ABSTRACT

Title of Dissertation: STRATEGIC PRODUCT DESIGN FOR RETAIL
CHANNEL ACCEPTANCE UNDER UNCERTAINTY
AND COMPETITION

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Significant recent research has focused on the marriage of consumer preferences and engineering design in order to improve profitability. However, in many markets, the profitability of new products for manufacturers is also a significant function of the retail channel structure through which the new products reach the ultimate customer. At the crux of the issue is the fact that channel dominating retailers, like Home Depot, Toys R' Us, Wal-Mart have significant power arising from their hundreds of billions of dollars of sales revenue and have the ability to unilaterally control a manufacturer's access to the customers.

A product design methodology is proposed that accounts for this new and important power asymmetry. Manufacturer's product success as defined by profit is affected by pricing at the retail and wholesale levels which in turn is dependent on the channel structure, i.e., retailer monopoly or duopoly. These channel structures are explored in this dissertation under an econometric or game theoretic framework and the results are shown to have important implications for designers. Additional non-traditional considerations for engineering product design such as bundling and exclusive

contracts which are typical for retail channels are also explored by integrating marketing models with a design optimization structure. Lastly, some design methods for mitigating uncertainty in the strategic landscape of retailer dominated channels are developed.

The dissertation has three research thrusts. Research Thrust 1 is devoted to developing a product design optimization approach with retailer acceptance as a probabilistic constraint on candidate designs. Slotting allowances are considered in concert with engineering design as complimentary approaches to achieving access to consumer markets. The retailer's decision framework and the design optimization approach of Thrust 1 are extended in Thrust 2 to include competitive pricing responses from both competing manufacturers and channel controlling retailers. In Thrust 2 the implications for product design when manufacturers face monopolistic and duopolistic retail channels is explored as well as the design implications of an exclusive manufacturer/retailer relationship. Finally, in Thrust 3 the prior thrusts are implemented for multiple product categories and product bundles in order to consider synergy and competition amongst multiple complementary designs. Under this final Thrust 3, an approach to mitigating the risk of uncertainty in competitor design attributes is also developed.

STRATEGIC PRODUCT DESIGN FOR

RETAIL CHANNEL ACCEPTANCE

UNDER UNCERTAINTY AND COMPETITION

by

Nathan Williams

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To My Dear Wife, Holly

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Slotting allowance ($)	A
Switching cost threshold ($)	b
Production cost of the ith product ($)*	C_i
Cost of goods (production costs) ($)	COG
Cost of merchandise ($)	COM
Objective functions	$\boldsymbol{f}$
Norm-inverse function	F^{-1}
Gross margin (%)	GM
Engineering constraint	$g(\boldsymbol{x}) \leq b$
Product index for an n product assortment	$i=1,2,..n$
Category index	$l=1,2,..L,B$
Overall market share of the ith product (units)*	m_i
Market share of the ith product in segment k (%)*	m_{ik}
Manufacturer's Suggested Retail Price ($)	$MSRP$
Market size (units)	N
Nest Multi-Nomial Logit function	$NMNL$
New Product Design/Development	NPD
Retail price ($) of the ith product* at retailer r	P_{ri}
Market segment size (%)	S_k
Total product utility for a product i in segment k*	U_{ik}
Utility for attribute j of product i in segment k*	u_{ijk}
Wholesale price ($) of the ith product*	W_i
Weight Adjusted Cost of Capital (%)	$WACC$
Engineering design variables	$\boldsymbol{x}$
Customer level product attributes*	$\boldsymbol{y}$
Number of Monte Carlo iterations	Z
Probability of retailer acceptance (0%-100%)	α
Mean market share*	μ
Retailer's profit on new assortment ($)*	π_N
Retailer's profit on prior assortment ($)*	π_O
Profit of Retailer r on product i ($)*	π_{ri}
Profit of manufacturer on product i ($)*	Π_i
Standard deviation of market share*	σ
Market penetration (%)	Φ
Value proposition ($)*	Ψ

* Functions of engineering design variables

CHAPTER 1: INTRODUCTION

This dissertation presents new methods for integrating engineering design optimization with marketing and strategy models in the consideration of a major force in the modern retail market: *the channel dominating retailer.* The methods proposed improve upon existing methods by incorporating the retailer's ability to control and even possibly deny market access to manufacturer products by virtue of their consolidated position. Including this externality (the retailer) provides a more realistic product design context. Additionally, the product design optimization context is enriched through the proposed methods by allowing retailers and manufacturers to price products strategically in response to any introduction of a new design.

The impact of tightly controlled channels (by retailers) is the overarching theme for this dissertation and several methodologies and analyses are developed to address new design and marketing practices relevant to this type of market. The dissertation involves three research thrusts. In research Thrust 1, a design methodology that accounts for the common practice of paying a retailer a fixed fee (slotting allowance) to guarantee shelf space is developed. This analysis is performed under static competitor prices (i.e., retail and wholesale prices are assumed static). In research Thrust 2, an approach is presented that accounts for the strategic pricing of competitor products in response to any design introduction which allows designers to consider strategic response in advance of introducing any design. Using this approach, the impact of retailer characteristics (desirability to certain consumer segments) and the possibility of using one retailer exclusively as a channel partner are evaluated with respect to optimal designs. Finally, in research Thrust 3 the simultaneous design of multiple products and product bundles

competing across categories for market share is considered. In this final approach, the primary focus is on the strategic design of product bundles for greater profitability but additionally uncertainty in competitor strategy, cost models, and even design attributes is considered as a preliminary investigation into design for uncertainty in retail channels.

1.1 MOTIVATION AND OBJECTIVE

Engineering design is the foundation for product design. Engineering design decisions are ultimately realized in products as attributes and features that are important to customers and the retailers who carry the products. The realization that the decision for many of these attributes and features are made early in the design stage and are prohibitively costly to change in order to improve the marketability of the product, has led engineering design to focus on customer preferences in addition to the conventional engineering criteria. To that end, many approaches have been developed in recent years to collect and integrate customer preferences in the early stages of design in order to develop market-focused products. However, a new force has emerged in the modern marketplace that requires additional consideration: the dominant retailer. Consolidation in the retail market has created some of the world's largest corporations that control in excess of 70% of many markets (Cappo, 2003) thereby controlling the access manufacturers have to the consumer market. In some cases, retailers have even become principal buyers for a supplier's or manufacturer's entire product line (Smith, 2002, Useem et al., 2003; Dukes et al., 2006). In effect, the "Big-Box" retailers such as Wal-Mart and Home Depot are gatekeepers to consumer markets and the manufacturer's success depends on convincing retailers to carry their products (Bounds, 2006). In fact

accounting for just 7 select retailer revenues revealed a total revenue in excess of $562 Billion in 2006 (see Table 1.1.1) (Annual Reports, 2006).

Retailer	Revenue ($B)
Wal Mart	$313
Home Depot	$91
Target	$60
Lowes	$43
Best Buy	$31
Circuit City	$12
Toys R' Us	$12
Total	**$562**

Table 1.1.1:   Dominating Retailer Profits

This revenue total is nearly 4% of the U.S. gross domestic product and higher than the 2007 U.S. Department of Defense Budget of $502 Billion (GPO, 2006). While these figures convey the consolidated nature and sheer size of modern retailers they do not express the drastic power shift from manufacturers to retailers. As little as 30 years ago, the majority of retail products were sold through small local retailers frequently referred to as "Mom and Pop" stores (Boyd, 1997). U.S. census data (U.S. Census, 2002) reveals that the number of retail establishments is continually dwindling and fell by 800,000 establishments to 1.1 million establishments between 1972 and 2002. Considering a population increase of 50% during that same period the number of retailers per person has declined by 60% since 1972.   Not surprisingly, the revenue per establishment also supports this consolidation trend: $650K/establishment in 1972, $1.1M/establishment in 1992 and $3M/establishment in 2002 (controlled for inflation). Further evidence of this power comes from the fact that multinational chains of stores have become commonplace as the rate of chain store openings continues to increase. In the early 1960s the number of Wal-Mart stores numbered less than 15 while today they

amount to over 6,600 stores internationally. Similarly, Circuit City and BestBuy now operate over 1,500 and 750 stores respectively (Annual Reports, 2006). Lastly, this power shift is important because for most of the 20th century the manufacturers capable of developing and distributing products were the larger of the two parties involved in the retail channel (manufacturer and retailer) and could in effect "push" products on retailers. One need not search too hard to observe the reversal of this relationship. Examples of retailers greatly overshadowing manufacturers include Home Depot's $91 Billion in revenue vs. $6.5 Billion for its largest power tool supplier or Toys "R" Us $12 Billion vs. Mattel's less than $5 Billion (Annual Reports, 2006). Manufacturers are already forced to take this retailer power into account in the area of pricing and marketing. In this dissertation, the retailer focus is extended to an overall product design approach in the belief that manufacturers should be proactive in their engineering design considerations as they price and market their products.

Retailers are primarily interested in vastly different metric than the manufacturers such as revenue per square foot versus the profit of a specific product offering. Logically, a retailer will only carry those products that maximize overall category profit. For example, Home Depot will only carry the five out of twenty available drills that generate the greatest revenue for the drill category. This revenue depends on the competitive environment (e.g., prices at Lowes), preferences of customers toward the assortment of drills carried at Home Depot, and the accessories that are available for the drills. The retailer puts together these assortments and accessories in such a way to maximize the chances that customer will buy a product (and spend more) on any visit to the store. Given that the retailer's shelf space is limited, manufacturers have to carefully

consider (1) the attributes and features of their product vis-à-vis the assortment the retailer carries, (2) the strategic environment of the retailer (monopoly, duopoly, oligopoly, exclusive contract etc.), (3) the possible bundle of the product and the accessories, and (4) uncertainty in parameters supporting the design selection, all at the early design stage.

In considering the gate-keeper role of retailers and the competitive products and their designs, a product designer cannot afford to take a "myopic" perspective in the design decisions by considering only his/her design and its impact on the market. Because engineering design decisions determine product cost and attribute positioning at the foundation of the development process it is logical to conclude that engineering decisions are transmitted to competitors and retailers as strategies to which they are forced to counteract. For example, just as a manufacturer considers retailers' assortment, profit criteria, and competitors' existing products in designing a new product, other competitors may anticipate this strategy and make their own move to influence the retailer. They might, for example, reduce their wholesale prices to the retailers to make the retailer margins more attractive. Or they may offer some additional features to their products to make them more appealing to retailers as well as consumers.

Retailers, on the other hand, may also consider such strategic maneuvers in new product offerings and wholesale prices to make their own assortment decisions. Thus, these counteractions leading to a "game of moves and countermoves" in the marketplace call for the manufacturer to be "strategic" in their design decisions – that is, make design decisions by anticipating the moves of the competitors and retailers so that when the market is in equilibrium, none of the competitors or retailers have any incentive to

change the status-quo. This dissertation seeks to integrate the strategic decision perspective with design engineering and marketing in a quantitative manner. The strategic design of the firm depends upon the projected market share of a new product offering as well as manufacturing costs estimated in the engineering phase considering the anticipated moves of competition and the retailers. Marketing relies upon engineering design to produce customer desired product attributes. Engineering design is charged with the complex task of developing products for uncertain customer preferences and competitive environments.

Last but not least, uncertainty arises in many forms in product design. Traditionally, engineering design has focused on uncertainty in design parameters, customer usage and more recently customer preferences. Given the aforementioned lack of attention to strategic considerations and dominant retailers it should come as no surprise that uncertainty in competitor responses and channel controlling retailers have not been addressed. This uncertainty can arise from lack of knowledge about competitor or retailer assessments of: equilibrium pricing strategies, customer segment preferences, competitor costs (fixed and variable), competitor's or retailer's aversion to risk or existence of future competitor offerings. Ultimately, the manufacturer would like to mitigate risk from uncertainty and exploit opportunities presented by the strategic environment. Ideally a manufacturer's decision making approach (See Figure 1.1.1) would simultaneously:

- Maximize the chance of the product being selected by the dominant retailers

- Maximize his/her own profit under strategic/competitive wholesale and retail price responses

- Reduce the uncertainty in the projected profit propagated from uncertainties in competitor strategies, customer preferences, demand fluctuations and cost projections.

None of the current design methodologies reported in the literature account for the gate-keeper role of the retailer or the strategic interactions inherent in a channel environment while designing a product for success. The focus of this dissertation is on addressing this gatekeeper role using the objectives listed above as overarching goals for any method developed.
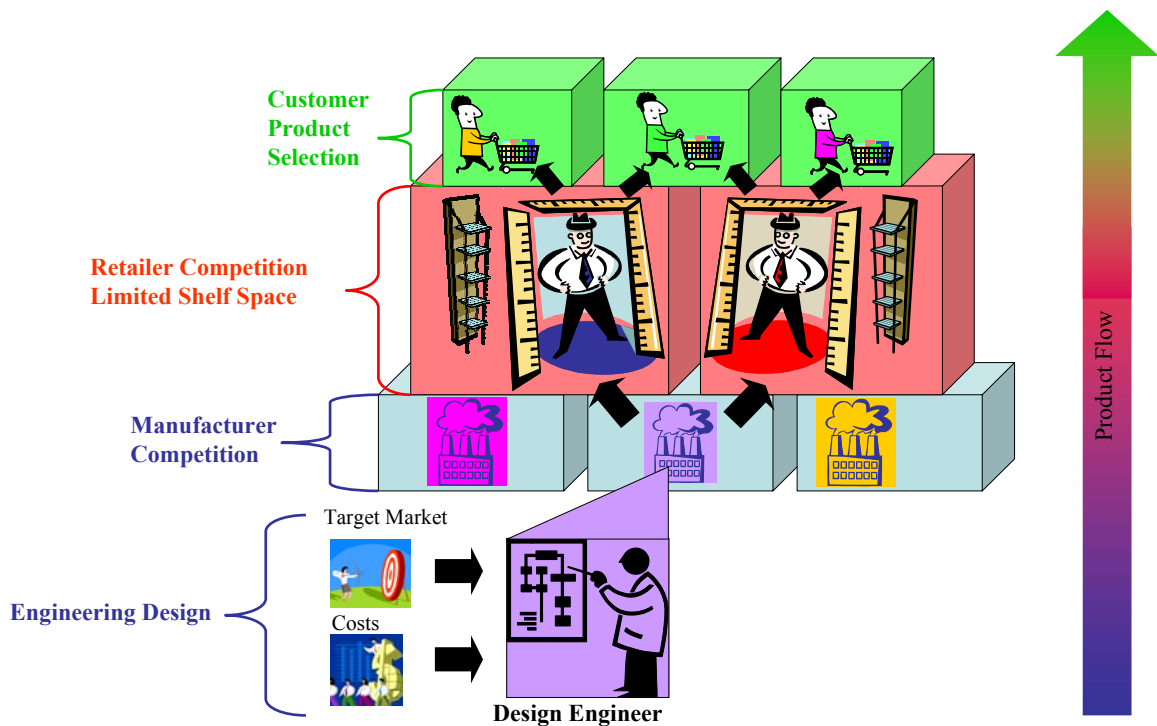
Figure 1.1.1: Product Design for Dominant Retailers with Competition

1.2   RESEARCH THRUSTS

There are three main concerns (See Figure 1.2.1) that a manufacturer faces when developing products for retailer markets which will make up the thrusts of this dissertation. First the manufacturer must ensure that the product makes it to market and

therefore must have a tractable approach for predicting the retailer's acceptance decision (Research Thrust 1). Second, responses of competitors will affect the profitability of the retailers and the focal manufacturer. Realizing this, in Research Thrust 2 an econometric approach to accounting for competitive response at retail and wholesale levels will be integrated into the basic framework developed in Research Thrust 1. Thrusts 1 and 2 only consider strategic and design interactions within one product category. In Thrust 3, the very common retail practice of bundling complimentary products (e.g., two different tools) from different product categories to compete in multiple product categories is explored. Additionally, this thrust implements an initial investigation of the important elements of uncertainty in the channel environment.

