A Market-Driven Approach to Product Family Design

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Abstract

In an effort to meet the diverse needs of today's highly competitive global marketplace better, many companies are utilizing product families and platform-based product development to increase variety, shorten lead-times, and reduce costs. Current research in the area of product family design mostly focuses on the cost-savings benefits of the platform-based approach and does not sufficiently examine broader enterprise considerations such as profit and market share. Furthermore, very few existing design methods integrate market considerations (e.g., customer preferences, competition) with product development efforts in their formulation. In this work, in addition to integrating market considerations with traditional product family concerns (e.g., modular design, decisions regarding shared parts and processes), the scope of the product family design problem is expanded to include the product line positioning problem, i.e., the problem of determining the appropriate market niche for each product variant in the family. The novel Market-Driven Product Family Design (MPFD) methodology proposed here is introduced to systematically examine the impact of increasing the variety in the product offerings across different market segments and explore the cost-savings associated with commonality decisions. A unique representation scheme is also introduced to enable us to integrate the qualitative market segmentation grid with mathematically rigorous demand models, and the demand modeling approach employed in this paper models the dissimilar impacts of competition in different market segments and plays a significant role in determining the appropriate platform leveraging strategy. The design of a family of universal motors is used to demonstrate the proposed approach.

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I. Nomenclature

A	=	Customer Desired Attributes
A_{wa}	=	Cross-Sectional area of the armature wire (m^2)
A_{wf}	=	Cross-Sectional area of the field wire (m^2)
C	=	Total cost associated with the product family
C_D	=	Design cost
C_L	=	Labor cost
C_M	=	Material cost
C_n	=	Choice set available to customer *n*
C_O	=	Overhead costs
C_R	=	Repair/warranty costs
E	=	Engineering attributes
$\mathbf{G}_1$	=	Product positioning substring
$\mathbf{G}_2$	=	Commonality substring
I	=	Current drawn by the motor (Amperes)
L	=	Stack length (m)
M	=	Manufacturing attributes
N	=	Number of performance/price tiers in each market segment of the Market Segmentation Grid
N_c	=	Number of wire turns on the motor armature (turns)
N_s	=	Number of wire turns on each field pole (turns)
O	=	Operating conditions (e.g., temperature, pressure)
P_{ij}	=	Price of product in i^{th} tier and j^{th} segment
Q_{ij}	=	Demand for product launched in tier *i* and segment *j*
r	=	Radius of the motor (m)
S	=	Demographic attributes or Customer-specific information (e.g., customer's age, income)
S	=	Number of market segments in the Market Segmentation Grid
t	=	Thickness of the motor (m)
U_{ni}	=	True utility of i^{th} choice alternative to the n^{th} customer
W_{ni}	=	Deterministic part of the utility of i^{th} choice alternative to the n^{th} customer
X	=	Design options (e.g., shape, size, material)
β	=	Coefficients of the utility function in the demand model
ε_{ni}	=	Random part of the utility of i^{th} choice alternative to the n^{th} customer
η	=	Efficiency of the motor
μ	=	Scale parameter used in the Nested Logit demand model; used to help interpret the level of correlation between the choice alternatives in the nest (market segment)

II. Introduction

In an effort to meet the diverse needs of today's highly competitive global marketplace better, many companies are utilizing product families and platform-based product development to increase variety, shorten lead times and reduce costs (Halman et al., 2003). In general terms, a product family refers to a set of products that have been derived from a common product platform to satisfy a variety of market niches (Simpson, 2005). Individual members of the product family normally share common parts and subassemblies. Platforms, in the most general sense, are intellectual and material assets shared across a family of products, and their use helps minimizing manufacturing complexity without compromising the ability to satisfy a variety of customer requirements. In addition to improving economies of scale and scope, a product platform can facilitate customization by enabling a variety of products to be quickly and easily developed to satisfy the needs and requirements of distinct market niches (Pine, 1993).

Most existing product family design approaches (Simpson et al., 2001, Messac et al., 2002b, Messac et al., 2002a, Nayak et al., 2002, Fellini et al., 2002, Farrell and Simpson, 2003, Dai and Scott, 2006, Dai and Scott, 2004, Akundi et al., 2005) are targeted at identifying the optimal commonality decision in order to minimize the manufacturing cost while meeting pre-specified performance goals. It should be noted, however, that while increasing commonality may reduce costs, it might also compromise the performance of some of the products in the family. Our goal in this paper is to integrate market considerations with manufacturing and product development considerations in platform-based product family design. Nested Logit (Williams, 1977), a demand modeling approach that recognizes the dissimilar impacts of competition in different market segments, is integrated within a design optimization model to make decisions on *product line positioning*[4] to determine appropriate *platform leveraging strategies* while simultaneously exploring the cost-savings benefits of increased commonality. Demand models help not only capture production costs (as a function of production volume) more accurately but also estimate revenues (as a function of market share). In recognition of the increasing importance of market considerations in product development, some recent developments (Moore et al., 1999, Kima and Chhajed, 2001, Li and Azarm, 2002, Michalek et al., 2006, Michalek et al., 2005) have included the use of a demand model as part of an enterprise-driven approach to the design of product families. However, in our opinion, these developments have only dealt with the problem of product line positioning in a limited way. Either an arbitrary number of products is assumed for the product family (Moore et al., 1999, Michalek et al., 2006) or an enumeration-type methodology to is used to determine the optimal number of product variants (Li and Azarm, 2002); commonality considerations are usually ignored in the interests of simplicity (Zhang and Jiao, 2005), but in reality, commonality can impact demand both positively and negatively. For instance, commonality in the cockpit has helped fuel demand for Airbus aircraft (Aboulafia, 2000), but too much commonality often leads to a lack of product distinctiveness (Robertson and Ulrich, 1998), which hurts sales, and it can also lead to cannibalization of ones own product line as products start to compete with themselves (Kim and Chhajed, 2000, Fruchter et al., 2006). A recent example can be found in the

[4] Product positioning is usually defined in marketing terms as developing a product and associated marketing mix that (a) is ‘placed’ as close as possible in the minds of target customers to their ideal in terms of important features and attributes, and (b) clearly differentiates it from the competition. Product line positioning refers to similar efforts for the entire product line. Here, product line positioning decisions are those that determine the optimal number of products in the line and their corresponding production volumes along with the appropriate market niches for each product in the line.

automotive industry: Volkswagen reportedly saved 1.5 billion USD per year due to lots of commonality among their four brands: Volkswagen, Audi, Skoda, and Seat (Bremmer, 1999, Wilhelm, 1997); however, too much commonality caused considerable confusion and dramatically hurt sales as people were buying lower-end models instead of higher-end models (Miller, 1999). Volkswagen has since set out to overhaul their brands to make them more distinct and improve sales (Miller, 2002, Anonymous, 2002). In order to determine an acceptable level of performance loss in platform-based product development, it is important to consider product performance in the context of market considerations (i.e., competitors' products and customer-preferences).Also, current approaches do not adequately examine the impact of competition or how new products added to a product family compete with existing products in the family.

The novel Market-Driven Product Family Design (MPFD) methodology proposed in this work attempts to overcome the limitations of existing approaches and offers a comprehensive strategy to deal with the product family design problem. It helps make decisions on 1) product line positioning, 2) commonality (i.e., deciding which parts and processes are to be shared among different products in the family), and 3) the optimal configuration of design variables for each product in the family. These decisions are based on engineering and manufacturing feasibility and economic considerations estimated from a demand model that predicts market performance as a function of product characteristics and market conditions (e.g., customer demographics, competition). The proposed methodology provides a framework to examine the impact of adding new products/removing existing products to/from the family. Unlike most existing approaches that assume a single platform, the proposed research also deals with the problem of determining the optimal number of product platforms for the product family (De Weck et al., 2003). The rest of the paper is organized as follows. First, background on the Market Segmentation Grid, a technique used to articulate platform leveraging strategies, and Nested Logit, the demand modeling approach employed in this work, is provided. Details of the proposed MPFD methodology are presented in Section IV. Section V discusses the case study that demonstrates the utility of the proposed methodology, while conclusions and future work are summarized in Section VI.

III. Technological Base

The primary contribution of this paper lies in integrating market considerations (i.e., customer preferences and competition) into the platform-based product family design formulation. In this context, some background on platform leveraging strategies, demand modeling and its role in enterprise-driven design is also provided

A. Market Segmentation Grid

The widespread use of market segmentation is the inevitable consequence of the increase in competition and the global nature of today's market place. A variety of data-driven approaches have been proposed in the literature (Wedel and Kamakura, 1999, Lilien and Rangaswamy, 2004) to formally segment the market, including Conjoint Analysis (Green and Krieger, 1991, Zufryden, 1977, Dobson and Kalish, 1993, Choi and DeSarbo, 1994), clustering (Mazanec, 1984) and neural networks (Vellido et al., 1999). However, our focus in this study is to add rigor to a more qualitative approach that has been gaining ground in the past decade, namely, the Market Segmentation Grid (Meyer and Lehnerd, 1997). It should be noted that the MSG is used for product differentiation and not for the segmentation of the customer-population. In recent years, the Market Segmentation Grid has become the *de facto* method to visualize product differentiation and platform leveraging strategies in the product family design community (Marion and Simpson, 2006) .

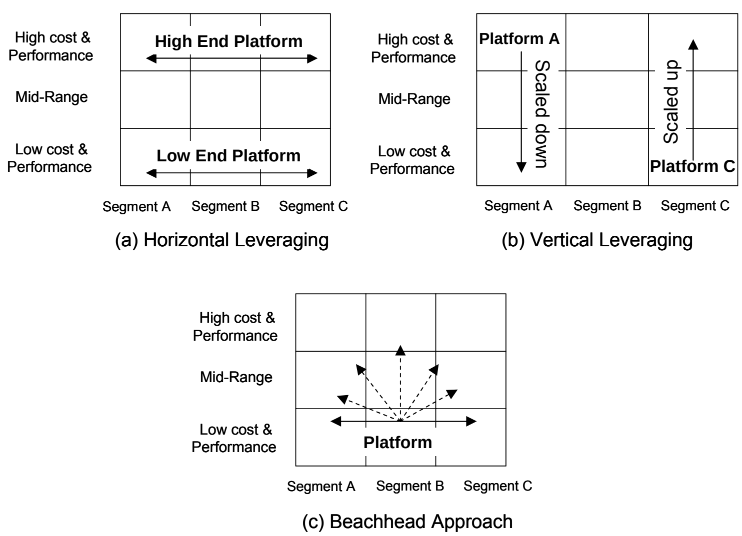


Figure 1. Platform Leveraging Strategies Illustrated Using the Market Segmentation Grid.

