and stomach and positioning thighs and chest (see Figure 3). The functional decomposition is continued until physical components that realize design options are reached. A portion of AND/OR tree based design representation for "Tummy Cruncher" is shown in Figure 3.

b. ***Defining Node Interactions:*** Node interactions are usually defined based on material and design functionality. Plastic material used for one physical component of a design option usually requires using plastic material for other physical components. The designer has to discern this based on the specific design process and node interactions should be assigned to create feasible design options. Material homogeneity is the factor considered for node interactions for "Tummy Cruncher".

c. ***Defining Mapping Functions:*** Mapping Functions are defined between design and performance attributes by the designer. The mapping process has two steps. Firstly, mapping between design attributes of predefined types and their corresponding performance attributes are done. Finally mapping between real valued design attributes and their corresponding performance attributes are done. Table 2 shows the mapping of design attribute length, breadth, height and weight to performance attribute, portability levels.

Table 2: Mapping of a Real Valued Design Attribute

Design Attribute	*Mapping Procedure*	*Performance Attribute (Portability Levels)*
Length (l) Breadth (b) Height (h) Weight (w)	If l x b x h ≤100in^3 and w≤10lbs	Fits underneath bed
	If 300in^3 ≤ l x b x h ≤500in^3 or 20lbs ≤ w ≤100lbs	Not portable
	All other cases	Fits in closet

7.3 Define Procurement Options

The two main steps in this process consist of identifying suppliers for the physical components and defining cost function. It is assumed that all the physical components necessary to realize a product design are procured. Suppliers available to purchase the components/assemblies are added to the leaf nodes of the AND/OR tree based design representation.

7.4 Selecting the Design Option

The information collected at three earlier steps is utilized to select a product design. Heuristic search procedure is utilized for selecting the design option. If the suppliers that are available to procure the components or assemblies are changed, the product design also changes. This is shown by the difference in profit and product design obtained for the following two hypothetical cases:

1. ***Supplier Set-I:*** Consider the case in which aluminum components cheaply are available from a supplier. In this case design option selected contained the following physical components: {Rubber band holder, Rubber band sets, Aluminum pins. Aluminum cylinder piston arrangement, Double C shaped aluminum structure with rubber grips, Aluminum rod with rubber grips}. This product configuration corresponds to the performance attributes: {Sitting, Beginner to Average Level, 15mts, Fits Underneath Bed}. Recommended price for selling this product is $49.99. The estimated profit is equal to $3,769,000.
2. ***Supplier Set-II:*** Now consider that the supplier that offers cheap aluminum components is removed from the set. In this case design option selected contained the following physical components: {Spring holder, Spring sets, Plastic pins, Plastic cylinder. piston arrangement, Double C shaped plastic structure with rubber grips, Plastic rod with grips}. This product configuration corresponds to the performance attributes: {Sitting, Average to professional level, 15mts, Fits in closet}. Recommended price for selling this product is $199.99. The estimated profit is equal to $2,855,200.

8. CONCLUSIONS

New algorithms and representations for integrated decision making were developed in the following areas:

1. *Demand Estimation Algorithm:* A new demand estimation algorithm was developed which could distinguish when customer choices will change from "acceptable" to "unacceptable". Therefore, we can estimate demand in situations when market size is independent of available product choices.
2. *Integrated Design Decision Model:* This paper provides a framework to integrate the marketing, product design and procurement functions in product development.
3. *Heuristic Search Technique:* Heuristic search technique for pruning unpromising design alternatives in solving the design problem was developed. Using purely enumeration approach for solving the design problem for the exercise machine design example, the average time taken was 78 minutes. When the heuristics were applied, the average time for solving the design problem dropped to 8 minutes, savings in time being 89 percent.

In our current work we make use of conjoint analysis for estimating demand. Other market analysis tools can also be used for estimating demand using a similar approach.

The current algorithm requires that all the design nodes be enumerated before starting the design selection process. We envision that ultimately this method can be extended and used in an iterative manner. Initially only a portion of design tree will be defined. Nodes that are unpromising will be pruned and new nodes that might appear promising will be added in the next iteration. This process will be repeated multiple time to find a near-optimal design.