Research Thrust 1:
Access to Customers
and Customer Preferences

Retailer

Research Thrust 3:
Multi-Category Design
(Investigation of product
bundling under
uncertainty)

Which Product Design?

Research Thrust 2:
Competitive/Strategic
Pricing

Cost   Demand
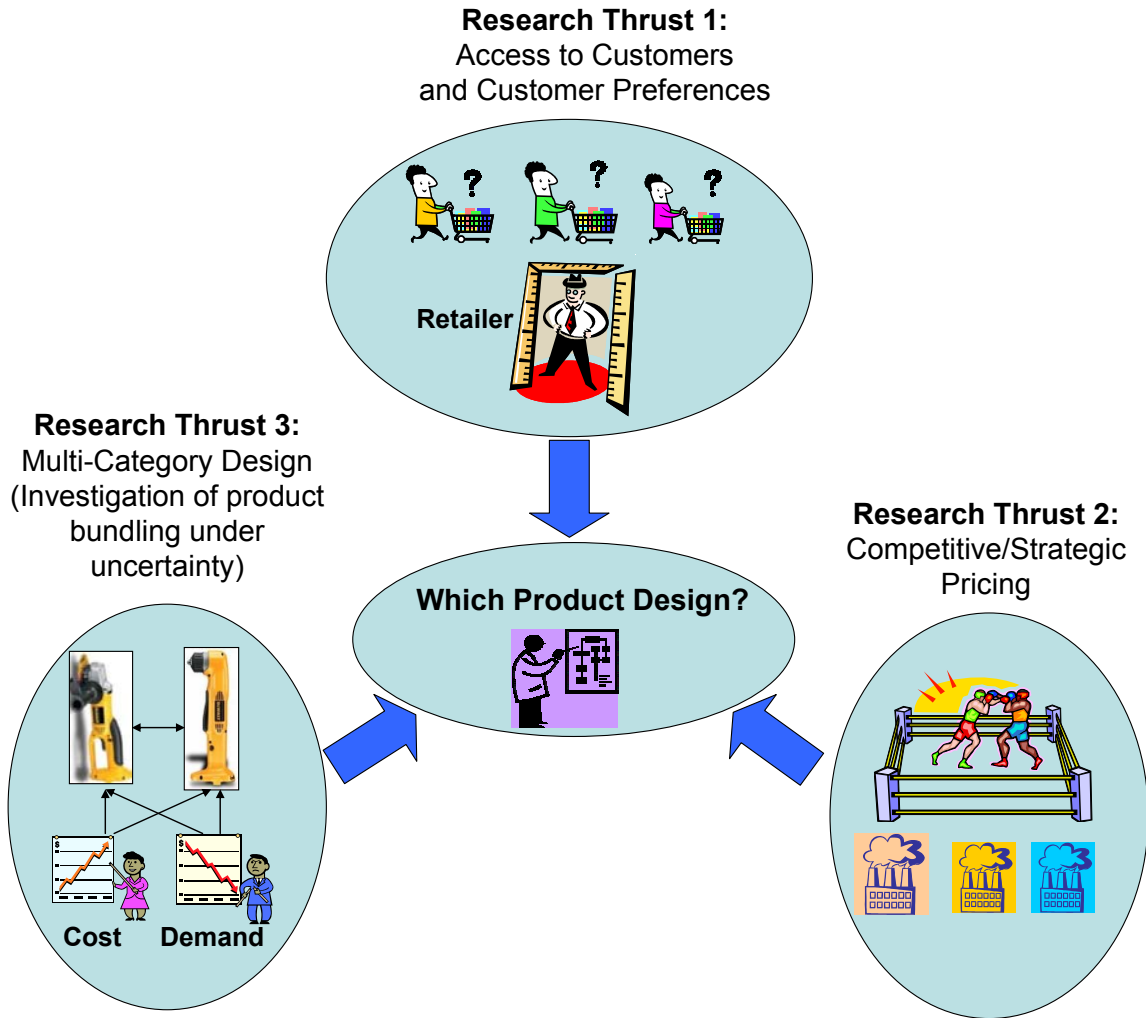
Figure 1.2.1: Design Considerations for Retail Channels

1.2.1   RESEARCH THRUST 1: ENGINEERING PRODUCT DESIGN

OPTIMIZATION FOR RETAIL CHANNEL ACCEPTANCE

An approach to modelling the importance of product acceptance by a dominant

retailer will be investigated.   This foundational effort will assume that competing

manufacturers do not have the capability to change their wholesale prices or product

attributes in the near term, although the effects of competition will be addressed in

subsequent chapters.   The purpose of the thrust will be to provide a manufacturer with a

decision framework under which engineering design variables can be optimized for profit

while simultaneously ensuring that the dominant retailer remains as profitable or more profitable (indicating a high probability of accepting the new product by the retailer). The approach will endogenize the uncertainty in market segment's preferences through a bottoms-up[1] transformation of deterministic engineering design variables to customer relevant product attributes. This is important because the value placed by each customer segment on each product attribute is uncertain and directly affects the decision framework of the risk-averse retailer.

1.2.2   RESEARCH THRUST 2: DESIGN FOR EQUILIBRIUM PRICING IN CHANNEL MARKETS

In the short term, a price change is the only strategic move that is possible for a competitor (i.e., a design cannot change overnight for a competitor). However, the prices are fixed for two quarters to several years. Strategic moves are analyzed in the context that equilibrium is reached where none of the competitors (at the wholesale and retail level) can be made better off by changing their price. This equilibrium pricing will ultimately affect the profitability of the retailers and manufacturers. As such, a methodology is proposed that allows a manufacturer to predict both retail and wholesale price equilibria that result from engineering design decisions. The manufacturer's equilibrium profit is proposed as a substantially improved engineering optimization objective as it more accurately reflects reality. Several cases are investigated that

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[1] Bottoms-up refers to the selection of specific engineering variables that when aggregated at the highest level result in quantifiable customer level product attributes. This approach is distinct from the extant literature where attributes are selected at the highest level before engineering takes place (see e.g., Luo et al., 2007).

highlight the importance of: (1) monopolistic retailers, (2) duopolistic retailers , (3) customer preferences for different retailers, (4) and the possibility of exclusive contracts (which are prevalent for many retailers).

1.2.3 RESEARCH THRUST 3: MULTI-CATEGORY DESIGN OF BUNDLED PRODUCTS FOR RETAIL CHANNELS CONSIDERING DEMAND DEPENDENCIES AND UNCERTAINTY IN COMPETITIVE RESPONSE

One prevalent approach to increasing both retailer and manufacturer revenues is to improve the attractiveness of a product offering (to end customers) by bundling related items together for one price. To be most effective, bundled products should be developed with an integrated design approach that seeks to achieve synergies of value for the end customer as well as cost efficiencies through measures such as using common parts. Given these important interactions, a bundled product design approach is developed that takes into account strategic reactions (price changes) of retailers across the bundled and unbundled product categories and accounts for demand dependencies between bundled and unbundled goods. Additionally, there exists poorly defined uncertainty in terms of competing manufacturer product attributes, customer preferences, and even engineering design tolerances for many product categories. To mitigate the risk of these multidisciplinary uncertainties a robust design approach is implemented in a novel manner to ensure acceptable product profitability and market share under a range of uncertain possibilities. A bundled product design case study is presented for two complimentary power tools that offer a synergy in value. Manufacturer profit and market share are optimized both deterministically and under intervals of uncertainty (robust optimization) surrounding competitor actions, cost models and engineering parameters.

1.3   ASSUMPTIONS

In developing the design approaches in this dissertation, a few assumptions are made that are common to each of the research thrusts:

- Firms have multiple competing objectives that are, to a large extent, functions of engineering design variables. Foremost, a firm wishes to maximize profit but additionally a firm may wish to maximize market share or the profitability of its channel partners. These objectives are usually competing and therefore candidates for multi-objective optimization.

- During game theoretic or econometric price setting it is assumed that strategy sets of each competitor are known to all competitors and that players (retailer and manufacturers) are rational, strategic and exhibit foresight. Rationality implies that decision makers attempt to maximize utility (Osbourne and Rubinstein, 1994). Maximizing utility for game players (retailers and manufacturers) will generally mean maximizing profit.

- Firms are risk averse and value the ability to choose less risky alternatives. Akin to some investors preferring high yield risky stocks and others preferring the 10 year treasury, it is assumed that firms are not merely risk neutral (i.e., wanting to maximize expected value). Each firm can have a different risk tolerance or preference. As such, analyses are presented to show the tradeoff between predicted profit and a risk metric. Frequently, in this dissertation, risk is quantified in terms of design rejection by the channel controlling retailer.

1.4   ORGANIZATION OF DISSERTATION

The dissertation is organized in a sequential fashion as presented in Figure 1.4.1. Chapter 2 provides terminology and nomenclature common to the rest of dissertation as well as background information on tools such as Multiple Objective Genetic Algorithm (MOGA). The initial analysis of the decision making by channel dominating retailers is made in Chapter 3. This chapter provides an approach to design optimization assuming that retailers will only accept products that reliably improve profitability (Thrust 1). It also assumes other retailers and manufacturers do not change their wholesale and retail prices. In Chapter 4 additional layers of complexity are added to the modeling process by allowing manufacturers and retailers to alter prices in response to any new design offered by the focal manufacturer. The goal of this effort is to understand how competitors will react to a presumably strong new design entrant. A strategic or game theoretic framework is developed in Chapter 4 that allows these pricing reactions to take place (Thrust 2) and be accounted for during design optimization. Chapters 3 and 4 analyze optimal design for the retail channel but for one product category only. Chapter 5 extends the effort to multiple product categories and includes an analysis and case study of product bundle design optimization for retail channels. As shown in Figure 1.4.1 uncertain modeling parameters are considered in Chapters 3 and 5 while Chapter 4 is deterministic. Similarly, competitive pricing is only considered in Chapters 4 and 5 with the greatest emphasis on multilayered strategic pricing in Chapter 4.   In each chapter a multidisciplinary case study is presented that demonstrates the approach. Finally, in Chapter 6 conclusions about the work are presented and comments about contributions of the dissertation are made along with options for future research.

Figure 1.4.1 shows the organization and flow of information in this dissertation.

Chapter 1
Introduction;
Motivation and Objectives;
Research Thrusts;
Assumptions

Chapter 2
Definitions and
Terminology

Non-Strategic Pricing

Chapter 3
Probabilistic Design for Retail
Channel Acceptance with
Static Competitor Pricing

Channel Uncertainty Considered

Chapter 4
Strategic Engineering
Product Design For
Monopolistic and Duopolistic
Retail Channels

Strategic Pricing Response Considered

Chapter 5
Multi-Category Design of
Bundled Products for Retail Channels
Considering Demand Dependencies
and Uncertainty in Competitive Response

Chapter 6
Conclusions
Main Contributions
Future Research

Figure 1.4.1: Organization of Dissertation

CHAPTER 2:   DEFINITIONS AND TERMINOLOGY

In this chapter, several definitions and terminologies are provided to facilitate understanding of the multidisciplinary environment that is the focus of this dissertation. Marketing and economics definitions that may not be well known in the engineering community are discussed in Section 2.2. In Section 2.3, Multiple Objective Genetic Algorithms (MOGA) are describe to facilitate understand of Chapters 4 and 5 where a MOGA is used extensively.

2.1   INTRODUCTION

In the past, engineering and marketing practitioners have been accused of each operating in a vacuum. Although there have been several methods put forward to integrate engineering and marketing, none have specifically address the growing power of the retailer. This issue is addressed in the present dissertation. Due to the cross-disciplinary nature of the problem we provide introductory definitions and terminologies in Section 2.2. Additionally, less common definitions related to decision making and robust optimization are presented in Section 2.2.

An overview of MOGAs is also presented in this chapter as one of the preferred methods for solving non-convex problems with discrete design variable inputs. Additionally, MOGAs are capable of handling multiple objectives clearly very realistic given the sales and profit targets simultaneously pursued by most firms. Solving such multi-objective problems generally yields and optimal set of solutions (Pareto frontier) which is discussed. In this chapter we focus on the details of MOGA computations and demonstrate its usefulness in subsequent chapters for solving multidisciplinary problems.

2.2   MARKETING AND ECONOMICS DEFINITIONS AND TERMINOLOGIES

A few terms from the marketing and economics literature are used throughout this dissertation that it may be useful to define:

Assortment - For this work an assortment is defined as the products within a product family offered to consumers by the retailer (e.g., the 5 handheld angle grinders in the angle grinder product category at Home Depot) (Kotler, 2002).

Bundle – The sale of two or more different products or services as a package. Bundling can occur with varying levels of independencies between products. Product bundling has significant dependency while price bundling does not. Product bundling requires significant foresight as the designs of the two or more products must perform well together to create any demand synergy. In offering a bundle to a retailer the manufacturer should be mindful that the offering will likely cannibalize from two different product categories.