(Adapted from Meyer and Lehnerd (1997))

Meyer and Lehnerd (1997) introduced the Market Segmentation Grid shown in Figure 1 to more clearly articulate platform leveraging strategies in a given market. In a MSG, the total market for a product family is defined through a matrix of market niches that identify particular user groups and price/performance tiers. Market segments are plotted horizontally in the grid while price/performance tiers are plotted vertically – the intersection of each price/performance tier with each market segment defines a specific market niche. The horizontal leveraging strategy illustrated in Figure 1(a) is one in which subsystems and/or manufacturing processes are leveraged across different market segments within the same price or performance tier. The vertical leveraging strategy, see Figure 1(b), scales key platform subsystems and/or manufacturing processes across price/performance tiers within a market segment. The advantage of this strategy is the capability of the company to leverage its knowledge about a particular market segment without having to develop a new platform for each price/performance tier. The beachhead approach shown in Figure 1(c) combines horizontal leveraging with vertical leveraging to develop an effective, low-cost platform with efficient processes. It is able to scale up the performance characteristics of the platform for low-end users to the mid-end and high-end users, as well as be applied to different market segments. In the product family literature, MSGs have only been used as visual aids to arrive at the appropriate platform leveraging strategy. In this work, the effectiveness of the MSG is enhanced by mathematically expressing the product positioning decisions and platform leveraging strategies in the MSG, and including it directly in the optimization formulation. We also recognize that all products in the market do not compete equally, and products in a given market segment compete more closely with each other than with products in other market segments. The segmentation in the market, as illustrated in the MSG, is modeled using the Nested Logit technique, which is discussed next.

B. Role of Demand Models in Enterprise-driven Design

Current design approaches view demand modeling as a critical link between market research and engineering product development. Product demand Q plays a critical role in assessing both the revenue and life cycle cost C, and ultimately the profit (i.e., net revenue) V (see Figure 2). Demand, Q, is expressed as a function of the customer-desired attributes, $\mathbf{A}$ (i.e., what product attributes do customers care about), customer demographic attributes, $\mathbf{S}$, price P and time t. By linking attributes $\mathbf{A}$ to corresponding engineering design attributes $\mathbf{E}$, the optimal level of $\mathbf{E}$ can be identified through maximizing the expected value of profit (enterprise-level utility optimization) to guide product development.

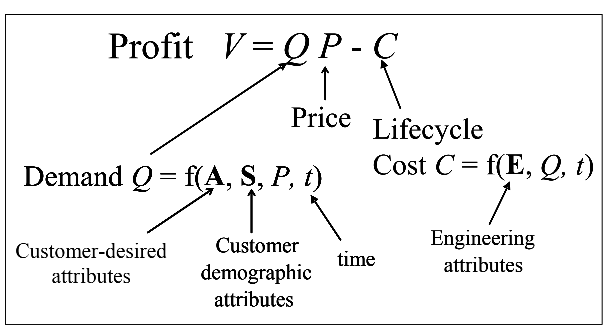


Figure 2. Role of Demand Modeling in Enterprise-Driven Design

C. Nested Logit

Nested Logit is a probabilistic modeling technique used to express the choice-behavior of individual customers and can be used whenever some choice-alternatives are similar to others (Williams, 1977). The NL demand model has been applied in a variety of situations, including energy, travel demand forecasting, housing, telecommunications, and airline revenue management (Forinash and Koppelman, 1993, Train et al., 1987, Ben-Akiva, 1973, Train, 1986, Lee, 1999, Garrow and Koppelman, 2004). In the product family design problem considered here, the key decision is the selection of the most profitable market niche (i.e., the market segment, and performance/price combination) for each new product being launched. Since multiple market segments are being considered, it is important to model the dissimilar nature of competition in different market segments accurately. The mathematical structure of the NL demand model allows us to capture the segmentation of the market, and estimate more accurate and realistic demand models. The rest of the discussion is geared towards providing a basic understanding of some of the relevant mathematics behind the NL model.

According to the Random Utility Maximization (RUM) theory (McFadden, 2001), the basis for most demand modeling techniques, each individual n has a utility function U_{ni} associated with each of the i alternatives, choosing the one which maximizes his/her utility. The utility U_{ni} can be divided into a deterministic component W_{ni}, and a random component ε_{ni}. The deterministic part utility W can be parameterized as a function of observable independent variables (i.e., customer desired attributes **A**, socioeconomic and demographic attributes **S**, and price P). The utility function terms are represented with the double subscript '*ni*' representing the n^{th} respondent (i.e., customer) and the i^{th} choice alternative.

$$U_{ni} = W_{ni} + \varepsilon_{ni} \tag{1}$$

The most commonly used demand modeling technique is Multinomial Logit (McFadden, 1974), which is derived assuming that the error terms ε_{ni} are *independent and identically distributed* and follow an extreme value distribution. Consider the form of the choice probability function for Multinomial Logit (MNL) models in Eq. (2). In this expression, $\Pr(i{:}C_n)$ refers to the probability of choosing alternative i from choice set C_n available to customer n, μ refers to the scale parameter, W_{ni} refers to the utility of alternative i to customer n and is expressed in terms of unknown β's and explanatory variables **Z** (i.e., customer desired attributes **A**, socioeconomic and demographic attributes **S**, and price P). Usually, μ is set to 1 and the choice model is estimated for unknown β's by maximizing the likelihood. The MNL model implies *equal competition between all pairs of alternatives*, an inappropriate assumption in many situations, which is famously known as the *Independence of Irrelevant Alternatives* (IIA) in the literature (see (Train, 2003) for details).

$$\Pr(i:C_n)=\frac{e^{\mu W_{ni}}}{\sum_{j\in C_n} e^{\mu W_{nj}}}=\frac{e^{\mu \boldsymbol{\beta}'\mathbf{Z}_{ni}}}{\sum_{j\in C_n} e^{\mu \boldsymbol{\beta}'\mathbf{Z}_{nj}}} \tag{2}$$

The Nested Logit (NL) model, on the other hand, *can incorporate elements of unequal competition* by modeling correlation among the choice alternatives. The NL technique assumes that the set of alternatives can be partitioned into subsets, called *nests*. The technique is best explained with an example. A hypothetical automobile market that only includes cars from the sports and sedan segments is considered. While the sports segment has two cars (i.e., *A* and *B*), the sedan segment has only one (i.e., *C*). The situation is represented in the choice tree shown in Figure 3. While the grouping of the two sports segment alternatives in one nest and the sedan in the other nest represents the customer's decision making process (i.e., he or she is assumed to consider sports cars *A* and *B* as more similar to each other than to sedan *C*), it also serves to illustrate the similarity in the error components. The following utility and error functions for the different alternatives further clarify this point:

Utilites	**Error terms**	
$U_C = W_C + \varepsilon_C;$	ε_C	$\sim G(0,1)$
$U_B = W_B + \varepsilon_B + \varepsilon_{sports};$	$\varepsilon_B + \varepsilon_{sports}$	$\sim G(0,1)$
$U_A = W_A + \varepsilon_A + \varepsilon_{sports};$	$\varepsilon_A + \varepsilon_{sports}$	$\sim G(0,1)$

(3)

It should be noted that the error terms for alternatives in the sports segment (i.e., *A* and *B*) are no longer independent; they share an error component (i.e., ε_{sports}). While both error components (i.e., ε_A & ε_{sports} corresponding to alternative *A* and ε_B & ε_{sports} corresponding to alternative *B*) play a role in selecting between the entire sports segment and the family sedan segment, only the uncorrelated error components (i.e., ε_A for alternative *A* and ε_B for alternative *B*) are important when choosing among the nested alternatives *A* and *B*. The NL choice probability functions for the different car alternatives in the hypothetical vehicle market are listed next, and all expressions are with respect to customer *n*.

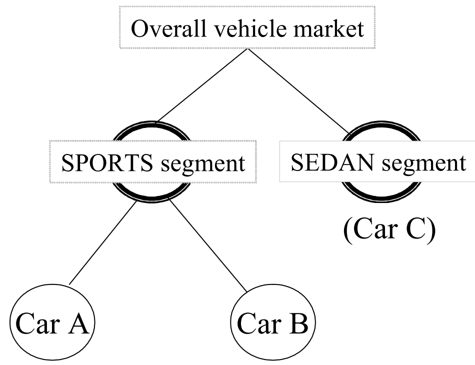


Figure 3. Choice Tree Representation for a Hypothetical Automobile Market

a) For the alternative in the sedan segment

$$\Pr_n(C:C_n) = \frac{e^{W_{n,C}}}{e^{W_{n,C}} + e^{W_{n,C}+\mu_{sports}\times\Gamma_{n,sports}}} \tag{4}$$

b) For the alternative in the sports segment

$$\Pr_n(A:C_n \mid sports) = \frac{e^{\frac{W_{n,A}}{\mu_{sports}}}}{e^{\frac{W_{n,A}}{\mu_{sports}}} + e^{\frac{W_{n,B}}{\mu_{sports}}}} \tag{5}$$

In these two probability expressions, $\Gamma_{n,sports}$ is equal to $\ln(e^{W_{n,A}/\mu_{sports}} + e^{W_{n,B}/\mu_{sports}})$ and is referred to as the logsum parameter and $C_n = \{\mathrm{A,B,C}\}$ is the choice set available to customer n; $\Pr_n(C:C_n)$ is the probability of choosing alternative *C* from the vehicle market, and $\Pr_n(A:C_n \mid sports)$ is the conditional probability of choosing alternative *A* assuming the sports segment has been already chosen. Finally, μ_{sports} is the scale parameter associated with the sports segment and plays an important role in modeling unequal competition. A value closer to 0 indicates that the alternatives in the sports segment (i.e., *A* and *B*) compete more closely with each other for market share than with alternatives that do not belong to the sports segment (i.e., *C*), and a value closer to 1 indicates that the "within-segment" competition is not significant.

The motivation behind the use of a NL demand model in product family design is to model the impact of market segmentation on the market share of each of the products in the family by exploiting NL's unique error structure. This is accomplished by grouping products in each market segment under a separate nest in an NL choice tree representation similar to the one shown in Figure 3 which is then followed by the estimation of the NL model by determining the values of the unknown β's and scale parameter (μ) for each of the nests (i.e., segments).

IV. The Market-Driven Product Family Design Methodology

The proposed Market-Driven Product Family Design (MPFD) methodology seeks to integrate market considerations with traditional product family design issues (e.g., commonality, manufacturing cost) to design the most profitable product families unlike traditional product family design methods which mostly focus on the cost benefits. The MPFD methodology (see Figure 4) consists of the following four steps: 1) creation of the market segmentation grid, 2) estimation of the Nested Logit demand model and building a choice simulator program, 3) construction of models for product performance and cost, and 4) optimization of the product family by maximizing profit. Each of the steps is performed sequentially, but Steps 2) and 3) can be accomplished in parallel if desired. A short discussion on each of the MPFD steps follows.