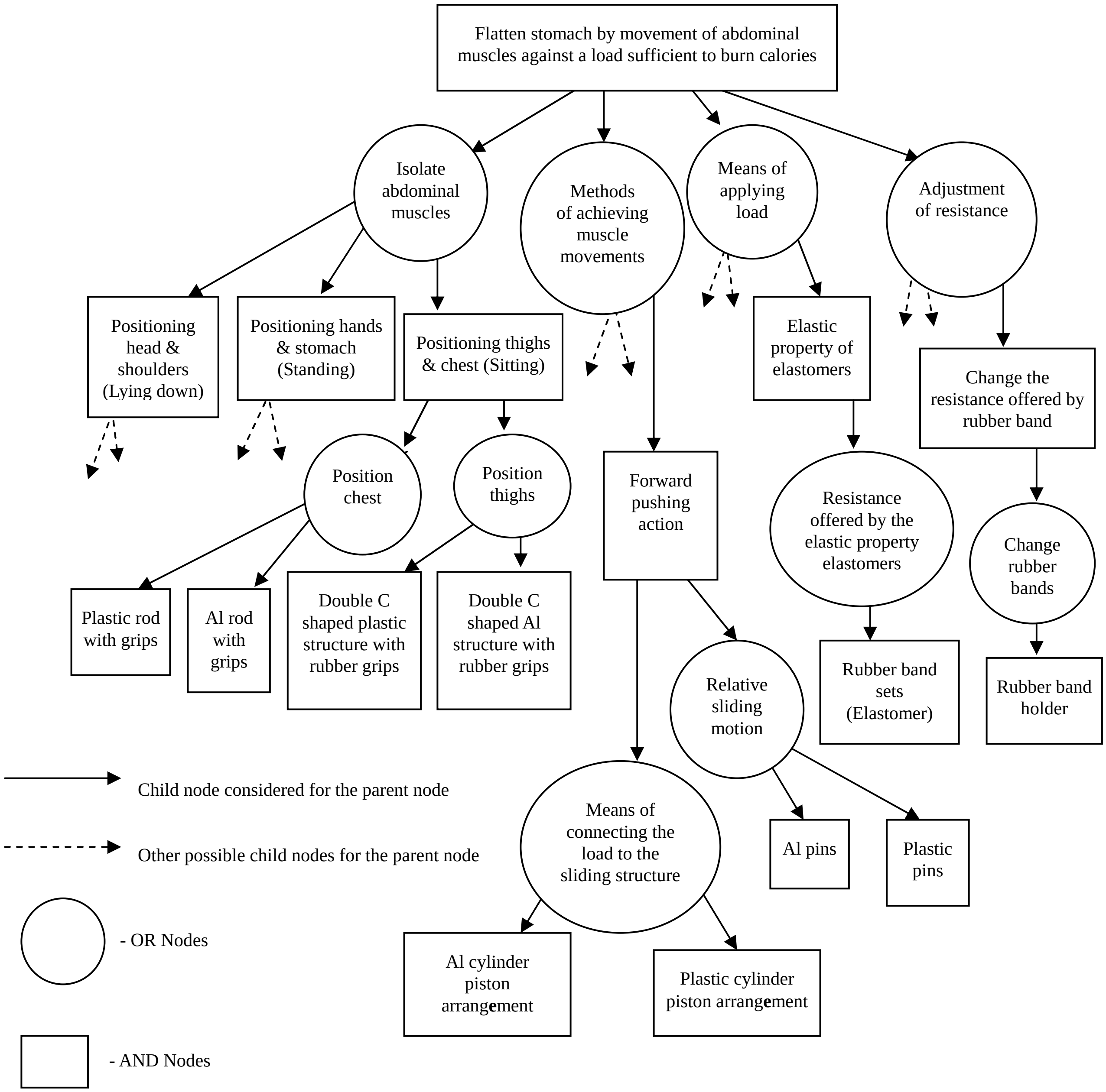

Figure 3: AND/OR Tree for 'Tummy Cruncher"

The integrated design decision making during product development process are expected to result in the following benefits:

1. *Reduction in Design Iterations:* Concurrent engineering approach reduced the design iterations between design and manufacturing departments. The algorithms described in this paper will help realize the notion of integrating the marketing, design, and procurement functions, thus reducing design iterations.
2. *More profitable designs:* The selection criteria for the design decision model described in this paper was to find the most profitable product design. The key variables determining the profitability of a product design namely, demand, price and cost were utilized to make the decision. This helps in finding the most profitable product design.

Some of the directions for the future research are:

- *General Mapping Functions:* More general mapping procedures that will allow the design decision model to be utilized for a large spectrum of product development area.
- *Improved Cost Estimation Function:* Cost estimation functions that are more comprehensive need to be

developed which will include manufacturing cost in addition to procurement costs.

- *Better Heuristics for Solving the Problem:* Efficient heuristics for pruning unpromising alternatives and estimating good lower bounds on partial solutions needs to be developed
- *Higher Order Interaction in Conjoint Analysis:* Market survey developed for our approach provided only first order and limited second order interaction checking. Models that are able to handle higher order interactions need to be developed.
- *Influence of Risk and Uncertainty:* The effect of risk and uncertainty on the decision making process needs to be studied.

ACKNOWLEDGMENTS

This research has been supported in part by the NSF Grant SES9906265. Opinions expressed in this paper are those of authors and do not necessarily reflect opinion of the National Science Foundation.

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