Cannibalization – When a vendor introduces a new product that decreases demand for an existing product of the same vendor cannibalization of the existing product occurs (Kotler, 2002).

Channel – A channel is a conduit by which goods or services are transferred from the producer to the customer (Coughlan, 2001). For this dissertation, retail channels are explored where manufacturers use intermediaries (retailers) to transfer their goods to customers.

Choice (Demand) Model – Choice or demand models predict the demand for a product for a particular market or segment through the comparison of its utility to all other products available in the assortment (competing products) (Lourviere et al., 2004).

Conjoint Analysis – A methodology for utility function estimation that relies on the comparison of hypothetical product profiles by potential customers. The results of customer scoring, ranking or rating of the profiles are evaluated with a statistics package to estimate utility for individual attributes of a product which can in turn be used to obtain the overall utility for all attributes and based on choice model used to design or position a product (Green and Srinivasan, 1990).

Duopoly – a special type of oligopoly where only two producers exist in one market.

Exclusive (exclusive channel) – a strategy where a manufacturer uses only one reseller or retailer for his products (Moner-Coloques, 2006).

Games or Game theory– refers to a broad array of microeconomic techniques used to analyze interactions amongst decision makers (Osborne and Rubinstein, 1994). In this dissertation competition for profitability of firms is modeled as game amongst non-cooperative players. That is, players do not form coalitions are collude to raise prices but rather compete to maximize their individual profitability. Thus we are interested in non-cooperative games. Additionally, the games are modeled under the assumption of "perfect information". Perfect information implies that that all players know the state of nature. For example, all manufacturers and retailers know the preferences of customers with certainty. Additionally, perfect information implies that all players know that the other players know the state of nature (consumer market in our case) and vice versa.

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Monopsony – A single customer exists for a service or product. This is similar to the situation where a single producer or manufacturer exists (e.g., monopoly).

No Choice Option – The no-choice option is the option for customers to choose to not purchase any of the competing products. It is included with a utility value for the no-choice option in the demand model (Lourviere et al., 2004).

Nominal Optimum – An optimal value for a deterministic (i.e., without uncertainty) optimization problem.

Oligopoly – a market with only a few competitors (Vives, 1999).

Price Equilibrium – A price equilibrium is reached when none of the players (competitors) has an incentive to change their product's price: commonly referred to as a Nash equilibrium. A Nash equilibrium is a widely accepted solution to competitive games that makes no claim about how the solution is reached only that it is a solution reached by rational decision makers taking into account the objectives of his/her opponent. A Nash equilibrium exists under the competitive circumstances frequently encountered by manufacturers and retailers. In games where the player's profit functions are assumed to be continuous and twice differentiable in price it is sufficient to say that a Nash equilibrium exists if the profit functions for each player are quasi-concave in own-price (Osborne and Rubinstein, 1994). Many profit functions exhibit quasi-concavity and for the basic cases of the logit choice model it has been proven that quasi-concavity exists (Anderson et al., 1992).

Rational Decision Maker – A rational decision maker is one that is aware of his alternatives, forms expectations about unknowns (e.g., competitor pricing), has clear

preferences (e.g., prefers more profit to less) and chooses his action deliberately after some process of optimization.

Robust Optimum – A robust optimum (for a maximization problem) for this dissertation will assume the definition that it is a design that with the highest value that does not vary outside of an acceptable objective variation range when the uncontrollable (or uncertain) parameters are considered. For this approach a decision maker must specify the acceptable variation range. See Li et al. (2006) for full implementation details.

Slotting Allowance - A slotting allowance is a fixed payment to a retailer by a manufacturer that entices the retailer to carry a product. This payment offsets the retailers risk in committing shelf space to a product with uncertain demand (Lariviere and Padmanabhan, 1997), (Sudhir and Rao, 2006).

Segments – Frequently consumers have heterogeneous preferences as an entire market yet can be grouped in to several groups or segments with significant internal homogeneity (Kamakura and Russell, 2003).   Segments have utility functions that are distinct from one another which provides an opportunity for increased accuracy in estimating demand. For example, one segment of consumers may prefer heavy products for their perceived robustness while another segment might prefer light products for mobility. If one just averages the two segment preferences the two extremes (heavy and light) could have equivalent utility which cannot provide insight as to which attribute to design toward (heavy or light). In contrast, this is not a problem if distinct segment utility functions are used. For example, when three products already exist in the heavy product segment the designer will be able to automatically identify the greater

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profitability of the light segment which is underserved (fewer products with the light attribute exist).

Utility – Utility is a measure of satisfaction that one derives from a good or service (Von Neumann and Morgenstern, 1944).

Value Proposition – The added benefit of a seller's product relative to the next best alternative (Kotler, 2002 or Donaldson et al., 2006). The value proposition made by a manufacturer to a retailer would be the improved profit for the retailer resulting from the improved product attributes. From the retailer's perspective an acceptable value proposition would result in a greater retailer profit by increasing the retailer's overall market share or by reducing wholesale cost.

2.3   MULTI-OBJECTIVE GENETIC ALGORITHM (MOGA)

MOGA is an optimization technique capable of optimizing two or more objectives, f, at one time. It has the desirable property of being capable of globally optimizing non-convex problems with or without discrete design variables (Deb, 2001). MOGA will be used in chapters 4 and 5 to simultaneously optimize profit and market share objectives for the focal manufacturer. Like all genetic algorithms, the MOGA is population based in that it starts with an initial set of designs (or a population) which are successively altered based on a strategy until the best population is found. As shown in Figure 2.3.1 our MOGA implementation proceeds through a few simple steps. First, design variables are generated as candidates to make up the first population. These design variables are encoded and concatenated as binary strings for each instance of design variables or "individual" that is a member of the population. Each individual is evaluated by an objective function call. This is referred to as "simulation" in Figure 2.3.1.

Once the objective values are known for the population the individuals can be ranked in terms of performance. This is known as fitness assignment or evaluation which is performed using a non-dominated sorting algorithm (NDSA) (Deb, 2001). Consider Figure 2.3.2 which is the minimization of two objectives f_1 and f_2. Using NDSA, the purple dots are ranked lower (better) than all blue dots. Essentially, the algorithm ranks lowest (best) the designs that no other design can claim to be better with respect to all objectives.

The best ranked points are removed from the population and the NDSA is run repeatedly until all points are ranked. Each time the NDSA loops through the population the rank index increases by one which means successive designs are ranked (worse) as they are selected by the NDSA.

Once all points are ranked fitness assignment or evaluation is complete. In the next two steps (Figure 2.3.1) after fitness assignment a new population is created. One approach (as employed in this dissertation's MOGA) is to partition the current population in to dominated and non-dominated designs. The non-dominated designs and possibly more low ranked designs are copied to elite fractional space of the population to preserve the best members of the current population. The remaining population members are generated using mutation or crossover functions with non-dominated and dominated designs as parents. This mutation (flipping chromosome bits) and crossover procedure (swapping binary chromosome sections) guarantees that some offspring retain some of the non-dominated parent's chromosome and can even improve upon the parent's performance depending on the outcome of the mutation. Since the process is random it is also possible to have two dominated parents mate and create non-dominated offspring.

Once the new population is developed and sent back to the simulation stage for evaluation one generation has passed. The process is repeated until a stopping criterion is met. The stopping criteria can be a number of generations or a geometric evaluation of whether the Pareto Frontier (best ranked designs) is still getting better relative to a reference position in objective space.   The approach is implemented in Matlab's genetic algorithm toolbox (Matlab, 2007) and uses the feasible over infeasible approach (Deb, 2001) for constraint handling. That is during fitness evaluation infeasible designs are ranked worse than all feasible designs regardless of their objective function performance.
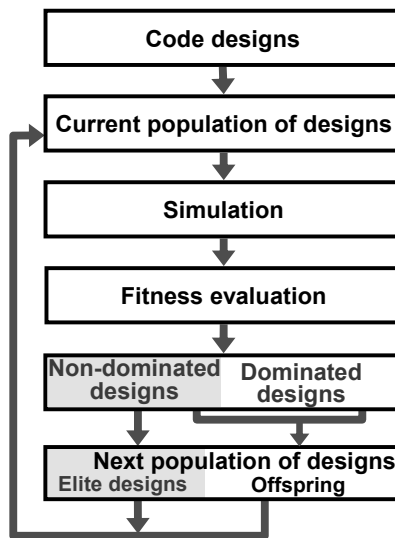
Figure 2.3.1: Flowchart of MOGA in One Generation

f_2

f_1
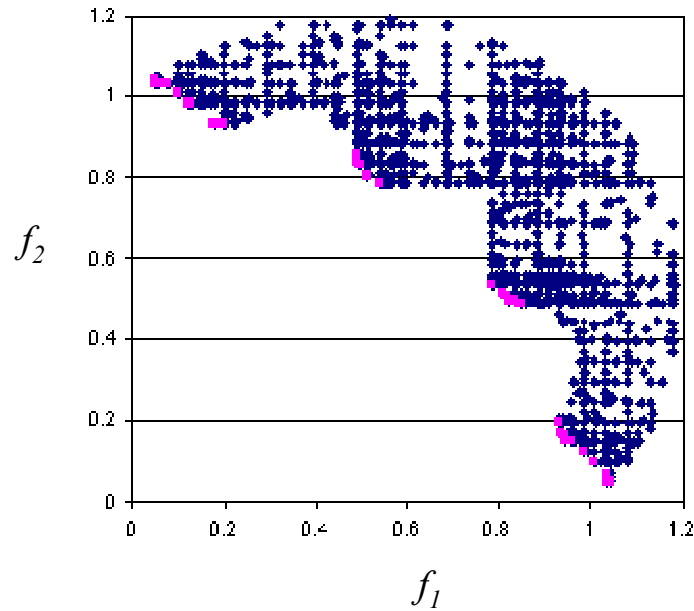
Figure 2.3.2: Solutions to Multi-Objective Problem

2.4   SUMMARY

This chapter has provided an introduction to background economics and marketing material that may not be familiar to some engineers. These definitions will be used throughout subsequent chapters in the development of our multidisciplinary approach.   Additionally, MOGAs were described briefly because they are used extensively in Chapters 4 and 5 to deal with multiple objectives simultaneously. MOGAs are also ideal for solving discontinuous objective functions with discrete design variables such as those frequently encountered in product design.

In the next chapter the channel design optimization problem will be tackled considering uncertainty in end customer preferences but will be limited non-strategic competition in terms of wholesale and retail product pricing. That is prices are developed from a firm level analysis of margins rather than a game theoretic approach as presented in Chapter 4.

CHAPTER 3:   ENGINEERING PRODUCT DESIGN

OPTIMIZATION FOR RETAIL CHANNEL ACCEPTANCE

Significant recent research has focused on the marriage of consumer preferences and engineering design in order to improve profitability. The extant literature has neglected the effects of marketing channels which are becoming increasingly important. At the crux of the issue is the fact that channel dominating retailers, like Wal-Mart, have the ability to unilaterally control manufacturer's design decisions as gatekeepers to the consumers or market. In this chapter, we propose a new methodology that accounts for this power asymmetry and will be used by all subsequent chapters. A chance constrained optimization framework is used in this chapter to model retailer acceptance of possible engineering designs and accounts for the important effect on the profitability of the retailer's assortment through a latent class estimation of demand from conjoint surveys. The approach allows the manufacturer to optimize a product design for its own profitability while reliably ensuring that the product will make it to market by making the retailer more profitable with the addition of the new product to the assortment. As a demonstrative example, we apply the proposed approach for product design selection in the case of an angle grinder. For this example, we analyze the market and are able to improve expected manufacturer profitability while simultaneously presenting the designer with tradeoffs between slotting allowances, market share, and risk of retailer acceptance.

Section 3.1 provides the introduction and motivation for designing for retail channel acceptance along with a review of the extant research of integrated engineering and marketing design models. An overview of the framework that is used to tackle the

problem multidisciplinary problem is provided in Section 3.2. Sections 3.3 and 3.4 model the decision criteria of the retailer and manufacturer respectively while Section 3.5 provides a demonstration example that will be used throughout this dissertation. Section 3.6 provides analysis and discussion of the approach and conclusions are provided in Section 3.7.

3.1   INTRODUCTION

Manufacturers have traditionally focused on consumers' preferences as a strategic guiding light for designing successful products. The recent development of the "superstore" and strong retail channels has rendered this consumer-centric paradigm somewhat inadequate. In an expose (Frontline, 2004) of Wal-Mart business practices the question was asked "Is Wal-Mart good for America?" To answer this question one must delve into the changes brought about by massive consolidation of retail storefronts by companies like Wal-Mart, Target and Home Depot. The changes are sweeping to say the least. One salient example exists in the lawnmower product category:

> *Americans now buy more than 8.5 million push and riding lawn mowers a*
>
> *year – and they buy more than 70% of them at Wal-Mart, Home Depot,*
>
> *and Lowes. Just twenty years ago 80 percent of lawn mowers were sold at*
>
> *independent retailers.*
>
> *The Wal-Mart Effect* (Fishman, 2006)

The answer to the Frontline's question largely depends upon whether or not you are a consumer, a producer (manufacturer) or competing retailer. Consumers have benefited tremendously from reduced prices (8-27%, Singh, 2006), competing small retailers have obviously been negatively impacted or even driven out of business but the

less obvious affect is that manufacturers have less market power and must take into account strategic dominance of these retail players to gain access to consumers.

This change in power over the last 20 years amounts to a shift from "push" to "pull" production (Frontline, 2004). Traditionally manufacturers operated in a push mode where they designed products they determined consumers wanted and tried to convince or "push" retailers to carry the product. This worked for a large part of the 20th century when manufacturers were relatively large compared to the small retail stores that carried their products. The aptly named "pull" approach is a reversal of roles where the retailer partially dictates design requirements. The retailer "pulls" in products based on their own objectives rather than entirely making the decision base on the desires of end customers. The retailer still makes an assessment of what the consumer wants to stay competitive but, in a way, insidiously arranges assortments to maximize retailer profits rather than customer utility. Thus the "pull" paradigm as discussed in this chapter amounts to a retailer profit focus vs. a focus totally on consumer utility.