A. Step 1) Creation of the Enhanced Market Segmentation Grid

Data on the existing market is required to create an "enhanced" Market Segmentation Grid (MSG) that includes information not only about the market segments and the performance/price tiers but also about the competitors in each niche (i.e., the market segment and performance/price combination). Collecting market data involves gathering sales data ideally at the level of the individual customer in order to determine the choice set available to each individual customer as well as incorporate biases associated with demographics (e.g., age, income). Information on the performance characteristics of competitors' products in the market must also be collected and can be usually obtained from product catalogs. An important consideration is the choice of the performance attribute to include in the grid as the vertical axis of the MSG. The use of "Differentiating Attributes" (DA), defined in (Robertson and Ulrich, 1998) as "characteristics that customers deem important in distinguishing between products," is used for this purpose. For example, interior noise level is a DA for automobiles; customers generally expect different values of this DA for different kinds of vehicles, such as audible cues from the engine in sporty vehicles but near silence in luxury vehicles (Robertson and Ulrich, 1998). In this work, DAs are assumed to be identical to the customer-desired attributes (**A**) described earlier. Developing the market segmentation grid in this step is independent from developing the product design details and building product performance models (Step 3), and it is this aspect of our methodology that enables the seamless integration of the market analysis with the engineering modeling activities.

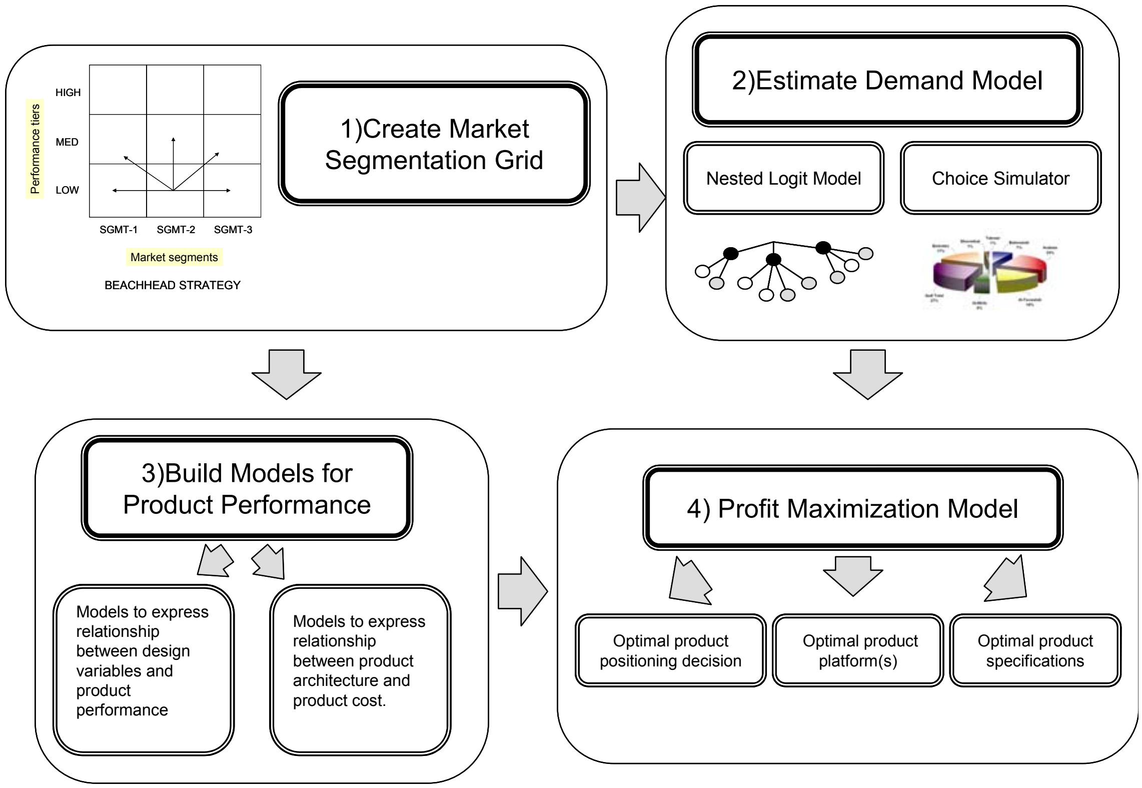


Figure 4. The MPFD Methodology to Design Platform-Based Product Families

B. Step 2) Estimation of the Demand Model

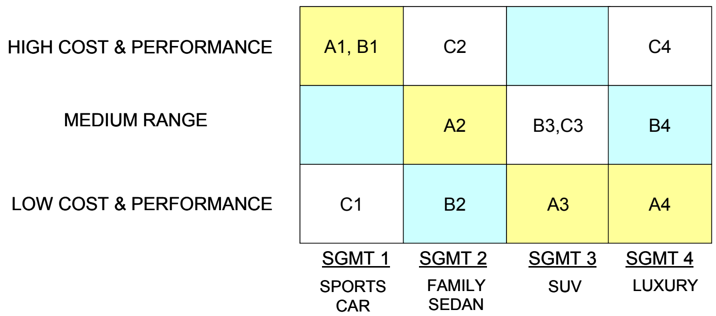
The information in the MSG has to be converted into an equivalent choice tree representation before the estimation of the NL model. A hypothetical vehicle market is used to describe this procedure. The MSG consists of four market segments along the horizontal axis (corresponding to sports, family sedan, SUV, and luxury segments) and three performance/cost tiers on the vertical axis, leading to twelve niches in all (see Figure 5(a)). For simplicity, horsepower is used as the performance measure along the vertical axis. The grid is populated with cars from three manufacturers: A, B and C. Consider the tree representation of the grid in Figure 5(b) in which the cars under each segment are grouped together in a nest. This representation is used to group cars that compete more closely with each other and enable the use of the Nested Logit technique. Such a choice tree representation may also be used to simulate the customer's decision-making process, i.e., customers may choose among different vehicle segments before choosing among the different vehicles in each segment.

The next step involves the estimation of the Nested Logit (NL) demand model. Each nest in the NL model corresponds to a particular market segment. In this work, terminology for design attributes is borrowed from our earlier work on Decision-Based Design framework (Wassenaar et al., 2006, Kim et al., Kumar et al., 2006, Wassenaar and Chen, 2003)). The demand model used in this work, establishes the relationship between the customer desired attributes, **A**, the socioeconomic and demographic attributes, **S**, price, P, and the demand, Q, i.e., Q(**A**, **S**, P). In order to aid engineering decision-making, customer desired attributes (**A**) are replaced by corresponding engineering attributes **E** in the model, where **E** are any *quantifiable product properties* that are used in the engineering product development process. Estimating a NL demand model is similar to estimating a MNL model (Wassenaar and Chen, 2003, Wassenaar et al., 2006, Kumar et al., 2006) except that the scale parameter (μ) corresponding to each of the nests has to be estimated. As discussed earlier, the values of the scale parameters help evaluate the validity of the nesting structure and also serve as a measure of the "within-segment" competition.

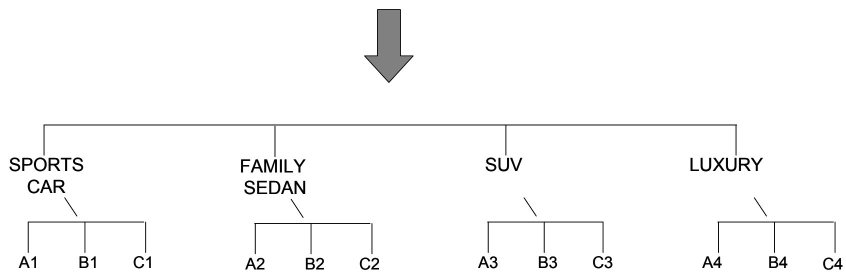
Once the NL demand model is estimated, it can be used repeatedly to estimate the impact of design changes or the effect of adding/removing products from the line using a *choice simulator* program. A choice simulator is a computer program that simulates the demand model and uses the market data as inputs to estimate changes in market share for each product as a function of engineering attributes, customer demographic attributes and price values (i.e., **E**, **S**, and P). One challenge in building a choice simulator for the product family optimization problem is the complexity introduced due to the addition of multiple products into the market simultaneously--new products encoded in the product line positioning decision have to be grouped with similar competitors' products in corresponding market segments and the data set has to be updated in each optimization iteration.

C. Step 3) Construction of Models for Product Performance and Cost

Building models for product performance functions **E**(**X**) involves building models that represent the relationship between engineering attributes **E** and design options **X** (which includes decisions on size, shape, material, etc.) through engineering analysis. These relationships can be expressed through analytical models, finite element models, simulation models, metamodeling techniques, etc. Similarly, cost is modeled as a function of the design options (**X**). The cost model is used to evaluate the benefits of different commonality decisions (i.e., shared parts and processes between different product variants in the product family). In this work, the total cost (C) is expressed in terms of material cost (C_M), labor cost (C_L), repair and warranty costs (C_R), design costs (C_D), and overhead costs (C_O). Material cost is expressed in terms of production volume V, design options **X**, and manufacturing attributes **M**. Examples of manufacturing attributes (**M**) are tooling and fixturing specifications, production plans and schedules, and inventory control schemes. The repair/warranty costs (C_R) are expressed as a function of the product's reliability, which in turn is expressed as a function of **X** and operating conditions **O** (e.g., temperature, pressure). These two models can be used to *make trade-offs between cost and performance*, in conjunction with the demand model.



(a) Market Segmentation Grid



(b) Equivalent decision (choice) tree representation

Figure 5. A MSG and Its Equivalent Choice Tree Representation

D. Step 4) Optimization of the Product Family

The product family design optimization problem primarily involves the determination of the (1) optimal product line positioning decision, which involves choosing the optimal number of product variants in the family and the market niches they should target, (2) optimal "commonality" decisions (i.e., the number of platforms in the family and the design variables that should be shared by product variants assigned to each of the platforms), and (3) optimal levels of engineering design attributes (**E**), and corresponding design options for each product in the family. In this work, the problem is formulated as an all-in-one problem to make these decisions simultaneously and solved in a single stage using an iterative procedure. In each iteration, a random binary string that has information on (i) product line positioning decisions as well as (ii) commonality decisions is supplied to the profit maximization model. The "product line positioning" substring (i.e., the part of the binary string that is used to make the product line positioning decision) not only sets bounds on the performance variable used to define tiers along the vertical axis (e.g., power in the case of electric motors) but also has an impact on the market share garnered by each “new” product since the product line positioning substring decides the targeted market segment and therefore the competitors’ products which have the biggest impact on the market shares for each “new” product.