As mentioned in the Chapter 1, modern retailers have grown to such disproportionate size compared to their supporting manufacturers that one should expect a paradigm shift from the push to pull production to persist. An obvious conclusion from massive retailer revenues present in Chapter 1 (Table 1.1.1) is that market power or control is derived from these revenues. Given this position of power, the manufacturer must admit (perhaps grudgingly) that the retailer's concerns ought to be taken into account in the manufacturer's design decision process. The retailer and manufacture both have the customer's interests in mind but have conflicting objectives to maximize their own profits while serving the customers. These conflicting objectives put them on

adversarial positions. Thus if the manufacturer is hoping to maximize profits, he should realize this and try to co-opt the retailer by taking his considerations into account while serving the ultimate market (consumers). This is our purpose in developing this chapter.

It is generally agreed that retailers are profit maximizing entities who make decisions on which manufacturer products to carry based upon the availability of shelf space and the effect on their current assortment (Simpson et al., 2001). Additionally, the channel controlling retailers can be influenced by human relational factors, and a myriad of manufacturer side incentives such as advertising or slotting allowances (Gilliland, 2004). Because as much as 90% of all new products fail (FTC, 2001), slotting allowances are offered by manufacturers as a risk mitigation feature for retailers. Much of the business literature that has analyzed manufacturer/retailer relationships has concluded, with an almost obvious assertion, that while many of the factors are important, no single factor is as important as the short term profitability of the product selected to be carried by the retailer (Wagner et al., 1989, Shipley, 2001).

In nearly all cases of retail environments and especially with retailer dominated channels, shelf space is finite (with the notable exception of online merchants). It is therefore important for a manufacturer to evaluate his value proposition to the retailer (i.e., relative improvement for the retailer's product line from a profitability viewpoint) within the context of the retailer's assortment in order to assure channel acceptance (Simpson et al., 2001). A product offering that completely cannibalizes (captures market share from) an equivalently profitable product will be poorly received. In contrast, an unrepresented product (that has negligible cannibalization) with somewhat less demand or margin can be well received and added to the product category vice replacing an

existing model. A retailer will add a product without replacing a competitor when shelf space is valued at less than the candidate product's value proposition. That is, the additional shelf space dedicated to the new product creates more profit than alternative products regardless of category. Thus the manufacturer must ensure that his product makes the assortment more profitable than the existing assortment by supplanting a less profitable product or in fitting a niche. This can be done by convincing some of the retailer's customers, who currently are not buying any product in the category, to buy the new product (McIntrye, 1999). We take the effect of the retailer's assortment into account in our model of the retailer's decision process using preferences of customer segments in the market, identified through a latent class preference (Section 3.3.4).

The integration of marketing and engineering design is a burgeoning field, yet no model to date adequately addresses the role of the channel retailer as a gate keeper for the market (Luo, 2005). Recent research has explored the interaction of collected marketing data and realistic engineering design constraints, e.g., (Li and Azarm, 2000, Wassenaar and Chen, 2003, Wassenaar et al., 2005, Michalek et al., 2005, Georgiopoulous et al., 2005, Cooper et al., 2006, Besharati et al., 2006), to find an optimal solution for a financially oriented objective function. For instance, Wassenaar and Chen (2003) and Wassenaar et al. (2005) use demand modeling or discrete choice analysis based on customer information (surveys) in the design of a universal motor. Georgiopoulous et al. (2005) use a simple demand model for resource allocation and production capacity in the design of products. They argue persuasively that "engineering decisions do not take place in a vacuum" and "economic, investment, and engineering design decisions affect each other implicitly or explicitly". While the reported approaches have been

improvements in the internal coordination of the manufacturer's engineering design and marketing objectives they neglect to account for the retailer's control of market access to end customers. Our method is distinct in that we incorporate the concerns of an externality: the retailer.

The objective of this chapter is to find product design solutions with maximum profit for a manufacturer consistent with previous work but also account for the growing importance and risk associated with the channel retailer. We propose a manufacturer profit design optimization framework that treats customer segment preferences probabilistically in predicting retailer product acceptance. A chance constraint that focuses on improving retailer profit in the face of uncertain customer preferences is employed to that end together with other engineering design constraints.

3.2   BOTTUM-UP DESIGN FRAMEWORK

The model we developed incorporates the channel power of a strong retailer through a bottom-up approach where a detailed engineering design module provides the foundation for marketing and cost estimating modules. In actual industrial practice, marketing executives of the firm frequently select a target design for a product based on market research without regard to specific knowledge of the impact on engineering design. We term this a naïve top-down approach because customer level product attributes are simply selected and passed down to the engineers to achieve with only occasional feedback. It should be noted that there are top-down approaches (e.g., Waterfall in: Verner and Cerpa, 1997), Analytical Target Cascading (ATC), (Michalek et al., 2005), and others (Kumar, et al., 2006) that are not naïve in that they take into account multiple stages and feedback (waterfall) or multiple discipline objectives and

constraints with repeated feedback (i.e., ATC) or even multiple products in a family considering cost and manufacturing synergies (Kumar et al., 2006).

While a naïve top-down approach is simple to understand and fits the hierarchical structure of many firms it has the deleterious effect of dictating high level attributes that may not be feasible (in terms of engineering design) or cost effective as cost is dependent principally on the engineering design. Take for example, a firm executive that dictates that a new angle grinder must be extremely light and powerful and his conjoint studies suggest that a 1-lb angle grinder with an amp rating of 30 amps that costs less than all other products on the market would capture a large market share. Such a target would not be feasible in the engineering design domain and also unachievable in the cost domain. The only recourse in a naïve top-down approach is for the firm executive to guess which product attributes might be feasible and also a cost effective design. Clearly, the naïve top-down approach can not approach optimality in terms of firm profit for these weaknesses. ATC is an alternative top-down approach that with considerable additional complexity in sub-discipline coordination may be capable of performing such an information flow (top to bottom) with an optimal result.

In contrast, our method begins at the engineering level or the lowest level decisions (e.g., selecting armature diameter instead of power output). Unlike the naïve top-down approach the bottom-up approach (Figure 3.2.1) as used in our model is capable of incorporating the marketing models as a portion of the mapping that transforms engineering design variables, x, into product attributes, y, and to utility, u, and finally market share, m. Additionally, costs, C, are dependent upon the engineering design variables. As such, the bottom-up approach allows the firm to develop a

generalized profit model which can be optimized and is completely dependent on engineering design yet incorporates the externalities of customer preferences and competitor offerings.

Ultimately, the choice between a top-down and bottom-up approach may be most dependent upon the maturity of the product category in question and the commitment of the firm to innovation. For fledgling product categories with a wide range of expansion and innovation possibilities the top-down approach may retain greater flexibility in simply setting performance goals at the top-level and allowing new sub-discipline models and options to be integrated as they become available. For mature industries with well known costs, the bottom-up approach provides an efficient and logical method to quickly translate engineering design attributes into an estimated market share and profit.

In the broadest sense, this is exactly what our model does but with the additional concern of satisfying the retailers profitability concerns (Figure 3.2.1). It takes the inputs of engineering design variables x, conjoint surveys (customer utility estimates), and channel retailer shelf surveys (competitor product attributes) and outputs designs x that are acceptable to the retailer and provides optimal profits for the manufacturer. The retailer's decision is whether or not to carry a product which is of significant concern to the manufacturer as this determines market access in a highly consolidated retail market. This decision by the retailer is represented with a decision node near the top of Figure 3.2.1. The retailer decision is supported by the marketing module and takes into account the effect of a new product introduction on all products in the assortment. The manufacturer's decision of which product to produce or to what levels should design variables x be set is more complicated and influenced by feedback from the engineering

module, marketing module, and the cost estimating module. The entire system is controlled by an optimization algorithm which in this case is single objective – manufacturer expected profit. The latent class model (Kamakura and Russell, 1989) will compute the customer segment preferences prior to the optimization using conjoint surveys as an input and the number of segments defined by the user. Thus the relative utility of a trial design will be readily known and as a consequence so will market share and profit.

Engineering design (the selection of x) is the foundation of this approach although there are a number of intermediate steps as depicted in Figure 3.2.1. Intermediate variables that are functions of design variables are denoted with an asterisk (*) in the nomenclature section of Chapter 1. Each of the steps depicted in Figure 3.2.1 and the variables displayed will be explicated in detail in subsequent sections. The overall objective of our formulation is to maximize manufacturer profit through the selection of engineering design variables x and a manufacturer's suggested retail price MSRP. The design space is bounded by a chance constraint that describes the probability of retailer acceptance as well as deterministic engineering constraints (e.g., heat flux, stress, etc.). We develop a model for the retailer's product acceptance decision as a chance constraint in Section 3.3 and return to the manufacturer's objective in Section 3.4.

Legend | Optimization Algorithm
Intermediate Computation
External Data
Module
Decision

Finish

Yes | No

Optimal MFR Profit?

Yes

Reliably Improve Retailer Profit?

No

Back to Start

m_i

Compute Market Share m_i

Marketing Module Sec. 3.4

C_{NPD}

m_{ik}

Compute Segment Share m_{ik}

U_{ik}

Cost Module **Sec. 3.4.1**

Compute Production Cost: $C(x)$

Calculate Utility of Product i in segment k: U_{ik}

Existing Assortment Attributes y_i

y_{NPD} S_k, u_{jk}

x

Engineering Module **Ex. Sec. 3.5.3**

Feasible? $g(x) \leq b'$

Convert x to Product Attributes y (e.g. weight) $y_{NPD} = f(x)$

Latent Class Estimate of Segment Sizes S_k, and Preferences u_{jk}

No x

x

MSRP

Conjoint Market Surveys

Select Engineering Variables: $x = (x_1 x_2 ... x_n)$

Set MSRP

Start

Figure 3.2.1: The Bottom –Up Framework

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3.3   THE RETAILER'S PRODUCT ACCEPTANCE DECISION

We begin our modeling process of retailer acceptance of products, which will act as a constraint for the manufacturer's problem, with several simplifications. First, we are interested in a channel environment where a single or a few dominant retailers hold the majority of the channel power. Singular dominance for many product categories in many regions of the United States is very much the case with Wal-Mart (frequently referred to as a monopsony). Signs of slightly more dispersed channel power asymmetry also exist in the power tool industry (Home Depot and Lowes) and the consumer electronics industry (Best Buy and Circuit City). The centralized power enjoyed by these retailers is a major concern for manufacturers and can result in a "produce/not produce" decision based solely on the acceptance of the dominant retailer. As a result, we model using Eq. (3.1) the channel decision maker as a chance constraint (Birge and Louveaux, 1997) on the manufacturer's design selection problem, where the left side of Eq. (3.1) computes the probability P of the value proposition ψ being greater than the switching cost threshold b. To satisfy this constraint, the probability computed on the left side must be greater than the acceptance level α specified by the designer:

$$P(\Psi \geq b) \geq \alpha \quad \alpha \in [0,1] \tag{3.1}$$

The probability of acceptance can be selected by the designer to determine what type of design will satisfy the retailer $\alpha\%$ of the time since the retailers actions cannot be known with certainty. Also, one can solve for α if a product design (including MSRP) is already known. Such a constraint can be thought of as being similar to a traditional reliability constraint where, for example, a beam of design x_1 will fail with a probability of $(1- \alpha)\%$ given the uncertainty in loads and beam characteristics.

Frequently, in the literature, it is mentioned that retailers act on relational factors as mentioned previously. The relationship with the various manufacturers' sales people would be an example. The switching cost threshold, *b*, can be used to take this into account along with the decision maker's personal aversion to change (Simpson et al., 2001). A risk neutral retailer would require a probability of acceptance marginally above 50% in order to justify switching to the new assortment. For our analysis we will examine various levels of retailer acceptance probability α. Manufacturers would obviously prefer that the dominant retailer will reliably accept their design and develop product designs to that end.

3.3.1 COMPUTING THE RETAILER VALUE PROPOSITION

The manufacturer's value proposition is the means by which it can convince a retailer to carry its product. The value proposition ψ is defined as the amount by which the proposed product offering will improve the retailer's profitability. It is a critical component of the acceptance criteria established in Eq. (3.1) and the only means by which a manufacturer can overcome the indifference of the retailer or the switching cost threshold. An assumption is made that the retailers evaluate all products within the context of the retail assortment. The manufacturer takes the retail assortment into account in trying to convince a retailer to carry their product. A model of the value proposition is shown in Eq. (3.2):

$$\Psi = \pi_N - \pi_O \tag{3.2}$$

The profits of the new and previous assortments, π_N and π_O, can be decomposed into several components as we refine our model.

$$\pi_N = \sum_{i=1}^{n} m_i (P_i - W_i) N \tag{3.3}$$

The contribution of each product, $i=1,...,n$, to the retailer's profit is the product of market share, m_i, market size N, and retail margin (P_i-W_i). The demand variable m is estimated with the latent class model, see Section 3.3.4. Summing the contribution of the n products in the assortment is the retailer's entire profit for the new assortment, π_N. Also:

$$\pi_O = \sum_{j=1}^{p} m_j (P_j - W_j) N \tag{3.4}$$

Where for the prior assortment profit, π_O, we sum the contribution for the p prior products just as we did for the original assortment. Essentially, the manufacturer is attempting to convince the retailer that the new assortment n will be more profitable than the old assortment p through this value proposition.

3.3.2   RETAIL MODELS WITH SLOTTING ALLOWANCES

In general, a slotting allowance is a monetary incentive offered to a retailer when a manufacturer knows little about the demand for a new product (Lariviere and Padmanabhan, 1997), (Sudhir and Rao, 2006).   Essentially, the manufacturer guarantees an initial fixed payment (slotting allowance) to the retailer in order to obtain acceptance and therefore shelf space. Retailer acceptance models that consider slotting allowances are relatively sparse in the literature. Lariviere and Padmanabhan (1997) and Desai (2000) develop deterministic models where manufacturers set prices and slotting allowances first and then the retailer's decision is developed as a subsequent profit maximization model. In contrast Shaffer (1991) and Chu (1992) (as noted by Sudhir and Rao, 2006) develop deterministic models where the retailer sets an optimal slotting allowance policy which is substituted into the manufactures profit maximization model.

Richards and Patterson (2004) develop a unique stochastic model where the value of a new product and slotting allowance as a *real option* with only product returns modeled as Brownian Motion/Poisson or a jump diffusion process.

Our approach (like Sudhir and Rao, 2006; Lariviere and Padmanabhan, 1997 and Desai 2000) is to add the slotting allowances to the value proposition in the retailer's decision model:

$$P(\Psi + A \geq b) \geq \alpha \tag{3.5}$$

Eq. (3.5), is modeled as a chance constraint (i.e., stochastic constraint) and takes into account the multi-dimensional uncertainty in segmented customer preferences. These uncertain customer preferences result in uncertain demand levels and are thus a critical portion of the value proposition in Eq. (3.5) (See Section 3.3.3 for implementation details).

Slotting allowances are interesting in the context of a chance constraint as in Eq. (3.5) in that the slotting allowance itself is a deterministic quantity that can be used to offset increased uncertainty in the value proposition for the retailer. Although empirical information about slotting allowances is scarce (Sudhir and Rao, 2006) our analytical interpretation of slotting allowances as a one time offset to retailer risk in accepting *new* products is consistent with the literature (Bloom et al., 2000; Sudhir and Rao, 2006; White et al., 2000). A variety of slotting allowance and product offering combinations satisfy the same constraint which we discuss fully in Section. 3.6.2. Manufacturers can use such a constraint to evaluate potential offerings of design variables.

3.3.3   SOLUTION TO THE FULL RETAILER MODEL

As mentioned previously (Section 3.3.2) our method is unique in its approach to modeling the retailer's decision under uncertainty although probabilistic and reliability constraints are frequently used in engineering design (Du and Chen, 2004, Zou and Mahadevan 2006). Specifically, we take into account in engineering design the uncertain utility that customer segments will assign to all preferences, not just rate of return as in Richards and Patterson (2004). We demonstrate the implementation of these uncertain preferences with the latent class model in this section and how the risk can be mitigated by a slotting allowance. To understand the mechanics of evaluating slotting allowances in light of this risk, it is useful to combine the previous equations for an aggregate view of the retailer's constraint:

$$P\left(\left(\sum_{i=1}^{n} m_i\left(P_i - W_i\right) N\right) - \left(\sum_{j=1}^{p} m_j\left(P_j - W_j\right) N\right) + A \geq b\right) \geq \alpha \qquad (3.6)$$

We can simplify the above equation prior to finding the deterministic equivalent of the chance constraint. For example, through the use of a representative retailer's annual report a retailer's margin can be assumed (e.g., Home Depot: 37%), which is equivalent to the quantity P_i-W_i written as $GM_{Retailer} \times P_i$. Using the prior market's known product offerings, we can compute the prior assortments profit π_o using market shares for m_j as:

$$\pi_o = \left(\sum_{j=1}^{p} m_j\left(GM_{Retailer} \cdot P_j\right) N\right) \qquad (3.7)$$

Initially we assume that the manufacturer is interested in only one channel retailer, has decided against slotting allowances, and assumes negligible switching cost so that the chance constraint can be further reduced to:

$$P\left(\sum_{i=1}^{n} m_i \left(GM_{Retailer} \cdot P_i\right) N \geq \pi_o\right) \geq \alpha \tag{3.8}$$

At this point it is useful to apply the well known result (Charnes and Cooper, 1963; Vajda, 1972; Birge and Louveaux, 1997) for developing the deterministic equivalent of a chance constraint which assumes that random variables are normally distributed. (However, even if this normal distribution assumption does not hold, it is possible to find a transformation that makes the random process approximately normal (Albada and Robinson, 2007).) Consistent with the normal assumption, the market share m_i is assumed to be stable and normally distributed random variable. The mean for each products market share is calculated as:

$$\mu_i = E(m_i) \tag{3.9}$$

It is assumed there will be some covariance amongst the product market shares so a variance – covariance matrix is developed through Monte Carlo simulation of uncertain customer utility estimates as explained in Section 3.3.4. This variance-covariance matrix is used to calculate the overall standard deviation of the jointly distributed random variables where:

$$V = \begin{pmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & & \\ \vdots & & \ddots & \vdots \\ v_{n1} & & \cdots & v_{nn} \end{pmatrix} \tag{3.10}$$

$$v_{ii} = Var(m_i) \tag{3.11}$$

$$v_{ij} = Cov(m_i, m_j) \tag{3.12}$$

$$\sigma = \left[P^T \cdot V \cdot P\right]^{1/2}, \quad P = [P_1, P_2, ..., P_n] \tag{3.13}$$

i and j are the column and row indices of the variance-covariance matrix. The variance makes up the diagonal elements and the covariance terms make up the off-diagonal elements of the variance-covariance matrix. All variance and covariance terms are easily estimated using Excel's built-in variance and covariance functions and the latent class model developed in Section 3.3.4. Taking the norm-inverse (F^{-1}) of the resulting standard deviation and the probability complement, the chance constraint takes the form (Charnes and Cooper, 1963):

$$\pi_o \leq \left(N \sum_{i=1}^{n} \mu_i \left(GM_{\mathbf{Re}\,tailer} \cdot P_i\right) - F^{-1}(1-\alpha)\left(P^T \cdot V \cdot P\right)^{1/2} \right) \tag{3.14}$$

We assume that the competing manufacturers maintain their current pricing levels. In reality, some of the manufacturers will respond to the new product by adjusting their value proposition. Generally, for directly competing products, the wholesale price will go down making the retailer's profit margin much more attractive for the entire assortment. This reduction in competitor prices actually aids the attacking manufacturer in strengthening his value proposition by increasing the right side of the chance constraint, Eq. (3.14). It is important to note that it has been observed that wholesale prices can increase under increased competition but this is not the norm (Berstein and Federgruen, 2003). We do not adjust pricing for competing products in our model for tractability but are able to provide a conservative and appropriate estimate of retailer acceptance through the use of the chance constraint. This is a significant improvement over deterministic models and is in keeping with the general perception that slotting

allowances are offered to mitigate the retailer's risk. Additionally, we consider risk related to uncertain customer preferences which have not been modeled stochastically with slotting allowances.

3.3.4 ESTIMATION OF PRODUCT DEMAND

The latent class approach (Kamakura and Russell, 1989) recognizes that there exists in the market distinct latent segments of consumers who use different choice criteria and that the accuracy of market share can be improved through this consideration of heterogeneity in preference modeling. The segments for the latent class approach are independent of demographics. Customers are grouped based on the similarity of their preferences for the various features that make up the power tool rather than ethnicity, gender or socio-economic backgrounds. For example a segment of consumers shopping for an angle grinder may prefer low weight models that by design are also usually lower in amperage. This segment could be made up of hull technician demographic (typically grinding fiberglass hulls overhead) and the DIY (Do-It-Yourself) single female who may want, for instance, a light tool for furniture paint stripping. The latent class model groups individuals based on similarity of their preferences (i.e., both demographics prefer a light tool) and estimates the overall size of the segments based on a least squares fit of the collected conjoint data. Additionally, to minimize errors in estimating customer preferences and maximize the use of marketing resources, conjoint experiments can efficiently be developed to reduce the number of experiments necessary to achieve acceptable levels of error by as much as 50% (Huber and Zwerina, 1996).

In order to estimate a given product's share of a segment using the latent class approach we sum up utilities u of the j attributes of product i within the segment (Kamakura and Russell, 1989):

$$U_{ik} = \sum_{j=1}^{m} u_{ijk}$$ (3.15)

A piecewise linear interpolation is assumed for all non-integer attributes in calculating utility.

The same procedure is performed for each of the n competing products (assortment). We are able to estimate the segment share of product i in segment k while taking into account the utility of the no choice (or no purchase) option U_{nc}:

$$m_{ik} = \frac{\exp(U_{ik})}{\sum_{i=1}^{n} \exp(U_{ik}) + U_{nc}}$$ (3.16)

This is one of the key steps in developing a model that adequately addresses assortment in the channel retailer situation. It should be obvious now that as a new product is introduced that has different attribute levels than the existing assortment the probability of selection is altered for all products. It is worth noting that b in Eq. (3.5) can also be used to represent the value that the retailer places on an additional unit of shelf space. In the case where a significant portion of the population is underserved (i.e., prefer the no choice or no purchase option) it may be advisable to design products that the retailer may *add* to the assortment instead of *displacing* an existing model. We suggest the additional space can be analyzed by setting the value b equal to the estimated value of the shelf space. This approach is necessary because the out-of-category product currently occupying the shelf space will not affect the in-category market share m_{ik} and

therefore the value of the shelf space must be accounted for outside of the market share computation.

The process in Eq (3.16) is performed for each of the segments k for the given assortment of products. The total market share (%) of a given product is computed from the segment size S (%), market share in each segment m_{ik} (%):

$$m_i = \sum_k S_k \times m_{ik} \qquad (3.17)$$

In order to take into account the stochastic nature of the utilities it is necessary to add a random element ε to the utility function.

$$U_{ik} = \sum_{j=1}^{m} \left(u_{ijk} + \varepsilon_{ijk} \right) \qquad (3.18)$$

The final distribution of m_i is used in the chance constraint and is estimated with Monte Carlo simulation of each attribute j, in each product i, in each segment k. Each m_{ik} is the average of the simulations after completing Z iterations of Eq. (3.16) with point estimates from Eq. (3.18). Thus the number of simulated attribute utilities necessary $Sims$ is the product of Monte Carlo iterations Z, the quantity of products i, the number of segments k and the number of attributes j:

$$Sims = Z \times i \times j \times k \qquad (3.19)$$

3.4   THE MANUFACTURER'S DECSION

The manufacturer develops products within a strategic context. This is significant because designs that are only profitable in the short term may not produce lasting competitive advantage (Porter, 1985). There are many methods for evaluating the strategy of a manufacturing firm in the strategic management literature (e.g., Drucker, 1973, Mintzberg, 1987, Porter, 1996). We propose a flexible profit maximizing function

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that allows the manufacturer to pursue a number of strategies depending upon the decision making process of the retailer. Under our model the manufacturer can pursue a cost leading (lowest cost), quality leading (highest quality), or differentiation[2] marketing strategy.

The manufacturer is concerned with a profit maximizing strategy for a given time horizon. The time horizon for this profit maximization is of critical concern. For example, in many industries it is acceptable to post losses on products to gain future sales in the form of predatory pricing (Lindsay and West, 2003). In addition, it has become common for manufacturers to develop a bundling strategy where losses are posted on one item in order to tie-in sales on another. The most frequently quoted example of this is the losses on inkjet printers for future profits in cartridges. And more recently there exists examples where manufacturers suffer losses on video game consoles to promote game sales. With some modifications our model should be capable of approaching these combined decisions through a generalized profitability model that accounts for the timing of revenue through Net Present Value (*NPV*) analysis as well as the bundling effect by using a combination of demand models in the objective function that include the prior profitability of unbundled assortments and the new profitability of bundled assortments. Bundling and the timing of cash flow are not explicitly modeled in the example problem of this work but are proposed as appropriate candidates for extending the approach.

As stated earlier we assume that the manufacturer has the intention of maximizing profit or shareholder value. It is well accepted (Grinblatt and Tittman,

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[2] *Differentiation* strategy refers to a strategy where a manufacturer offers products that differ from competitors along one or more attribute in order to fill a niche that prefers the offered set of attributes.

1998), (Cantor and Lippman, 1983) that financial decisions take into account time and financial uncertainty. Most simply put, our objective function is to maximize the *NPV* of profit:

$$MAX: \text{NPV}\big(\text{Cash Flows}\big) \tag{3.20}$$

The development of the manufacturer model based on cash flows is somewhat more complex (with the addition of production costs *C*) but consistent with our analysis of the retailer:

$$MAX: \sum_{i=1}^{M} m_i \big(W_i - C_i\big) N - A \tag{3.21}$$

This representation of the variable cash flow incorporates the fact that the manufacturer has to evaluate its production decision within the context of its current *M* offerings or product line. It would make very little sense for the manufacturer to expend the effort to develop a product that cannibalizes another product in his own line that is currently profitable. This model endogenizes the possibility of this cannibalization by summing over all products in the product line, *N*. We add the effect of time on our revenue where WACC is the weight adjusted cost of capital used to discount cash flows over *T* periods:

$$MAX: \sum_{t=1}^{T} \left(\frac{\sum_{i=1}^{M} m_i \big(W_i - C_i\big) N}{\big(1 + WACC\big)^t} \right) - A \tag{3.22}$$

3.4.1 PARAMETRIC PRODUCTION COST MODEL

Numerous methods for estimating the cost of production exist in the literature. Related methods vary from detailed design estimates to novel neural network applications. Parametric methods, initially developed by the Department of Defense in WWII to estimate the cost of producing additional warplanes, have been the most widely used over the last half century and remain so today in government and industry (D.O.D., 1999). For example, the most popular software cost estimating technique of the 80's and 90's is parametric and is still in use: Constructive Cost Model or COCOMO (Boehm, 1981).

A detailed estimate is far too expensive and cumbersome for the early stages of design and can limit the design space (Scanlan, 2002) whereas parametric methods are quick, efficient, and accurate so long as sufficient historical information is available, production methods have not changed, and an extremely refined design resolution is not necessary. The product of interest in this article exists in a mature industry where production techniques are well-established and significant historical and current market data exists. Parametric methods are suitable in this instance as our product category is essentially a slightly differentiated commodity where all producers have similar cost structures. Parametric estimation assumes that the commodity production techniques are well developed (nearly optimized already), that all producers are similarly competent, and that the economy of scale has already peaked due to large product volume (1 million units or more for our producer). Costs are simply then a function of higher level product attributes. This allows the designer/estimator to base cost relationships on engineering performance attributes such as: weight, speed, size, etc. (D.O.D., 1999). These are

similar characteristics to the project level parameters in the widely validated COCOMO (Boehm, 1981). That is not to say that the cost model and subsequent design considerations could not be made better with the inclusion of learning curves, and factors of scale but rather the parametric approach is sufficient for this application.

Additionally, under a scenario where a manufacturer is first entering a new product category it is unlikely that s/he will have access to detailed production cost estimates or even be inclined to expend resources in developing cost estimates without first developing a strategy. Parametric estimation is particularly well suited for this situation as performance characteristics and attributes for existing models in the product category are readily available. Retail prices are the most readily available cost data for retail products (as opposed to wholesale prices which are confidential) and with a little effort: wholesale and production costs can be estimated using constant retail and wholesale margins. For this chapter we begin with a dominant channel retailer's financial performance and compute its gross margin $GM_{Retailer}$ from its sales and cost of merchandise COM:

$$GM_{Retailer} = \frac{SALES - COM}{SALES} \qquad (3.23)$$

We use this gross margin to discount the retail price of a potential product along with an analysis of a manufacturer's annual report which has a similar structure yet Cost of Goods, COG, for a manufacturer:

$$GM_{MFR} = \frac{SALES - COG}{SALES} \qquad (3.24)$$

These margins determine the percentage of the retail price made up by the physical production costs, C:

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$$C = R(1 - GM_{\text{Re}\,tailer})(1 - GM_{MFR}) \tag{3.25}$$

This analysis yields a much generalized characterization of production costs relative to retail prices that is appropriate for the average product produced by the subject manufacturer and sold by the channel retailer. In order to develop a cost model that accurately fits the market characterized by the specific margins of interest we use multiple regression analysis (Winston, 2004) to relate engineering performance parameters to production cost. Further details and an example are provided in Section 3.5.2.