Figure 6 illustrates how a binary string can be used to represent product line positioning decisions. Consider a MSG with three segments and three performance tiers forming a (3x3) grid. A one-dimensional binary string whose size corresponds to the number of the cells in the MSG is used to represent such a grid. The “1”s in the string and the crossed cells in the grid correspond to the decisions to introduce products in corresponding market niches. Similarly, the “0”s in the string and uncrossed cells correspond to decisions to not launch products in the corresponding niche. Competitors’ products are represented in the MSG in Figure 6 by shaded cells are not represented in the string. Consider segment two (corresponding to column 2 in the MSG): the two crossed squares indicate that the firm is considering launching two new products in that segment while the two shaded boxes represents competitors’ products in the corresponding niches. In all, four products compete for market share in this segment. It should be noted that competitors’ products are not numerically encoded in the binary string (the corresponding blocks in the binary string are only shaded for ease of understanding), and only a one time conversion of the competitors’ products in the grid to equivalent nodes in the Nested Logit tree is necessary.

Figure 7 illustrates how product line positioning and product commonality decisions can be simultaneously encoded in a numeric string. The string is essentially divided into two parts: the first part of the numeric string corresponds to the *product line positioning* decision, and the second part is used to store *commonality* decisions. Each product is by an ordered pair (market tier, market segment)

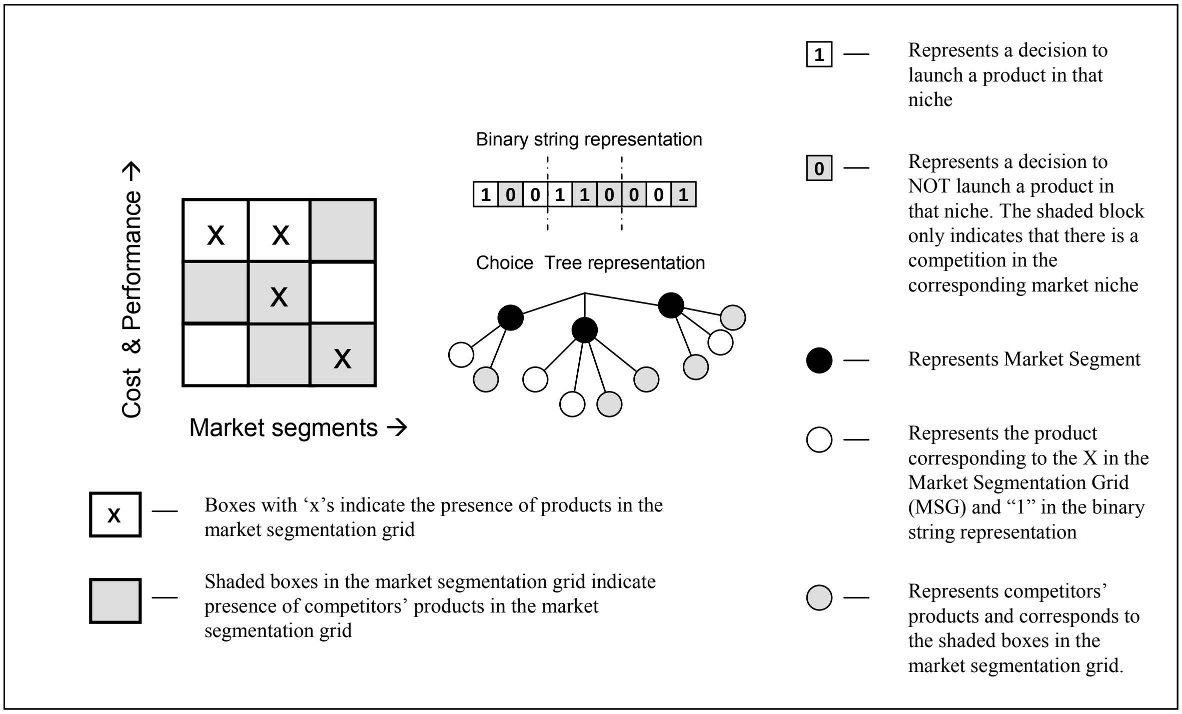
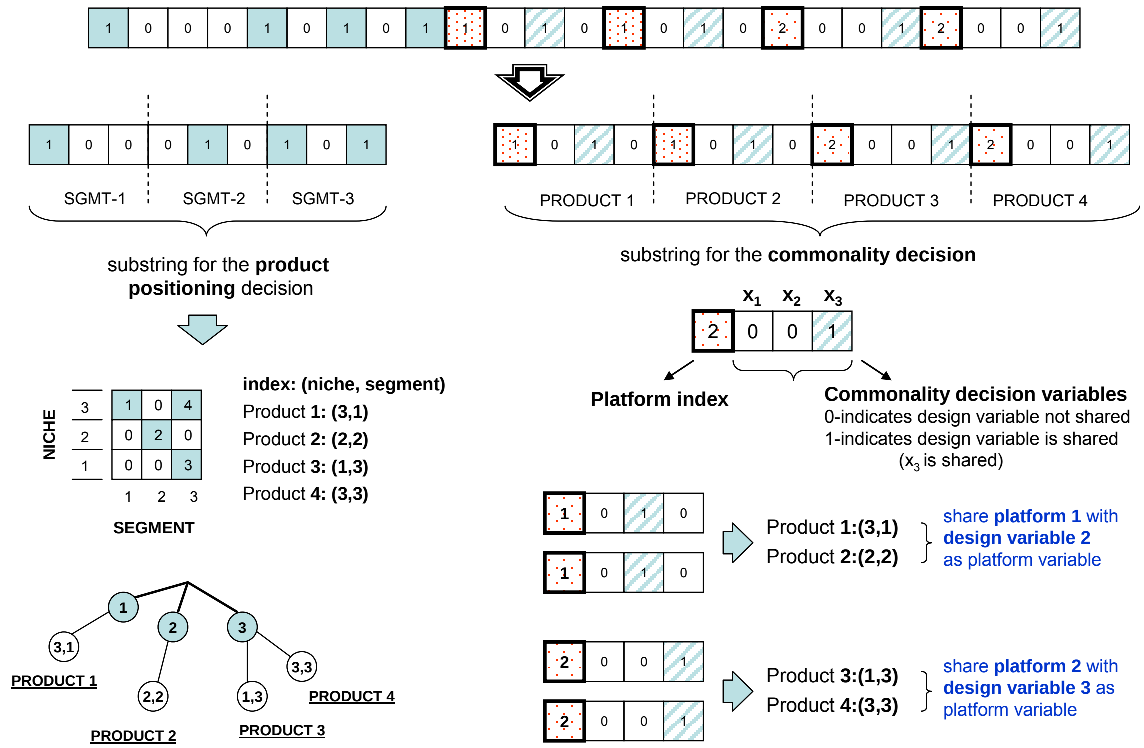


Figure 6. Equivalent MSG, Binary String and NL Tree Representations or a Given Product Line Positioning Decision

. For example, Product {1: (3,1)} indicates that Product 1 is from market segment 1 and market tier 3. Assuming each of the products in the family has three design variables (say x_1, x_2, x_3), then each product is represented by a 4-bit commonality sub-string. The first bit represents the *platform index*, and the following three bits are binary *commonality decision variables*, which indicate if the corresponding design variable is common across all the products sharing the platform. For example, if the third commonality decision variable is 1, then it indicates that the design variable x_3 is being shared. From Figure 7, it is clear that Products {1: (3,1)} and {2: (2,2)} share Platform 1 and Products {3: (3,3)} and {4: (1,3)} share Platform 2. Products 1 and 2 share Design Variable 2, and Products 3 and 4 share Design Variable 3. It should be noted that the *product line positioning* and *commonality substrings* together express *the platform leveraging strategy*. In this manner, existing products can be represented in the string by fixing the values of the bits corresponding to the (tier, segment) pairs to "1" during the optimization. Including the existing product(s) in the formulation can help when redesigning and/or re-pricing that product (i.e., determining optimal levels of **E**, and *P*). Cost savings due to sharing parts and production infrastructure and parts with existing products can also be explored.



Note: Competitors' products are not included in the MSG and choice tree representations

Figure 7. String Representation of Product Line Positioning and Commonality Decisions

The product family design problem is formulated as shown in Figure 8. The formulation captures the key product family design decisions considered in this work. The set of design options corresponding to product is represented as $\mathbf{X}_{ij}$. N represents the number of market tiers in each market segment, and S represents the number of market segments. X_{ijk} represents the k^{th} variable corresponding to product $\mathbf{E}_{ij}$ corresponds to performance characteristics of the product. $\mathbf{E}_{ij}$ can be expressed as a function of design options $\mathbf{X}_{ij}$ using relationships $\mathbf{r}$. Design constraints are expressed as $\mathbf{g(X,E)\leq 0}$. The market segment-specific variable bounds for design options of all products $\mathbf{X}_{ij}$ in segment j are represented by $\mathbf{LB}_j$ and $\mathbf{UB}_j$ while Π_{G_1,G_2} corresponds to the profit with respect to binary string $\mathbf{G}$:$\{\mathbf{G}_1,\mathbf{G}_2\}$. Product line positioning decisions are represented by $\mathbf{G}_1$ while commonality decisions are expressed using $\mathbf{G}_2$. It is expressed as a function of demand Q_{ij}, price P_{ij}, the demand and price values for product (i,j), and cost C. While a description of the different cost components was provided earlier, it should be noted that both $\mathbf{G}_1$ and $\mathbf{G}_2$ have a direct impact on cost since $\mathbf{G}_1$ decides the number of product variants and the production volumes of different products in the family while $\mathbf{G}_2$ decides which of the **X**'s are shared between different product variants.