3.4.2 THE COMBINED MANUFACTURE/RETAILER MODEL

The combined model for the manufacturer's decision is then formulated to maximize future cash flows based on a latent class market share function and a parametric cost model subject to engineering constraints *and* retailer acceptance:

$$\underset{x,R}{MAX}: \quad \sum_{t=1}^{t} \left(\frac{\sum_{i=1}^{M} m_i (W_i - C_i) N}{(1 + WACC)^t} \right) - (A)$$

$$S.T.: \quad P\left(\left(\sum_{i=1}^{n} m_i (P_i - W_i) N \right) - \left(\sum_{j=1}^{p} m_j (P_j - W_j) N \right) + A \geq b \right) \geq \alpha$$
$$g(x) \leq b'$$

$$\tag{3.26}$$

The engineering constraints $g(x)$ are endogenous to the model.

The simplest scenario is one where the manufacturer offers only one product (*NPD)*, and only one retailer exists to sell that product (a very strong channel relationship). Additionally, we make the assumption that the retailer has fixed shelf space and that the manufacturer's product must replace an existing product. For this

dissertation, we assume that consumer preference does not change in time so we know that a decision that maximizes profit in the first period will maximize profit in all subsequent periods.

3.5   CASE STUDY APPLICATION

A demonstration example for our methodology was developed based upon a popular consumer product category: right angle grinders. These tools are used for in a variety of industrial and home settings and provide an excellent example of a product with multiple disparate customer segments. The tool is used for applications ranging from cutting high modulus steel to shaping wood and fiberglass products. We develop the latent class estimation of demand in Section 3.5.1, a parametric cost model in Section 3.5.2, and a detailed engineering model to ensure feasibility in Section 3.5.3. The problem demonstration is optimized using variations of Eq. (3.26) in Section 3.6.

3.5.1   MARKETING MODEL EXAMPLE: ANGLE GRINDER

The latent class segmentation portion of the Sawtooth Software Market Research Tools (SMRT) (Sawtooth, 2001) was used to analyze 249 conjoint surveys of angle grinders (Figure 3.5.1) in the development of Table 3.5.1.

Figure 3.5.1: 4.5" Angle Grinder Commonly Used for Masonry and Metal Work

As shown in Table 3.5.1 each segment has an estimate of utility mean (μ) and standard deviation (σ) for several possible alternatives of product attributes. The utilities

are normalized by Sawtooth (Sawtooth, 2001) and therefore add up to zero for an
attribute category.

Segment	One		Two		Three		Four	
Share	37.80%		24.80%		12.10%		25.30%	
	μ	σ	μ	σ	μ	Σ	μ	σ
Brand								
W	-0.5	0.12	0.5	0.08	2.2	0.11	-0.2	0.05
X	0.2	0.12	1.1	0.09	-2.4	0.12	-0.2	0.14
Y	0.8	0.14	0.1	0.12	-1.5	0.15	1.2	0.16
Z	-0.5	0.13	-1.6	0.11	1.7	0.06	-0.8	0.16
Price								
$79.0	-0.1	0.16	-0.1	0.01	0.0	0.07	0.0	0.12
$99.0	-0.9	0.13	-1.2	0.04	1.9	0.08	-0.2	0.08
$129.0	1.0	0.13	1.2	0.07	-1.9	0.09	0.3	0.08
Amps								
6.0	1.3	0.08	0.5	0.12	-1.5	0.11	-0.5	0.13
9.0	0.1	0.09	-1.4	0.13	-0.7	0.12	-2.4	0.12
12.0	-1.4	0.10	1.0	0.15	2.1	0.12	2.8	0.22
Life (hrs)								
80.0	-0.9	0.10	-0.1	0.12	-4.7	0.07	0.8	0.15
110.0	1.3	0.11	-0.5	0.08	-5.8	0.03	0.7	0.18
150.0	-0.5	0.12	0.6	0.11	10.5	0.01	-1.5	0.12
Switch type								
Paddle	0.4	0.14	0.3	0.10	-3.3	0.04	-0.7	0.13
TopSlider	-1.0	0.19	-0.7	0.12	-3.0	0.04	0.4	0.15
SideSlider	2.4	0.16	-0.1	0.07	2.5	0.04	0.6	0.05
Trigger	-1.8	0.16	0.4	0.15	3.9	0.03	-0.3	0.15
Girth								
Small	2.5	0.10	0.7	0.15	1.5	0.02	2.4	0.11
Large	-2.5	0.08	-0.7	0.13	-1.5	0.05	-2.4	0.13
Weight								
16lbs	-2.3	0.06	-0.8	0.07	-0.5	0.03	1.5	0.13
9 lbs	0.5	0.10	-1.2	0.08	2.0	0.03	0.5	0.03
6 lbs	1.8	0.17	2.0	0.02	-3.5	0.02	-2.0	0.13
No Choice	-0.2		-0.2		-0.2		-0.2	

Table 3.5.1:   Utility Estimates for Four Segments

An example of segment shares is shown in Table 3.5.2 for a sample set of attributes for 4 existing tools (A to D) and the new product development (NPD) of the focal manufacturer:

Tool	A	B	C	D	NPD
Brand	W	X	Y	Z	X'
Price ($)	$79.00	$99.00	$129.00	$79.00	$101.93
Amps	6.00	9.00	12.00	6.00	6.59
Life (hrs)	80	110	150	110	110
Switch	Paddle	Trigger	Side	Side	Side
Girth	Small	Large	Large	Small	Small
Weight (lbm)	5.00	9.00	16.00	5.00	7.2
Segment %	21.3	0.04	18.9	22.8	36.9

Table 3.5.2:   Example Segment Share

Customers in Segment One prefer high prices, low amp ratings, small girth, light weight, side slider switch etc. Each of the designs in Table 3.5.2 partially satisfy these desires as the designs are truly intended for all segments at once. Each of the segment shares in Table 3.5.2 are dependent upon how well the product fits the segment preferences as well as the competing product attributes as the total utility of all products forms the denominator in Eq. (3.16). It is worth noting that negative attributes such as the heavy weight and large girth of Tool C can be overcome by positive segment attributes such as high price (a signal of quality to some consumers (Daughety and Reinganum, 2007, Fluet and Garella, 2002) and the side slider switch.

3.5.2   COST MODEL EXAMPLE: ANGLE GRINDER

Twenty available grinder models were collected from two large retailers that can be characterized as channels in and of themselves. *C* was computed for each model using the margins developed in the preceding paragraphs. Many characteristics available for the twenty models were investigated as explanatory variables for cost, including: switch type, amp rating, mass, torque, RPM, body length, etc. Production cost was set as the

dependent variable with each of the characteristics tested as independent variables. Conveniently multiple-regression is capable of obtaining β values (see Eq. (3.27)) for binary data through the coding of dummy variables. An example of a dummy variable is a "1" for the presence of a slider switch and "0" for not present. The switch types for the grinders were coded as dummy variables in order to determine if a significant cost relationship existed between the switch type and production cost. The model was tested for its assumptions using usual diagnostics (i.e., normality test, test of homoskedasticity, and tests for independence of error terms and validation of linear assumption) and it was determined to be reliable and valid for the application. See Winston (2004), Milton and Arnold (2003) or Render et al., (2006) for a detailed review of multiple regression and selection of predictor variables. All variables from Table 1.1.1 were tested with *t-Stat*, *P values* and *R-Squared* statistics. The only two variables that had significance in terms of *t-Stat,* and the corresponding *P value* were the amps *I* of the tool and the power to weight *P/W* ratio.   Additionally, the *t-Stats* for Amps and Power to Weight ratio were significantly higher than required for the number of degrees of freedom applicable. Thus the null hypothesis is rejected for Amps and Power to weight ratio yielding a 78.5% explanatory value. The functional form of the regression model is shown below:

$$C_i = \beta_0 + \beta_1 I + \beta_2 (P/W) + e \qquad\qquad (3.27)$$

where β_1 and β_2 are the multiple regression coefficients with values of 3.6160 and 0.1865 respectively, and the estimate's intercept β_0 is found to be -29.294. The error in the prediction is represented with *e.* The ANOVA table for this multi-regression is presented in Appendix A.

3.5.3 ENGINEERING MODEL DEMONSTRATION: UNIVERSAL MOTOR AND BEVEL GEARS

An engineering model is necessary to produce feasible designs that generate product attributes that can be evaluated within the context of the latent class model. As mentioned previously, this chapter explores the design space of an angle grinder. Several existing and validated design models exist for the major components of the angle grinder such as the universal motor (Simpson, 1998) and the American Gear Manufacturers Association standard for bevel gears (Hurricks, 1994). We used these design models to develop optimal products in concert with the latent class segment model by transforming engineering attributes into consumer level product attributes. The two components of greatest interest (motor and bevel gear set) are shown in Figure 3.5.2.
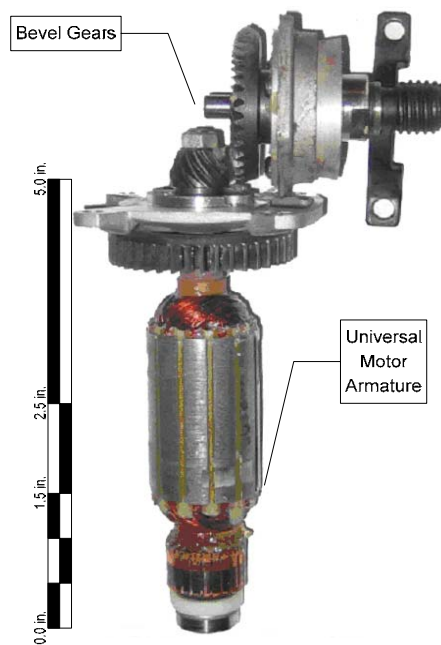
Figure 3.5.2: Engineering Components

Pinion pitch diameter D_p (m)	$0.009 \leq D_p \leq 0.03$
Current I (amps)	$6 \leq I \leq 12$
Gap thickness l_{gap} (m)	$0.0005 \leq l_{gap} \leq 0.07$
Stack length L (m)	$0.01 \leq L \leq 0.02$
Armature turns N_c (# of turns)	$20 \leq N_c \leq 300,\ N_c \in Z$
Stator turns N_s (# of turns)	$10 \leq N_s \leq 200,\ N_s \in Z$
Gear ratio r	$0.2 \leq r \leq 4$
Stator outer radius R_o (m)	$0.01 \leq R_o \leq 0.01$
Stator thickness t (m)	$0.0001 \leq t \leq 0.1$

Table 3.5.3:   Engineering Design Variables

The engineering design variables x make up the physical characteristics of the motor and bevel gear assembly (Table 3.5.3). These design variables go through a series of engineering computations in the process of transforming them to measurable customer level attributes used in the latent class model (Table 3.5.4 and Table 3.5.5). Table 3.5.4 and Table 3.5.5 develop in a sequential fashion to facilitate the readers understanding of computation dependencies. For example, A_r in line two of Table 3.5.4 depends on l_r in line one. Those designs that meet the physical constraints (Table 3.5.6) are eventually realized as customer relevant attributes (Table 3.5.7).

Armature diameter l_r (m)	$l_r = 2(R_o - t - l_{gap})$
Armature section A_r (m^2)	$A_r = (\pi \cdot l_r^2)/4$
Wrap length l_{rw} (m)	$A_r = 2l_r + 2L$
ρ (ohm-m) 20 awg	$0.036\ ohms\text{-}m$
Wire area A_w (mm^2) 20	$0.504\ mm^2$
Arm. resistance R_a (ohms)	$R_a = (\rho N_c l_{rw})/A_w$
Stator resistance R_s (ohms)	$R_a = 2(\rho N_s l_{rw})/A_w$
Resistance losses P_{copper}	$P_{copper} = I^2(R_s + R_a)$
Brush coefficient α (volts)	$\alpha = 2$
Brush losses P_{brush} (W)	$P_{brush} = \alpha \cdot I$
Voltage V (volts)	$V = 120\ v$
Power in P_{in} (W)	$P_{in} = I \cdot V$
Motor output P_{out} (W)	$P_{out} = P_{in} - P_{brush} - P_{copper}$
Density Steel ρ_s (kg/m^3)	$\rho_s = 8000 (kg/m^3)$
ρ_{copper} (kg/m^3)	$\rho_{copper} = 8900\ (kg/m^3)$
Stator mass M_s (kg)	$M_s = (\pi(R_o)^2 - \pi(R_o - t)^2) \cdot L \cdot \rho_s$
Armature mass M_a (kg)	$M_a = A_r \cdot L \cdot \rho_s$
Windings mass M_w (kg)	$M_w = l_{rw}(N_c + 2N_s)A_w \cdot \rho_{copper}$
Motor mass M_m (kg)	$M_m = M_s + M_a + M_w$
Motor constant K	$K = N_c / \pi$
Magnetomotive force $\Im$	$\Im = N_s I$
Mean stator path l_c (m)	$l_c = \pi(2R_o + t)/2$
Stator cross section A_s	$A_s = L \cdot t$
Armature section A_a (m^2)	$A_a = L \cdot l_r$
Gap cross section A_g (m^2)	$A_g = L \cdot l_r$
Permeability of steel μ_{steel}	$\mu_{steel} = 1000$
Permeability, free space μ_o	$\mu_o = 4\pi \cdot 10^{-7}$
Stator reluctance $\Re_s$	$\Re_s = l_c / 2(\mu_{steel} \cdot \mu_o \cdot A_s)$
Armature reluctance $\Re_r$	$\Re_r = l_r /(\mu_{steel} \cdot \mu_o \cdot A_a)$
Air gap reluctance $\Re_g$	$\Re_g = l_{gap}/(\mu_o \cdot A_g)$
Total reluctance $\Re_{tot}$	$\Re_{tot} = \Re_s + \Re_a + 2\Re_g$
Flux ϕ	$\phi = \Im / \Re_{tot}$
Torque T (N-m)	$T = K \cdot \phi / I$
Revolutions per minute N	$N = 9.549 \cdot P_{out}(kw)/T(N - m)$

Table 3.5.4:   Universal Motor Design Computations

The computations in Table 3.5.4 are dependent upon the input of the design variables and the inputs of several constants such as the resistivity and cross sectional area of 20 awg copper wire. Looking forward to how our engineering design variables will affect the customer level attributes one can see that decisions such as stator diameter and stator thickness will invariably affect the overall weight of the tool and the girth, which are attributes analyzed in the conjoint study.

Pinion torque (load RPM) T_p (N-m)	$T_p = 9.459 \cdot P_{out} / 6500\, rp$
Gear torque (load RPM) T_g (N-m)	$T_g = T_p \cdot r$
Pressure angle φ_p	$\phi_p = 20°$
Cone distance C (m)	$C = D_p /(2 \cdot SIN(\phi_p))$
Face width b (m)	$b = .008\ m$
Gear pitch diameter D_g (m)	$D_g = D_p \cdot r$
Tooth loading intensity F_i (N)	$F_i = 2 \cdot T_p \cdot C /(D_p \cdot b(C -$
Elasticity factor (Carbon steel) Z_e	$Z_e = 189$
Zone factor Z_H	$Z_H = 4/(SIN(2 \cdot \phi_p)^2$
Pinion pitch angle θ_g	$\theta_p = ASIN(D_p / C)$
Shaft angle γ	$\gamma = 90°$
Gear pitch angle θ_g	$\theta_g = \gamma - \theta_p$
Pinion cone depth d_v (m)	$d_v = D_p \cdot SEC(\theta_p)$
Gear cone depth D_v (m)	$D_v = D_p \cdot SEC(\theta_g)$
Amplification (light/medium shock)	$K_a = 1.35$
Load distribution (precision gears)	$K_m = 1.2$
Geometry factor J	$J = .25$
Number of pinion teeth N_t	$N_t = 11$
Module (pinion) m	$m = D_p / N_t$
Pinion mass M_p (kg)	$M_p = (\pi \cdot D_p^2 \cdot b \cdot \rho_{steel}) / 4$
Gear mass M_g (kg)	$M_g = (\pi \cdot D_g^2 \cdot b \cdot \rho_{steel}) / 4$
Bevel gears mass M_{bg} (kg)	$M_{bg} = M_p + M_g$

Table 3.5.5: Bevel Gear Design Computations

Two design variables are necessary for modeling the bevel gears in addition to those already chosen for the motor. The pinion pitch diameter D_p (m) and gear ratio are allowed to vary as design variables and allow for a wide range of gear designs (Table 3.5.5).

The engineering constraints $g(x)$ (Table 3.5.6) help avoid the stereotypical problem of the marketing domain dictating solutions in the engineering domain that are infeasible. We fuse the two domains in our objective function and the constraints of Table 3.5.6 to ensure that the optimal product in terms of manufacturer profit and market share is also feasible. In addition to the constraints used in previous work (Simpson, 1998, Wassenaar and Chen, 2003) we use several physical constraints to ensure sustained operability of the motor such as limiting the magnetic flux B and the heat flux K_s.

Flux density armature B_r (T)	$B_r = \phi / A_a \leq 1.5T$
Flux density stator B_s (T)	$B_s = \phi / (2 \cdot A_s) \leq 1.5T$
Flux density air gap B_g (T)	$B_g = \phi / A_g \leq 1.5T$
Armature heat flux K_s (A/m)	$K_s = \dfrac{N_c \cdot I}{\pi \cdot l_r} \leq 10000$
Stator heat flux K_s (A/m)	$K_s = \dfrac{N_s \cdot I}{\pi (l_r + t)} \leq 10000$
Length to diameter ratio	$L / G \leq 5$
Integer turns	$N_c, N_s = \text{int}$
Grinding wheel RPM N_{out}	$N_{out} = N / r \leq 10000$
Bending stress σ_b (Pa)	$\sigma_b = (K_a K_m F_i)/(m \cdot J) \leq 145 MPa$
Contact stress σ_f (Pa)	$\sigma_f = Z_H Z_e \sqrt{\dfrac{K_a K_m F_i (d_v + D_v)}{(d_v D_v)}} \leq 720 MPa$
Armature tip velocity v_a	$v_a = \pi \cdot N \cdot l_r \leq 3658 \, (m/s)$

Table 3.5.6:   Grinder Constraints $g(x)$

Motors are also limited in terms of speed because a mechanical failure of the armature wire is possible due to centripetal force. Also of concern are the grinding wheel's material limitations which are frequently stamped on the wheel as not to exceed 10,000 RPM. Serious injury could result as the wheel shatters if the 10,000 RPM is exceeded. The grinding wheel RPM and armature velocity need to be considered separately as we have gear ratio, r, as one of our design variables. Lastly, we employ two constraints for the bevel gears to ensure that the contact stress, σ_f, and the bending stress, σ_b, of the gear tooth do not exceed the, σ_y, yield strength of the carbon steel. Numerous other calculations were not included as they were never active during the optimization search. Examples include constraints for shear stress in the bevel gear shaft, armature, and stator.

Girth G (m)	$G=2(R_o+.004(m))$
Amperage I (Amp)	I
Fixed mass M_f(kg)	$M_f = M_{cord} + M_{commutar} + ... = 1.58\,kg$
Total mass M_t (kg)	$M_t=M_{bg}+M_m+M_f$

Table 3.5.7: Customer Level Product Attributes y

As mentioned previously the girth of the tool and the total mass of the tool are important customer level attributes. We assume a fixed mass for the grinder's cord, commutator, gear shafts, plastic body and $5/8^{th}$ inch (industry standard) arbor, and safety shield. The weight of 1.58 kg was determined empirically and assumed fixed as preliminary calculations show that all of the fixed components were capable of handling 12 Amp motors. It is conceivable that one could develop a set of design variables x for each of these components and include them in the overall optimization problem. In this section we have shown how the customer level attributes of weight, amperage, and girth are dictated by engineering level design variables.

3.6   CASE STUDY RESULTS

The Power Tool Institute (Luo, 2005) estimates the size of the angle grinder market to be 9 million units with our channel retailer controlling at least $1/3^{rd}$ of this market or 3 million units. For comparison an original assortment that included a tool from brand W generated an objective function profit of $15.95 Million for the subject manufacturer. Initially, we focus on the case that the market is mature (little incentive for advertising), the manufacturer does not consider slotting allowances and s/he has already sunk costs into plant property. This type of analysis is demonstrated in Section 3.6.1. In Section 3.6.2 we reinsert the slotting allowance A and demonstrate the effect of slotting allowances on retailer acceptance of the optimal design generated in Section 3.6.1. Comparing the two approaches to reliable acceptance shows that different combinations of engineering designs and slotting allowances can achieve the same reliability with varying success in terms of profitability.

For this problem we used 1,000 Monte Carlo simulations Z. We examine 5 products with 7 attributes within 4 segments for a total of 140,000 random variables. A deterministic optimization of the model takes approximately 5 seconds but when the chance constraint is added the additional computations of 1,000 market shares requires approximately 150 seconds. The m_i are computed as before and Table 3.6.1 is an example of estimated market shares for the 5 products in the assortment.

Tool	A	B	C	D	NPD
Margin	$29.23	$36.63	$47.73	$29.23	$44.03
Market	19.49%	0.04%	18.67%	12.94%	52.49%

Table 3.6.1:   Example Market Share

As mentioned previously the latent class model simulations are used to estimate the variance-covariance matrix using Excel's built in functions. This matrix and the product margin complete the chance constraint. The *Standard Evolutionary Solver* (Nenov and Flystra, 2003) (a genetic optimization algorithm from Frontline Systems Premium Solver) was used with the following genetic algorithm parameters: population (1,000), generations (1,000), mutation rate (0.075), precision[3] (0.000001), convergence[4] (0.0001). It is possible to use other optimization algorithms for problems such as this but we found the genetic algorithm most suitable because some of the engineering design variables are integers and discontinuities exist in the calculation of market share due to linear interpolation of utility between adjacent points. After running the optimization problem through the genetic algorithm the manufacturer's profit improved for the NPD (Table 3.6.2) substantially when requiring a 75% probability of satisfying the chance constraint. The new product of the profit per unit and the market share increased to $13.09 unit which yields a total profit of $39.29M or an increase in total profit of $23.34.

Tool	Brand	Price	AMP	LIFE (hrs)	Switch	Girth	Weight
Prev.	W	$89.00	10	80	Side	Small	9.00
NPD	Y	$129.00	6	110	Side	Large	8.8

Table 3.6.2:   Previous and New Product Development (NPD) Comparison

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[3] *Precision* – amount of allowed constraint violation for both equality and inequality constraints.

[4] *Convergence* – a user specified parameter that terminates the problem when 99% of the members of the final population are different by less than the convergence parameter in terms of the objective function.

3.6.1 TRADEOFFS IN MANUFACTURER'S PROFIT VS. RETAILER'S ACCEPTANCE

In a sense, for this example we have two objectives where the first objective is to maximize profit and the second is to ensure meeting our chance constraint with a high probability, e.g., the constraint epsilon approach to multi-objective design (Deb, 2001). Figure 3.6.1 shows that as we increase the requirement that the chance constraint be met with a higher probability the expected profit of the design falls. This result is expected because a higher probability of acceptance constricts the design space more than a low probability of acceptance and thus some more profitable designs are pruned from the set. It is worth noting that the retailer acceptance constraint was not active at an α level of 75% but was active for $\alpha=[80\%, 95\%]$ and no feasible solutions existed for $\alpha=99\%$. That is, there were no designs that could create a 99% probability of retailer acceptance given the level of uncertainty in customer preferences.

A Pareto set of designs (see Chankong and Haimes, 1983, Steur, 1986, Miettinen, 1999, Deb, 2001) is presented in Table 3.6.3. Interestingly, although somewhat expectedly, we see that designs that are highly profitable yet have lower probability of acceptance have similar characteristics. These designs are characterized by heavy weight, large girth, low power, and high prices. At the other extreme are designs that have a very high chance of satisfying retailer acceptance. The right side of Table 3.6.3 and Figure 3.6.1 show that very acceptable designs (to the retailer) are lower in price, lighter in weight, larger in girth, and are more powerful. A grouping of moderately acceptable designs with moderate profit has been identified in the center of Figure 3.6.1. This middle group of designs has some attributes that lie between the ranges of the

61

extreme design groups (weight, price, and power). In apparent contradiction to general design trend the middle group is characterized by small girth.   A decidedly non-quantitative approach was used to group the designs along the Pareto Frontier.   We simply looked at the inflection points or where the curvature changed along the Pareto Frontier and in conjunction with the high level design trends in Table 3.6.3 with the purpose of demonstrating the affect of retail channel constraint on engineering design.

Profit vs. Probability of Acceptance
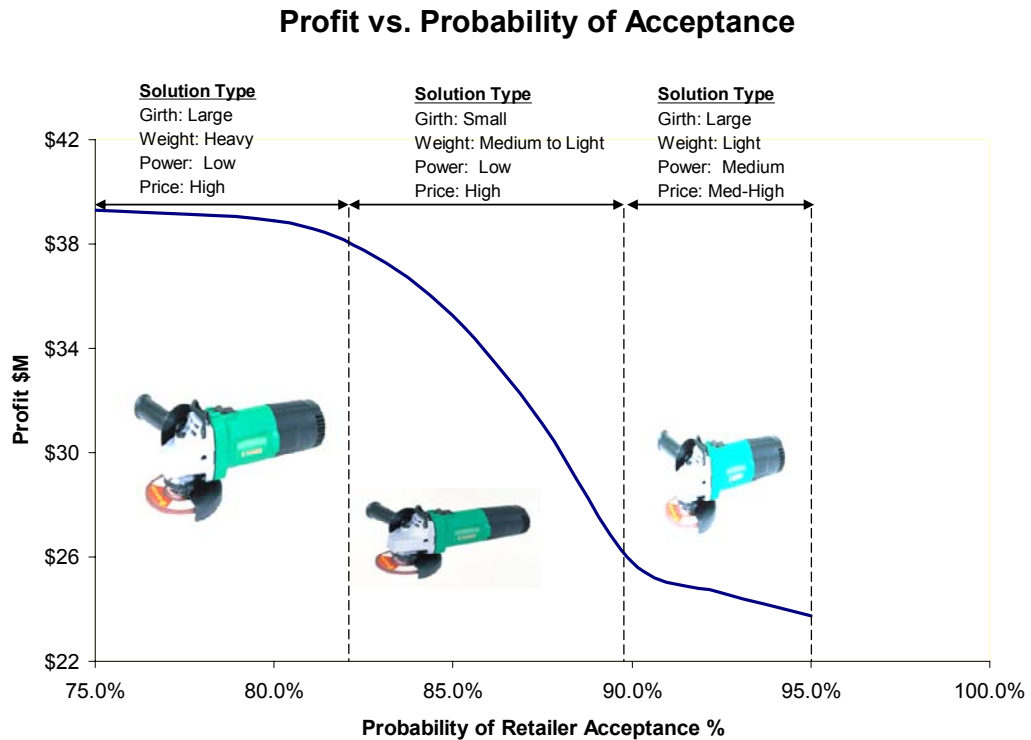
Figure 3.6.1: Profit vs. Probability of Acceptance (%)

The implications of results such as Figure 3.6.1 and Table 3.6.3 are discussed in detail in Section 3.7.