Given

a) Market data

Sales data of different products, buyer-specific information (e.g., age, income)

b) Demand model

Demand as a function of product attributes and buyer-specific information. Includes estimates for utility function coefficients (**β**), scale parameters (**μ**), etc.; **Q (E,S,P)**

c) Models for Product Performance

Analytical and Simulation models expressing relationship between $\mathbf{E}_{\mathrm{ij}}$ and $\mathbf{X}_{\mathrm{ij}}$

$$\mathbf{E}_{\mathrm{ij}} = \mathbf{r}(\mathbf{X}_{\mathrm{ij}}) \quad \mathrm{i} \le N, \mathrm{j} \le S$$

d) Cost models

Models for different cost components; material cost ($\mathbf{C}_{\mathrm{M}}$), labor cost ($\mathbf{C}_{\mathrm{L}}$), design cost ($\mathbf{C}_{\mathrm{D}}$), repair/warranty costs ($\mathbf{C}_{\mathrm{R}}$), overhead costs ($\mathbf{C}_{\mathrm{O}}$), etc.

$$\underset{\mathbf{G}_1,\mathbf{G}_2,\mathbf{X},\mathbf{M},\mathbf{O}}{C} = \sum_{i \le N, j \le S} \left(C_{\mathrm{M}}\left(Q_{\mathrm{ij}}, \mathbf{X}_{\mathrm{ij}}, \mathbf{M}\right) + C_{\mathrm{L}}\left(Q_{\mathrm{ij}}, \mathbf{X}_{\mathrm{ij}}, \mathbf{M}\right) + C_{\mathrm{R}}\left(\mathbf{X}_{\mathrm{ij}}, \mathbf{O}_{\mathrm{ij}}\right)\right) + C_{\mathrm{D}} + C_{\mathrm{O}}$$

Find

a) Product Positioning substring ($\mathbf{G}_1$)

Contains information on number of products, and market niches corresponding to each of them.

b) Commonality substring ($\mathbf{G}_2$)

Contains information on the number of platforms, the products sharing each platform, and platform composition (i.e., which design variables to share in each platform)

c) Design Options (X)

Choice of shape, size, material, etc., represented by $\mathbf{X}_{\mathrm{ij}}$, the vector of all design variables $\mathrm{X}_{\mathrm{ijk}}$ corresponding to product (i,j)

Maximize

a) Profit

$$\underset{\mathbf{G}_1,\mathbf{G}_2,\mathbf{X}}{\Pi} = \sum_{i,j} Q_{ij}\left(\mathbf{E}_{\mathrm{ij}}, \mathbf{S}, P_{ij}\right)P_{ij} - C$$

Satisfy

a) Design constraints

Relationships between **E** and **X**, and between different **X**

$$\mathbf{g}(\mathbf{X}_{\mathrm{ij}}, \mathbf{E}_{\mathrm{ij}}) \le \mathbf{0}; \qquad \mathrm{i} \le N, \mathrm{j} \le S$$

$$\mathbf{LB}_{\mathrm{j}} \le \mathrm{X}_{\mathrm{ijk}} \le \mathbf{UB}_{\mathrm{j}}; \qquad \forall\, \mathrm{X}_{\mathrm{ijk}} \in \mathbf{X}_{\mathrm{ij}}, \mathrm{i} \le N, \mathrm{j} \le S$$

Figure 8. Formulation for Profit Maximization-Based Product Family Design

V. Case Study: Design of a Family of Universal Electric Motors

The design of a family of universal motors is used to demonstrate the implementation of the proposed methodology. Motivated by Black & Decker's case study reported in (Lehnerd, 1987) an example problem involving the design of a family of universal electric motors was first used in (Simpson, 1998) and subsequently used by a number of researchers in the community as reviewed in (Simpson, 2006). Existing formulations of the universal electric motor product family design problem are briefly discussed in the next section. This is followed by discussions on the enhancements to the universal electric motor product family design problem, with special emphasis on market and manufacturing considerations. The section concludes with a discussion on the results and interpretations associated with the case study.

A. Formulation of the Universal Electric Motor Product Family Design Problem in the Literature

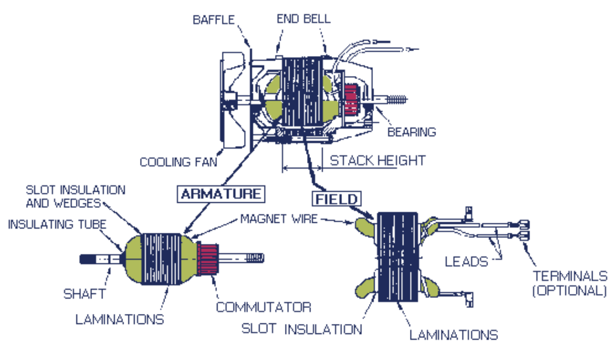


Figure 9. Universal Motors Schematic (Source: Simpson et al. (2001))

A schematic of a universal motor is shown in Figure 9. As shown in the figure, a universal motor is composed of an armature and a field, which are also referred to as the rotor and stator, respectively. The armature consists of a metal shaft and slats (armature poles) around which wire is wrapped longitudinally as many as a thousand times. The field consists of a hollow metal cylinder within which the armature rotates. Additional details on universal motors can be found in (Chapman, 1991). The objective of the design problem is stated as

"Design a family of ten universal electric motors that satisfies a variety of torque and power requirements by scaling a common motor platform"

Similar to the original Black & Decker case study, the aforementioned work seeks to find the optimal product family assuming a pre-specified product platform. Individual products in the family share identical values for all motor design variables except stack length (L) and current drawn by the motor (I). The motor design variables that are of interest are tabulated in Table 1. The terminal voltage V_t is fixed at 115 Volts to correspond to standard household voltage. A mathematical model for the design of a universal electric motor (Simpson et al., 2001) relates the design variables $\{N_c, N_s, A_{wa}, A_{wf}, r, t, I, L\}$ to the performance measures Power (P), Torque (T), Mass (M), and Efficiency (η).

The solution to the universal motor product family design problem should also satisfy the set of constraints given in Table 2. The constraint on magnetic intensity (H) ensures that the magnetic flux within each motor does not exceed the physical flux carrying capacity of steel. The constraint on feasible geometry ensures that the thickness of the stator (t) does not exceed the radius (r) of the stator; the thickness of the stator is measured from the outside of the motor inward. The required output power (P) is taken as 300W, and the ten torque values (T) for the motor family range from 0.05 Nm to 0.50 Nm, and there are minimum expectations for efficiency and mass of each of the motors. The product family design objectives are to *minimize mass* (M), and *maximize efficiency* (η) of each of the motors in the family while sharing the pre-specified platform variable.

Most of the aforementioned approaches require specifying the universal electric motor platform *a priori*. Some researchers do not impose this restriction and attempt to *optimize* the choice of platform variable(s) using a variety of formulations: the variation-based method (Nayak et al., 2002), penalty functions (Messac et al., 2002b), sensitivity analysis and cluster analysis (Dai and Scott, 2004) and a genetic algorithm-based approach (Akundi et al., 2005). However, these approaches only seek to minimize loss in motor performance (i.e., motor efficiency and mass) due to the commonality decisions without modeling manufacturing and market considerations explicitly.

B. Description of the "Enhanced" Universal Electric Motor Product Family Design Problem Formulation

In order to model the market for universal motors, in addition to achieving an understanding of different market segments for the universal motor, data on the size of the market, specifications of competitors' products, and market shares of different competitors' products needs to be collected. The product platform decisions also require an understanding of the manufacturing process and associated cost components. Discussions on the universal electric motor market and the manufacturing cost model used for the product family design follow.

Table 1. Universal Motor Design Variables and Bounds

Variable	Description
N_c	Number of wire turns on the motor armature (turns); $(0 \le N_c \le 1500)$
N_s	Number of wire turns on each field pole (turns); $(0 \le N_s \le 500)$
A_{wa}	Cross-Sectional area of the armature wire (m^2); $(0.01\times10^{-6} \le A_{wa} \le 1.0\times10^{-6})$
A_{wf}	Cross-Sectional area of the field wire (m^2); $(0.01\times10^{-6} \le A_{wf} \le 1.0\times10^{-6})$
r	Radius of the motor (m); $(0.01 \le r \le 0.10)$
t	Thickness of the motor (m); $(0.0005 \le t \le 0.10)$
I	Current drawn by the motor (Amperes); $(0.1 \le I \le 6.0)$
L	Stack length (m); $(0.01 \le L \le 0.1)$

Table 2. Universal Motor Design Constraints

Name	Constraint
Magnetizing Intensity, H	$H \leq 5000$ Amp. turns/m
Feasible Geometry	$t<r$ (m)
Power, P	P=300W
Torque, T	$T = \{0.05, 0.1, 0.125, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.50\}$Nm
Efficiency, η	$\eta \geq 0.15$
Mass, M	$M \leq 2.0$kg

1. Description of the Hypothetical Universal Electric Motor Market

The high performance characteristics and flexibility of universal electric motors have led to a wide range of applications (Veinott and Martin, 1986), especially in household use where they are found in products such as electric drills and saws, blenders, vacuum cleaners, and sewing machines. A hypothetical market for universal motors is assumed to comprise manufacturers of products that use the universal electric motor. One of the primary goals in this paper is to demonstrate the impact of market considerations on product family design. Towards this end, hypothetical market data for universal electric motors is constructed for the study. A description of the resulting Market Segmentation Grid (MSG) follows.

A MSG with four market segments—household/kitchen appliances, power tools, cordless power tools, and garden/lawn tools—is presented in Figure 10. *Power* and *Cost* are used as the Differentiating Attributes for defining tiers within each segment with the understanding that motors with higher power cost more. It should be noted that the overlap between the power bounds for adjacent tiers in a segment implies competition among universal electric motors from different tiers in the same segment. As illustrated in Figure 10, the segment for *household/kitchen appliances* includes (manufacturers of) blenders, vacuum cleaners, washing machines, and gas-heated dryers. The *power tools* segment includes drills, various types of saws (e.g., band saw, circular saw, and jigsaw), sanders and fastening tools. The *cordless power tools* segment includes approximately the same product mix as the power tools segment except for the fact that the motors used in these devices are required to run on battery-operated (DC) power supply. Finally, the *garden/lawn tools* segment includes string and hedge trimmers, garbage disposal units, yard blowers and lawn mowers. The distinguishing characteristic of the motors in each segment is included under each of the segments in the MSG representation. The motors used in household appliances tend to operate at *higher speeds* while motors used in power tools are characterized by *higher torque* requirements. The motors in the cordless power tools segments share the higher torque characteristic. In addition, they are also required to be *lighter and more* *efficient* since they need to be portable and operate on a battery-operated power supply. Finally, the motors in the garden tools segment are characterized by *higher power* requirements and tend to be bigger and heavier.

In all, data for 23 motor manufacturers and 40 industrial customers (device manufacturers) was generated for the hypothetical universal electric motor market, and a segment-wise listing of product offerings is provided in the Appendix. The size of the market is assumed to be 40,000 motors, and demand is assumed to be uniform across all the industrial customers (i.e., 1000 motors each). The industrial customers are assumed to choose among different motors based on the motor's attributes (i.e., Price *P*, Power (P: $\mathbf{E}_1$), Efficiency (η: $\mathbf{E}_2$) and Mass (M: $\mathbf{E}_3$)). Customers in each segment are assigned the same order quantity to simplify the analysis.

Figure 10. Market Segmentation Grid for Universal Motor Product Family

A number of NL demand models were estimated and on the basis of behavioral interpretations and goodness of fit estimates, the model in Table 3 was chosen for further consideration. The model coefficients (for attributes **A** = Price, Power, Efficiency, and Mass) have signs consistent with our understanding of preference behavior for different motor attributes. For example, price has a negative coefficient, and efficiency has a positive coefficient, implying that manufacturers prefer cheaper and more efficient motors. The values of all scale parameters are between [0 1], which justifies the nesting structure (i.e., the use of different nests for each market segment) that we employed. As discussed earlier, the value of the scale parameter associated with a particular market segment provides an indication of the level of competition among the different product offerings in that segment. All the scale parameters have fairly low values, indicating that the within-segment competition is significant in all four segments. This means that whenever a new product is introduced into one of the four market segments (say power tools segment), the market shares of the existing products change but the market shares of the products in the remaining segments (i.e., Segments 1, 3, and 4) remain relatively unaffected. μ_1 and μ_2 have lower values than μ_3 and μ_4, indicating that the "within segment" competition in Segments 1 and 2 (i.e., household appliances and power tools segments) is higher than the "within-segment" competition in Segments 3 and 4 (i.e., cordless power tools and garden tools segments). The estimation of the demand model is followed by building the choice simulator so that the market considerations can be integrated into the product family optimization problem. The choice simulator program requires the product line positioning string (see Figure 7) and the performance specifications (i.e., Price, Power, Efficiency and Mass) of each motor in the string as inputs. In turn, it calculates the market share both in terms of revenue as well as actual quantities for each of the motors in the market.

Table 3. Results of Demand Model Estimation for the Universal Motor Market

Parameter	**Price (*P*)**	**Power**	**Efficiency (η)**	**Mass (M)**	**Scale parameters for each market segment**			
					μ_1	μ_2	μ_3	μ_3
Coefficient	-0.011	0.0031	0.71	-0.51	0.29	0.25	0.50	0.50

The demand model also helps demonstrate the roles of competition and segmentation (on the market shares of individual motors) in the market. Figure 11 illustrates the difference in market share of the existing products (corresponding to products with serial numbers 1 to 23 in the figure) before and after the introduction of a new product (Product 24) in Segment 2, in Figure 11(a) and Figure 11(b), respectively. The product line positioning decision under consideration involves introducing a single new product in the "high power/high cost" niche in the *power tools* segment (i.e., in (tier, segment) ≡ (3,2)) with the specifications given in Table 4. While the introduction of Product 24 (code: NEW) in Segment 2 takes away significant market share from the other products in the segment (i.e., Products 10-14), the market share of each product in the remaining segments (segments corresponding to household appliances, cordless power tools and garden tools) are relatively unaffected. This indicates that the "within segment" competition in the *power tools* segment is significant, and products in that segment compete much more closely with each other for market share, than they do with products from other segments (e.g., household appliances, garden tools).

Table 4. Performance Specification of Product NEW:(3,2)

Parameter	Price *P* ($)	Power (Watts)	Efficiency η (%)	Mass M (kg)
Values for Product NEW	48.52	700.0	89.5	1.32

2. Description of the Cost Model for the Universal Motor Case Study

The primary objective of the cost model in this work is to help demonstrate the benefits of commonality (i.e., shared components, processes, etc.) among different products in the family. Here, the *manufacturing cost* is expressed as a function of *motor design variables* (**X**) *and the manufacturing processes*, and commonality in the design variables and processes are shown to lead to reduction in cost. Information from various motor manufacturer web sites and insights provided by Simpson et al. (2001) were used to arrive at the cost model.

In general, motor manufacturing cost is determined by two parameters:

a. *motor size* determined by motor radius (r), motor thickness (t) and stack length (L), and
b. *motor windings* determined by number of turns in the armature and stator windings (N_c & N_s) and the cross-sectional areas of the armature and stator wires (A_{wa} & A_{wf})

The stator manufacturing involves *core manufacturing*, *coil winding* and *finishing*. Equipment cost, fixturing costs, and set-up costs in *core manufacturing* operations are primarily decided by motor size. The cost of *motor winding* is mostly decided by the motor winding variables (i.e., N_c, N_s, A_{wa}, A_{wf}). *Finishing* involves lacing and forming operations. The former is usually manual, and the latter is dependent on motor size variables. The most cost-intensive operations involve core manufacturing, and therefore it is considerably more expensive to manufacture motor variants with "different" sizes (i.e., different radii (r), thickness (t), and stack length (L)), than to produce motor variants with "different" motor windings (i.e., different (N_c, N_s, A_{wa}, A_{wf})).

The cost model used in this paper is intended to reflect that; however, values used for equipment cost, fixturing and set-up costs are only indicative—as reported in (Choi and DeSarbo, 1994), "exact cost estimates are not necessary as long as the relative magnitudes are in order". In addition to motor components, the cost models also include descriptions for the motor casing (the cost of which is again dependent on motor size) and the motor fan, which is a function of the power output and efficiency of the motor. The cost model used in this work establishes the relationship between the design variables **X** and the total production cost *C*. The relationship between commonality and associated (manufacturing) cost is embedded in the cost model used here. The cost model thus penalizes "unique" fixturing and set-up costs. The model assumes that motor variants with design variables falling within a certain narrow range can be manufactured with the same set-up and fixtures. Therefore, for any two motor variants to share the same set of manufacturing processes (and hence minimize unique fixturing and set-up costs), it is not necessary for them to have "identical" values for the corresponding design variables; the corresponding design variables for the two motor variants are only required to fall within the same range. Additional details on the cost model are included in the Appendix.

SEGMENT 1			SEGMENT 2			SEGMENT 3				SEGMENT 4		
sl no	code	Q_j	sl no	code	Q_j	sl no	code	Q_j	%	sl no	code	Q_j
1	A11	189.7	10	B21	459.1	15	A31	1268.0	13.2	20	B41	1483.0
2	C11	841.1	11	C21	760.9	16	C31	1375.0	14.3	21	C41	1492.0
3	C12	1057.0	12	C22	962.3	17	C32	2290.0	23.8	22	C42	3078.0
4	B11	1255.0	13	A21	965.9	18	C33	2713.0	28.2	23	B42	3784.0
5	B12	1176.0	14	B22	4112.0	19	B31	1967.0	20.5			
6	B13	2204.0										
7	C13	2413.0										
8	A12	2090.0										
9	B14	2085.0										
13310.8			7260.2			9613.0				9837.0		

a) Market share distribution for existing market

SEGMENT 1			SEGMENT 2			SEGMENT 3				SEGMENT 4		
sl no	code	Q_j	sl no	code	Q_j	sl no	code	Q_j	%	sl no	code	Q_j
1	A11	176.6	10	B21	152.9	15	A31	1180.0	13.2	20	B41	1362.0
2	C11	783.0	11	C21	253.4	16	C31	1280.0	14.3	21	C41	1389.0
3	C12	983.8	12	C22	320.5	17	C32	2132.0	23.8	22	C42	2865.0
4	B11	1169.0	13	A21	321.7	18	C33	2526.0	28.2	23	B42	3522.0
5	B12	1095.0	14	B22	1370.0	19	B31	1831.0	20.5			
6	B13	2052.0	**24**	**NEW**	**7103.0**							
7	C13	2246.0										
8	A12	1946.0										
9	B14	1941.0										
12392.4			9521.5			8949.0				9138.0		

b) Market share distribution after introduction of product 24 in segment 2

Figure 11. Impact of Competition and Market Segmentation for the Universal Motor Market

3. *Description of the Analytical Model for the Universal Motor Case Study*

A mathematical model that expresses the relationship between the design variables **X**: {N_c, N_s, A_{wa}, A_{wf}, r, t, I, L} and the performance measures Power, Torque (T), Mass (M), and Efficiency (η) can be found in (Simpson et al., 2001). Variable bounds for the design variables and the constraints that govern the relationships between the design variables and the performance measures are as specified in Tables 1 and 2. Details on how segmentation of the universal electric motor market is expressed through additional constraints are provided in Table 5.

C. Description of the Optimization Problem for the Universal Motor Product Family Design

The general formulation of the product family design problem was presented in Section IV. The formulation specific to the universal electric motor product family is presented in Figure 12. The most important difference from the generalized formulation in Section IV is the absence of the commonality sub-string ($\mathbf{G}_2$) in the formulation. Due to the combinatorial and nonlinear nature of the formulation, the product line positioning problem within product family design is known to be a NP-hard optimization problem (Nair et al., 1995, Chen and Hausman, 2000). In order to reduce computational effort, commonality is enforced through the cost model for the universal electric motor product family. In this paper, the cost model is expressed purely as a function of the motor design variables **X**: {N_c, N_s, A_{wa}, A_{wf}, r, t, I, L} and manufacturing processes. In the cost model used here, the production volume for each motor variant *i* is assumed to be the same as its market demand Q_i for simplicity.

Table 5. Segment-Specific Bounds for the Universal Motor Product Family

Market segment	Primary Distinguishing Feature(s)	Constraints
SEGMENT 1 (Household appliances)	• Higher Speed	$T \geq 0.05$ (Nm)
SEGMENT 2 (Power tools)	• Higher Torque (T) • Higher Efficiency (η)	$T \geq 0.10$ (Nm)
SEGMENT 3 (Cordless power tools)	• Higher Efficiency (η) • Battery Power Supply • Lighter	$\eta \geq 30$ (%) $T \geq 0.10$ (Nm) $M \leq 1.5$ (kg) $V_t = 35$ (Volts)
SEGMENT 4 (Garden/lawn tools)	• Higher Power • Heavier	$M \leq 3.0$ (kg) $T \geq 0.05$ (Nm)

Given

a) Market data

sales data of different product offerings in segments 1: household appliances, 2: power tools, 3: cordless tools, and 4: garden/lawn tools

b) Demand model (refer to table 3)

coefficients of the utility function, scale parameters for nests corresponding to different market segments ; Q {Price (P), Power, Efficiency (η), Mass (M)}

c) Models for Product Performance

mathematical model expressing relationship between **Power**, **Efficiency**, and **Mass** of motor in terms of motor design variables **X**:{N_c, N_s, A_{wa}, A_{wf}, r, t, I, L}; see (Simpson et al., 2001)

d) Cost models

models for different cost components (see cost model description in Appendix)

Find

a) Product Positioning substring ($\mathbf{G_1}$)

the number of products, and the appropriate market niche to position each of them

b) Design options (**X**) for each of the motors in the family

values of N_c, N_s, A_{wa}, A_{wf}, r, t, I, and L

Maximize

a) Profit $\sum_{i=1}^{n} P_i \times Q_i\left(P_i, \mathrm{Power}_{(i)}, \eta_i, \mathbf{M}_i\right) - C(\mathbf{Q}, \mathbf{X})$

Satisfy

a) Design constraints

Relationships between **E** and **X,** and between different **X** , listed in (Simpson et al., 2001)

Segment-specific bounds for performance attributes (**E**) and design variables (**X**) in section V

Figure 12. Universal Electric Motor Product Family Design Optimization Problem

D. Results and Interpretations

The product family design formulation considered here, is a NP-hard optimization problem. In each optimization iteration, a different product line positioning decision is considered, and the corresponding product family is optimized based on this decision. Ideally, $2^{3\times4} = 4096$ product lines corresponding to the (3×4) universal motor MSG in Figure 10 have to be considered; however, in order to reduce the computational effort, some restrictions were imposed on the product line positioning string. Since products in the same market segment (nest) compete more closely with each other, each segment was allowed to have at most two products to prevent the "new" products from cannibalizing each others' market share. Also, only a maximum of six products is considered for the family. These restrictions reduce the number of total product line positioning combinations to 1,996. The problem was solved using the Optimization Toolbox in Mathworks' MATLAB® (Coleman et al., 1999)

Unlike the aforementioned existing formulations that require the product variants sharing a platform to have identical values for the platform variables, the definition of platform in this work is driven by manufacturing and cost considerations. Earlier in the discussion of the case study, it was established that motor size (expressed through variables motor radius (r), motor thickness (t), and stack length (L)) has the largest effect on the manufacturing cost; motor size has an impact on the *core manufacturing* processes but also on *coil winding* and *finishing* operations. In the cost model used in this work (see details in Appendix), motor variants that have motor design variables that have similar (not necessarily identical) values share fixturing and setup costs. For example, the cost model does not distinguish between motor radii (r) that are different by less than 2 mm, thicknesses (t) that are different by less than 1 mm, and stack lengths (L) that are different by less than 5mm. Consequently, in the following discussions, the definition of the platform is narrowed further to describe only those design variables related to motor size (i.e., motor radius (r), motor thickness (t), and stack length (L)). The platform leveraging strategies presented here only indicate if the motor sizes of the different motor-variants sharing the platform were similar enough to share manufacturing resources.

In order to study the impact of commonality on the different product variants in the universal electric motor family, two variations of the formulation given in Figure 12 are solved. First, cost considerations are excluded, and the problem was formulated as a revenue-based optimization problem. The results obtained were then compared to those obtained using the original profit-based optimization formulation in Figure 12. Figure 13 illustrates comparisons between the product line positioning decisions and platform leveraging strategies obtained using the revenue-based and profit-based product family design optimization, respectively. Figure 14 presents similar comparisons with respect to the design (i.e., the values of design variables **X**) of the different motor variants in the family. The results presented in Figure 13(a) and Figure 13(b) should be seen in conjunction with the product offerings displayed in Table 6 (see the Appendix). It is observed that the product line resulting from revenue-based formulation has six products while the profit-based formulation yields only five products for the optimal product line. Revenue-based optimization positions all of the products in the medium and high-power tiers in all the segments, avoiding the low-power/low-price niche altogether. These are reasonable results since cost considerations are not included, and higher prices translate to higher revenues. Also, as shown in Figure 13(a), in each segment, the products in the high price and medium price tiers have the same price, which is lower than that of comparable products in the existing market (see Table 6). This indicates that the higher power motors are being sold at below their actual cost[5], which is an expected result since this formulation does not include costs, and selling higher power motors at prices below their cost would increase revenues by capturing higher market share.

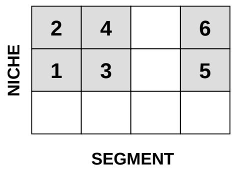
Apart from the difference in the number of products, there are several important differences between the product lines in Figure 13(a) and Figure 13(b). When the (quantity-wise) market shares of the two product lines are compared, the total market share (computed by adding the demand Q_j for each of the product variants in the family) of the product family from the revenue-based formulation is about 50% of the total market (i.e., 40,000 motors) whereas the market share of the product family from the profit-based formulation is only about 30% of the total market. However, the revenues corresponding to the two product lines are comparable, even considering that the profit-based line has one fewer product. Also motor-variants 1, 3, and 5 in the two formulations can be compared directly since they are positioned in identical (performance tier, market segment) pairs in both the formulations. It can be observed that motor-variants 1,3, and 5 in the profit-based formulation are more expensive than their revenue-based formulation counterparts. These are indications that the products in the revenue-based formulation are under-priced. Significantly, the profit-based formulation does not position any product in the high-price/high-power tier of any of the market segments. This is most likely due to commonality considerations; higher power motors tend to be larger (e.g., higher values for motor radius) and require more material (e.g., thicker and longer motor windings), making it more challenging to make them similar (i.e., common) to motors with lower power rating without sacrificing efficiency and adding mass.

The platform leveraging strategy is indicated in Figure 13(b) by the line segments connecting product variants that share a platform (i.e., motor variants with similar but not necessarily identical values for the design variables related to motor size). The product designs listed in Figure 14 are used to arrive at the platform leveraging strategies illustrated in Figure 13. For example in Figure 14(b), Motors 1 and 2 have identical values for radius (r) and stack length (L), and very similar values for motor thickness (t). Therefore the cells corresponding to Motors 1 and 2 are joined by a line segment. For the profit-based optimization, Motors 1 and 2 share one manufacturing platform and Motors 3 and 4 share another manufacturing platform (since they have similar values for the motor size variables)

[5] It is reasonable to assume that the motor in the high-power niche is likely to cost more to produce than the motor in the medium-power niche. It can also be seen from Figure 12(a) that in each segment, the higher power motor weighs more than the medium-power motor which suggests that more material (e.g., thicker windings) was used to produce the motor with the higher power rating.

while Motor 5 incurs unique fixturing and set-up costs. Since cost considerations were not included in the revenue-based product family during the optimization, there is no platform leveraging between the products. Interestingly, the *cordless power tools* segment (Segment 3) is avoided altogether, by solutions from both formulations. In the case of the profit-based formulation, this is because producing a motor for the *cordless power tools* segment would make it difficult to respect commonality considerations. Motors for the *cordless power tools* segment need to operate on a battery operated power supply (i.e., V_t= 36 Volts) and hence need to carry larger current to achieve the rated output power. While such motors could be produced within the same design considerations by using thicker windings, etc., it would be very hard to make them light enough to meet the weight constraint for that segment and still be of a similar size to the other motors in the family. In the case of the revenue-based formulation, the absence of any products in the *cordless power tools* segment is most likely due to the fact that the number of motors in the line is restricted to six, and the other segments are more profitable.

Finally, financial criteria need to be used to choose between the two product lines. The revenue-based formulation (see Figure 13(a)) results in higher revenues than the profit-based formulation (see Figure 13(b)). However, when the manufacturing cost is calculated for the motors chosen by revenue-based formulation, the profit earned by the revenue-based formulation is only roughly 20% of the profit earned by the profit-based formulation. This is primarily due to the fact that the products in the profit-based formulations are platform-based and are therefore cheaper to produce; hence, the product family design from the profit-based formulation needs to be chosen. Our view that manufacturing and market considerations are central to the product family design formulation is well supported in practice. For example, Black & Decker's decision to choose stack length as the scaling variable (Simpson et al., 2001) in their motor family is not optimal when considering motor performance in isolation. The decision is much sounder when manufacturing considerations are included; it is easier to manufacture different motor-variants that vary only in stack length since only the number of laminations in the stack needs to be varied.

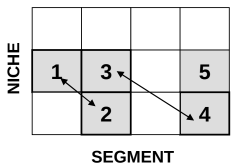


Revenue: $ 967219.6

Profit: $ 65997.16

#	Price ($)	Power (W)	η (%)	Mass (kg)	Q_j
1	30.36	450	84.9	0.93	2215
2	30.36	600	89.2	1.03	3369
3	46.31	550	88.1	0.92	3143
4	46.31	650	89.9	1.13	3870
5	54.12	750	89.1	1.53	3864
6	54.12	850	88.5	2.00	3970

a) Best case scenario obtained for revenue optimization (DESIGN: REV_BEST)



Revenue: $746143.7

Profit: $ 301629.3

#	Price ($)	Power (W)	η (%)	Mass (kg)	Q_j
1	37.43	550	87.0	0.94	2379
2	47.64	550	87.4	0.91	2662
3	54.20	626	88.2	1.03	3265
4	61.79	625	88.1	1.03	2834
5	68.78	750	86.1	1.57	2591

b) Best case scenario obtained for profit optimization (DESIGN: PROFIT_BEST)

Figure 13. Comparisons of Product Line Positioning Decisions from Revenue and Profit-Based Optimization

	N_c	N_s	A_{wa}(mm^2)	A_{wf} (mm^2)	r (cm)	t (mm)	I (Ampere)	L (cm)
1	125.67	100.00	0.37	0.37	4.00	10.00	5.50	2.00
2	118.09	100.00	0.53	0.53	4.00	5.51	5.85	2.00
3	100.00	100.00	0.65	0.65	4.07	1.43	6.29	2.00
4	100.00	100.00	0.72	0.72	4.39	1.21	6.80	2.00
5	100.00	100.00	0.94	0.94	5.36	0.86	8.36	2.00
6	100.00	100.00	1.00	1.00	5.71	0.79	8.90	2.00

a) Design for best case scenario obtained for revenue-based optimization (DESIGN: REV_BEST)

	N_c	N_s	A_{wa}(mm^2)	A_{wf} (mm^2)	r (cm)	t (mm)	I (Ampere)	L (cm)
1	125.79	100.00	0.36	0.38	4.00	10.00	5.49	2.00
2	100.00	100.00	0.35	0.35	4.00	10.00	5.47	2.00
3	100.00	100.00	0.52	0.53	4.00	1.50	6.17	2.00
4	100.00	100.00	0.46	0.55	4.00	1.49	6.17	2.00
5	100.00	100.00	0.56	0.65	5.00	3.49	7.58	2.00

b) Design for best case scenario obtained for profit-based optimization (DESIGN: PROFIT_BEST)

Figure 14. Comparisons of Motor Designs Obtained Using Revenue- and Profit-Based Optimization

VI. Conclusions and Future Work

Today's marketplace is a "buyers' market", and many manufacturers are faced with an ever-increasing demand for differentiating their products from those of competitors. More companies are adopting platform-based product development and product family design in order to increase the variety of their product offerings while keeping costs low. Designing product families requires not only engineering knowledge for platform decisions, but also an understanding of the impact that the platform will have on manufacturing and marketing. Relatively few of the existing optimization-based approaches to product family design include a demand model in the formulation, and those that do, do not provide a realistic examination of how different product offerings from a firm compete with its other products and with competitors' products in the same market segment.

The main contribution in this paper is to introduce the novel Market-Driven Product Family Design (MPFD) methodology to model product platform and product line positioning considerations simultaneously. We show how the segmentation in the market can be modeled using the Nested Logit (NL) technique and demonstrate the dissimilar impacts of competition on the market shares of products in different market segments. One of the main features of the methodology is the use of MSGs not just as visual tools as in current practice, but also as part of the product family optimization formulation. This is accomplished by mathematically expressing the product line positioning decisions and the platform leveraging strategies in the MSG. This allows us to determine the optimal product line positioning decision and corresponding platform leveraging strategy simultaneously. The design of a family of universal electric motors is used to demonstrate the MPFD methodology. Data for a hypothetical market is created, and a cost model that captures the relationships between motor design variables and shared manufacturing processes is developed. Solutions for i) revenue-based optimization (which includes only the product line positioning problem) and ii) profit-based optimization (which includes both the product line positioning problem and the product platform problem) are compared. The results show that there is a strong need to consider performance, as well as cost and market considerations simultaneously in order to make rational and economic decisions.

The focus in the present paper has been on demonstrating the methodology—including a novel representation scheme to integrate the qualitative MSG with mathematically rigorous demand models (NL in our case) – rather than on the development of a new computational algorithm for market-driven product family design. Future work will include a more thorough examination of the computational issues associated with solving the product family problem as we made several limiting assumptions to restrict the number of combinations to enable use of a standard Matlab optimization algorithm (see in Section V.D). While the Nested Logit is an effective tool to estimate accurate and realistic demand models, it does have its limitations. For example, in this paper, it was assumed that all products in a particular segment compete equally with each other. More sophisticated nesting structures and advanced modeling techniques (e.g., Mixed Logit) need to be evaluated for their effectiveness with respect to the product family problem.

Appendix

A. Product offerings in the Hypothetical Universal Motor Market

Nine products compete for market share in Segment 1; Segments 2 and 3 have five products each, and Segment 4 has four products. Each product is also represented by a 3 bit alphanumeric code in the table. Also listed are values of the performance attributes, i.e., Price P, Power (P: $\mathbf{E}_1$), Efficiency (η:$\mathbf{E}_2$) and Mass (M:$\mathbf{E}_3$), for each of the 23 products in the market. Customers are assumed to be appliance-manufacturers. The first bit is a letter and corresponds to the supplier; this is followed by the segment index and product index numeric bits. For example, A12 represents a motor by company A in Segment 1. It also tells us that this is the second product introduced by A in that segment.

Table 6. Product Offerings in the Hypothetical Universal Motor Market

SEGMENT	SL. NO	PRODUCT	PRICE ($)	POWER (W)	η	MASS (kg)
1	1	A11	60	600	47	1.42
1	2	C11	39	550	51	1.14
1	3	C12	33	500	53	0.97
1	4	B11	30	480	56	0.91
1	5	B12	29	450	57	0.82
1	6	B13	18	420	63	0.79
1	7	C13	17	400	66	0.7
1	8	A12	15	370	64	0.65
1	9	B14	9	300	71	0.56
2	10	B21	66	640	48	1.6
2	11	C21	61	600	52	1.36
2	12	C22	57	570	55	1.26
2	13	A21	51	520	58	1.23
2	14	B22	34	470	61	0.91
3	15	A31	70	450	66	0.65
3	16	C31	65	420	68	0.61
3	17	C32	45	360	70	0.54
3	18	C33	33	300	72	0.5
3	19	B31	25	180	76	0.46
4	20	B41	91	840	37	1.61
4	21	C41	84	760	42	1.45
4	22	C42	62	710	45	1.32
4	23	B42	60	600	47	1.42

B. Description of the Cost model Used for the Universal Motor Product Family

The total product cost C is divided into total material cost (C_{mat}), labor cost (C_{labor}), total fixturing and set up costs (C_{fxtr}) and investment costs (C_{fixed}).

$$C = C_{mat} + C_{labor} + C_{fxtr} + C_{fixed} \tag{6}$$

In the cost expressions presented below, the subscript 'i' is used to represent the motor variant 'i', and the total number of motor variants in the family is assumed to be 'n'. The production volume for motor variant 'i' is assumed to be Q_i, the market demand for motor variant 'i'. Also, it should be noted that two additional components, a steel casing and a cooling fan, are included in the cost calculations for the motor assembly. The expressions for material cost are as below.

$$\begin{aligned} C_{mat} &= \sum_{i=1}^{n} C_{mat(i)} \\ C_{mat(i)} &= C_{steel\_parts(i)} + C_{fan(i)} + C_{windings(i)} \end{aligned} \tag{7}$$

In the above expression, $C_{steel\_parts(i)}$ represents the sum of the material costs incurred due to the steel parts in the motor (armature laminations, stator laminations, and the casing); $C_{fan(i)}$ represents the cost of the fan used in the motor variant 'i', and $C_{windings(i)}$ represents the material costs incurred due to the stator and armature windings. The expression for cost of steel parts $C_{steel\_parts(i)}$ is included below. In the following expressions, $M_{component}$ represents the mass of the component under consideration.

$$C_{steel\_parts(i)} = (M_{casing(i)} + M_{stator(i)} + M_{armature(i)}) \times Q_i \times C_{steel} \tag{8}$$

where the mass of the casing is dependent on the motor radius.

$$M_{casing(i)} = \begin{cases} \left(\pi(25^2 - (25-2)^2) \times L_{max} + 2 \times \pi \times 25^2 \times 2\right) \times 10^{-6} \times \rho_{steel} & \text{if } 0.00 < r_i \le 0.02\text{ m} \\ \left(\pi(45^2 - (45-2)^2) \times L_{max} + 2 \times \pi \times 45^2 \times 2\right) \times 10^{-6} \times \rho_{steel} & \text{if } 0.02 < r_i \le 0.04\text{ m} \\ \left(\pi(65^2 - (65-2)^2) \times L_{max} + 2 \times \pi \times 65^2 \times 2\right) \times 10^{-6} \times \rho_{steel} & \text{if } 0.04 < r_i \le 0.06\text{ m} \\ \left(\pi(85^2 - (85-2)^2) \times L_{max} + 2 \times \pi \times 85^2 \times 2\right) \times 10^{-6} \times \rho_{steel} & \text{if } 0.06 < r_i \le 0.08\text{ m} \\ \left(\pi(105^2 - (105-2)^2) \times 10^{-6} \times L_{max} + 2 \times \pi \times 105^2 \times 2\right) \times 10^{-6} \times \rho_{steel} & \text{if } 0.08 < r_i \le 0.10\text{ m} \end{cases}$$

where $\rho_{steel} = 7800 \, {}^{kg}\!/_{m^3}$; $L_{max} = 0.10\text{m}$

$M_{stator(i)} = \pi \cdot \left(r_i^2 - (r_i - t_i)^2\right) \cdot L_i \cdot \rho_{steel}$ and

$M_{armature(i)} = \pi \cdot \left(r_i^2 - t_i - l_{gap}\right)^2 \cdot L_i \cdot \rho_{steel}$

The expression for fan cost for motor 'i' is expressed as

$$\begin{gathered} C_{fan(i)} = P_{fan(i)} \times C_{fan\ power} \times Q_i \\ \text{where} \\ P_{fa(i)} = 0.5 \times (1 - \eta) \times P_{input(i)} \\ C_{fan\ power} = 0.1 \, {}^{\$}\!/_{Watt} \end{gathered} \tag{9}$$

The cost of the windings depends on the diameter of the windings used. Higher diameter (or lower gauge) wires are necessary in high-power applications and tend to have better and more expensive insulation since high-power motors also typically mean higher heat losses. Here, it is assumed that the motor winding wire is bought from suppliers as opposed to being drawn in-house. The rate for motor winding wire ($C_{rate\_wndg(i)}$) is based on those used by Bulk Wire, a division of Powerwerks, Inc. The cost of windings is split into the cost of stator windings (C_{stat_wndg})and rotor windings (C_{rot_wndg}) and is expressed as

$$C_{windings(i)} = \left(C_{stat\_wndg(i)} + C_{rot\_wndg(i)}\right) \times Q_i \tag{10}$$

where

$$C_{stat\_wndg(i)} = \left(2 \cdot L_i + 4\left(r_i - t_i\right)\right) \cdot 2 \cdot N_{s(i)} \times A_{wf(i)} \times \rho_{copper} \times C_{rate\_wndg(i)}$$

$$C_{rot\_wndg(i)} = \left(2 \cdot L_i + 4 \cdot \left(r_i - t_i - l_{gap}\right)\right) \cdot N_{c(i)} \times A_{wa(i)} \times \rho_{copper} \times C_{rate\_wndg(i)}$$

and

$$C_{rate\_wndg(i)} = \begin{cases} 36.01(\$/kg) \text{ if } 0.00 < A_{wf(i)}, A_{wa(i)} \le 0.128\, mm^2 \\ 34.61(\$/kg) \text{ if } 0.128 < A_{wf(i)}, A_{wa(i)} \le 0.205\, mm^2 \\ 32.89\,(\$/kg) \text{ if } 0.205 < A_{wf(i)}, A_{wa(i)} \le 0.324\, mm^2 \\ 32.01\;(\$/kg) \text{ if } 0.324 < A_{wf(i)}, A_{wa(i)} \le 0.519\, mm^2 \\ 31.12\,(\$/kg) \text{ if } 0.519 < A_{wf(i)}, A_{wa(i)} \le 1\, mm^2 \end{cases}$$

While the cost expressions so far listed here generally imply that higher performance motors are also more expensive, they do not capture the relationships that reward commonality between the product variants in the universal motor product family. The fixturing and set up cost C_{fxtr} is used for this purpose and is expressed as shown below. The definitions of the terms used in the expression for C_{fxtr} are provided in Table 7.

$$C_{fxtr} = C_r \times n_r + C_t \times n_t + \; C_t \times n_t + \; C_{wa} \times n_{wa} + \; C_{wf} \times n_{wf} \tag{11}$$

Table 7. Nomenclature of Terms Used in the Expression for Fixturing and Setup Costs
(note: values used for fixturing and set up cost here are hypothetical)

Term	Definition
C_r	cost of fixturing/set up cost per unique motor radius variant; $10^4 \times n_r{}^2 + 5.0 \times 10^3 \times n_r$ ($)
n_r	number of motor variants with different motor radii. Motor radii (r_i) are considered different if they differ by more than 2mm
C_t	cost of fixturing/set up cost per unique motor thickness variant $2.5 \times 10^3 \times n_r$ ($)
n_t	number of motor variants with different motor thickness. Motor thicknesses are considered different if they differ by more than 1 mm.
C_L	cost of fixturing/set up cost per unique motor stack length variant; $5 \times 10^3 \times n_L$ ($)
n_L	number of motor variants with different stack lengths. Motor stack lengths are considered different if they differ by more than 5 mm.
C_{wa}	cost of fixturing/set up cost per unique armature winding variant. $2.5 \times 10^3 \times n_{wa}$ ($)
n_{wa}	number of motor variants with different cross-sectional area for armature windings. Armature windings are considered different if the cross-sectional areas differ by more than 0.1 mm^2
C_{wf}	cost of fixturing/set up cost per unique stator winding variant. $2.5 \times 10^3 \times n_{wf}$ ($)

n_{wf}	number of motor variants with different cross-sectional area for stator windings. Stator windings are considered different if the cross-sectional areas differ by more than 0.1 mm^2

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