Objective							
Profit $M	$39.29	$38.90	$35.27	$31.08	$25.80	$24.64	$23.73
Probability Acceptance (%)	75.0%	80.0%	85.0%	87.5%	90.0%	92.5%	95.0%
Design Variables							
N_c (turns)	150	150	150	150	149	149	149
N_s (turns)	25	18	12	13	23	22	22
R_o (m)	2.2	2.0	1.79	1.83	2.11	2.10	2.108
T(mm)	7.4	5.5	3.6	4.0	6.8	6.7	6.75
L_{gap} (mm)	3.3	2.0	0.05	0.06	0.06	0.06	0.06
I (amps)	6.0	6.0	6.0	6.44	6.82	7.74	7.88
L (m)	0.143	0.143	0.105	0.067	0.034	0.034	0.034
Gear Ratio (r)	2.00	2.00	2.78	4.00	4.00	4.00	4.00
Pinion Pitch D_p (cm)	1.35	1.35	1.35	1.35	1.35	1.35	1.35
Select Attributes							
Price	$129.0	$129.0	$129.0	$129.0	$127.4	$118.5	$116.2
Weight (lbm)	8.80	8.11	6.50	5.70	4.99	5.01	5.00
Girth (Large/ Small)	Large	Large	Small	Small	Large	Large	Large

Table 3.6.3: Pareto Frontier of Designs

3.6.2 SLOTTING ALLOWANCE SENSITIVITY

It is also possible to determine a slotting allowance necessary to ensure a specific probability of acceptance which precludes the need to change the design. As an example we compute the slotting allowance required to improve our optimal product's acceptance probability (Table 3.6.2 *NPD* solution) above the initial 75% threshold. The *NPD* design in Table 3.6.2 is held fixed and the right side of the chance constraint is manipulated by adding the slotting allowance *A*. The total slotting allowance for the assumed 3M units controlled by the channel retailer is graphed in Figure 3.6.2 for reliabilities ranging 75% to 99.9%.
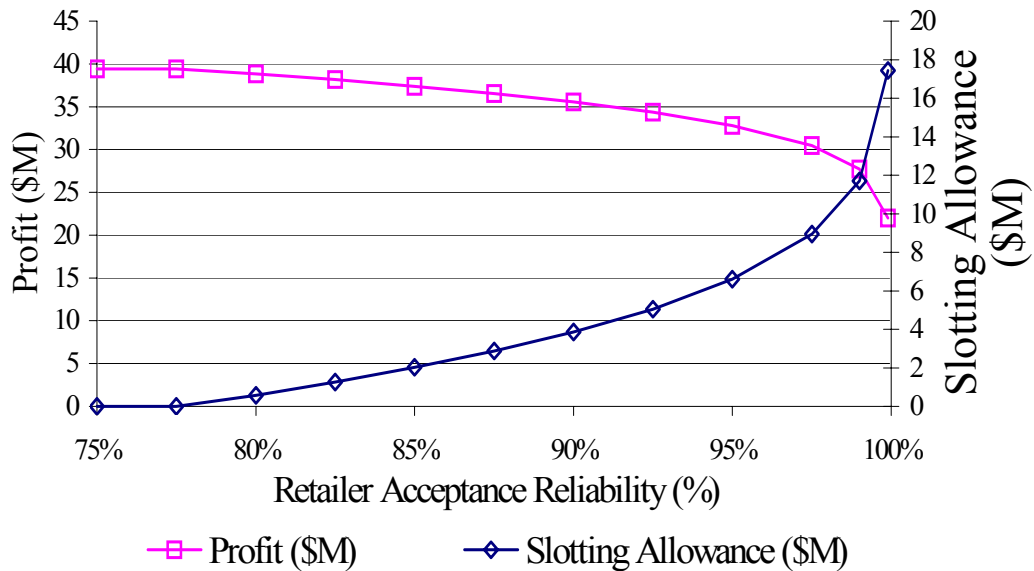
Figure 3.6.2: Effect of Slotting Allowance

These results will be compared to those of Section 3.6.1 in Section 3.7.

3.7   DISCUSSION OF APPROACH AND CASE STUDY

Based on our case study and through the development of our approach we believe there are several important results that might be generalized to the overall issue of designing products for retail channel acceptance. We feel that three primary areas provide the greatest insights for design and focus on them for our discussion. These areas are: (1) the importance of customer preferences and the retail assortment on design, (2) the impact of retailer acceptance on design, and (3) the considerations of slotting allowances along with the firm's strategic position in selecting a design.

3.7.1   IMPLICATIONS OF CUSTOMER PREFERENCES AND
ASSORTMENTS ON PRODUCT DESIGN

In performing the process proposed in this chapter a multidisciplinary design team can present a Pareto frontier of designs to upper management for selection. Clearly, a typical engineering approach of simply finding the Pareto set of designs with respect to

engineering constraints is not capable of finding these same solutions. For example, a traditional engineering approach would attempt to find design variables that minimize cost and maximize performance such as amp rating, power, or power to weight ratio. This is all very logical to an engineer to perceive high power ratings, low cost and high power to weight ratio as desirable although the most difficult to achieve. One only needs a cursory review of the consumer segment preferences (Table 3.5.1) to see that somewhat counter intuitively (to the engineer) many consumers prefer heavier products with lower power ratings which do not lie along the engineer's personal Pareto frontier. Some consumers even prefer a higher price which directly contradicts the downward sloping demand curves implemented in Georgiopoulous et al., (2005) and Michalek et al., (2005).

Beyond the issue of consumer utility not corresponding to an engineer's utility for designs there exists further complications with the assortment and market segments that exist. That is to say that, a designer cannot simply characterize an entire markets utility function and expect to design an optimal product without considering the assortment. Our approach aids manufacturing teams (marketers and engineers) in finding designs that take into account the positioning (product attributes) of competitive products and automatically obtains solutions that capitalizes on the most profitable segments. In fact, the first solution in Table 3.6.3captures 54%, 0%, 0%, and nearly 97% of segments 1 to 4 respectively while the last design captures 86%, 3%, 0%, and 42% of segments 1 to 4. It would be nearly impossible for an engineer to identify that a heavy product, with low power, large girth and high price best satisfy these segments which are evidently most vulnerable in terms of competitor offerings.

The problem is further complicated by the fact that segments vary in size S to a great degree (see Table 3.5.1). Integrating the latent class customer segment model or a model of equivalent resolution is an appropriate approach to dealing with this complexity. Likewise, without engineering model integration it would be impossible for a marketing manager to predict engineering design feasibility as well as the profitability of the segment due to a lack of knowledge about cost. A marketing manager can easily propose a set of product properties that are costly to achieve and erode profit yet appear to be desirable to many segments. The equivalent error in the engineering domain would be to design for high level product attributes that are desirable to a segment yet without regard to the positioning of competitive products (i.e., the segment may be already saturated). Our approach overcomes these problems by integrating the two domains with careful translation of engineering design variables to market share and finally to total profit.

3.7.2 IMPORTANCE OF RETAILER ACCEPTANCE CRITERIA TO DESIGN

Most importantly, our results indicate that one can actually design products with greater acceptability to retailers. We can observe that the design changes significantly as greater reliability is enforced between the 75% and 95% range (e.g., the transition from heavier, less powerful products to lighter, more powerful products). The change in design is observed for several reasons but they are all related to the enforcement of the chance constraint which we attempt to explain. In positioning the products in Table 3.6.3 the optimization algorithm will select products that only marginally satisfy retailer acceptance. Two types of designs are acceptable to the retailer. Those that increase profit without increasing uncertainty and those that increase profit enough to offset any

increase in uncertainty affecting the chance constraint. If we remember that the customer has a "no purchase" option it should be apparent that uncertain utilities can (in some realizations) result in a reduction of the overall market size.

As mentioned in previous sections, the algorithm presents new products to each of the segments for the computation of segment share. These new products obviously have different attributes and it can be observed in Table 3.5.1 that each attribute has a different level of utility uncertainty surrounding it. A design that has a high mean utility might also have a greater amount of uncertainty for a segment. Ideally, new attributes would have higher utility and lower uncertainty. New designs will replace segment shares of competitor designs that have higher or lower levels of uncertainty in the Monte Carlo simulation which, of course, yields varying levels of market share. The designs on the left of Table 3.5.1 and Figure 3.6.1 represent the most uncertain designs to the retailer in terms of utility uncertainty and relative to the competitor designs yet have the greatest expected profit for the manufacturer. The designs on the right of Table 3.5.1 have lower uncertainty in terms of utility and are less competitive (in terms of capturing market share for the manufacturer) with the more certain or profitable competitor designs in the existing assortment.

It is not the intent of this chapter to suggest that in all firms the design team must generate a Pareto set for management that satisfies engineering constraints and the acceptance constraint. Alternatively, management can set the reliability constraint level prior to optimization but for many the Pareto set will provide more information for upper level decision makers. When presented with the Pareto set decision makers can perform tradeoff analysis with knowledge of the range of possibilities as well as knowledge that is

not explicitly modeled. For example, a firm that has recently suffered common stock price erosion from negative press may select a higher level of acceptance probability to avoid the synergy of negative news. A tradeoff can be performed between the designs for actual design selection. For example, the risk neutral manufacturer might consider the expected profit to be $E[P]=\alpha \cdot Profit$ since a rejection results in zero profit. In the case of the results tabulated in Table 3.6.3 the risk neutral manufacturer would actually select the design corresponding to $\alpha=82.5\%$ as this has the highest expected profit ($E[P]=\alpha P$ $=0.825 \cdot \$37.76=\$31.15$) including the 17.5% risk of rejection. Other methods for including risk aversion of manufacturers can be employed in future work such as developing a utility function for the probability of success and profit (e.g., Clemen and Reilly, 2000).

3.7.3 SLOTTING ALLOWANCES: CONSIDERATIONS FOR THE FIRM IN DESIGN SELECTION

As mentioned previously, slotting allowances are commonly used in the retail sector to ensure retailer acceptance of a manufacturer's products. Providing the slotting allowance (Section 3.6.2) increases acceptability much the same way that altering the design can (Section 3.6.1). In comparing Figure 3.6.2 and Figure 3.6.1 the most obvious difference is that increasing the slotting allowance (Figure 3.6.2) is capable of achieving nearly 100% probability of retailer acceptance where adjusting the engineering design (Figure 3.6.1) was unable to do so. Second, we observe that a profit of $32.8M with a 95% probability is possible by increasing the slotting allowance to just over $6M where changing the design to improve acceptance reduces the profit to just under $23.9. This demonstrates that the manufacturer has two possible methods for achieving reliable

acceptance of designs that might be used separately or in conjunction as we'll try to demonstrate.

Realizing that the manufacturer can delay the slotting allowance decision until negotiations with the retailer adds considerable flexibility to the design selection process. The design decision and slotting allowance selection can be tailored to the focal manufacturer's unique cash flow and balance sheet position. For example a firm that has significant cash reserves might select a financially riskier design (lower probability of retailer acceptance) from Figure 3.6.1 in the anticipation that the subsequent negotiation of a slotting allowance with the retailer will produce the greatest profits along the curve from Figure 3.6.2. In contrast, a firm with lower cash reserves (i.e., unable to offer a $6M or higher slotting allowance) can select a *design* further along Figure 3.6.1 accepting lower profitability for higher acceptance reliability based solely on engineering design. A new slotting allowance tradeoff could be developed for this higher acceptance probability design in the same way that we did for Figure 3.6.2. The manufacturer with lower cash reserves could then evaluate the design selection with respect to the range of acceptability for his/her more limited slotting allowance reserves.

The Pareto frontier in Figure 3.6.2 is a valuable tool for the decision maker in evaluating the probability of channel acceptance in conjunction with a slotting allowance. It should be possible to perform engineering optimization using the slotting allowance as an additional design variable as a logical extension to our work. This would (as suggested by Georgiopoulous et al., (2005)) even further integrate business decisions with engineering which is critical to the competitive advantage of the firm. Additionally, even though competitors are considered static (i.e., not going through a product offering

refresh) in our analysis, the model is easily extendable to considering uncertainty in competitor offerings through a probabilistic treatment of assortment attributes in the market share and chance constraint formulation. For example, if a manufacturer is concerned about a simultaneous new offering from a competitor, additional uncertain parameters can be added to the chance constraint and the risk can be mitigated with the use of focal product design, slotting allowance or both as in Figure 3.6.1and Figure 3.6.2. We feel that this tradeoff between product design, slotting allowances, and the modeling of the risk aversion of the firm would be most useful to practitioners and academia alike.

3.8 SUMMARY

The primary contribution of this approach has been to provide a decision framework for manufacturers in developing products for an emerging economic force which we have termed the channel dominating retailer. Some previous work has been reported in integrating engineering with consumer preferences but those methodologies have not addressed the realities of modern retailer controlled channels. The design decision process presented in this chapter also enables the manufacturer to more accurately predict the market share of his/her own product by estimating demand across consumer segments. Lastly, this chapter provides a framework for the manufacturer to assess risk of channel acceptance through a chance constrained methodology and thereby make appropriate design decisions with regard to a slotting allowance. This constraint on retailer acceptance for product design will be used extensively in Chapters 4 and 5 as additional considerations are added to the modeling process.

The model is an improvement over extant methodologies but improvements and extensions are of course possible. Thus far, the approach has neglected the competitive

response of manufacturers and retailers to the entrance of a new product. Manufacturers can respond in the short term by changing prices and by designing new products in the long term. Even more importantly, retailers will price products to maximize their products which can affect manufacturer market share and profit remarkably. For this reason, econometric models or game theory models will be employed in Chapters 4 and 5 to account for such responses. These results provide a first step toward these enhancements as the decision framework of the manufacturer and retailer have now been formed.

In the next chapter this decision framework will be employed with a game theoretic modeling of prices at the retail and wholesale levels with the goal of more accurately determining design optimality under competition. This chapter arrived at an estimate of wholesale prices from fixed margins and assumed retail prices stay constant as a new product is introduced. The next chapter will address these limitations by allowing competitors to respond to new entrants with their best response which is taken into account by the new entrant in advance (i.e., a strategic game unfolds).

CHAPTER 4:   STRATEGIC ENGINEERING PRODUCT DESIGN FOR MONOPOLISTIC AND DUOPOLISTIC RETAIL CHANNELS

In this chapter, a method is presented for manufacturers to anticipate the reactions of retailers to new designs, in terms of their retail pricing, and consider them early in the engineering design process. A key consideration in the approach is that retailers carry multiple products and have to select and price them as an assortment while considering competitor retailer assortments. A multi-product price equilibrium is developed for retail markets with differentiated products and a demand function based on the multinomial logit (MNL) model. This equilibrium result is used to extend the approach developed in Chapter 3 to develop optimal engineering designs considering equilibrium pricing. The approach significantly improves the focal manufacturer's projected profitability by probing the design space for new designs that better fit the requirements of end-customer segments while considering several common channel pricing structures. The results show that the channel structure considered has a significant impact on optimality of product design.

The rest of the chapter is organized as follows. After the introduction in Section 4.1, an overview of our proposed framework along with model assumptions and justifications is provided in Section 4.2. In Section 4.3, we provide the specifics of the methodology in translating a product design to its corresponding market share estimate. Section 4.4 highlights the specifics of modeling the strategic interactions along with the key theorems that drive our proposed empirical methodology. In Section 4.5 we briefly discuss the application that provides an illustration of our methodology. In 4.6 different

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strategic cases are evaluated with the case study and results discussed. Section 4.7 provides some concluding remarks.

4.1   INTRODUCTION

The product development process has been defined as the transformation of a market opportunity into a product available for sale and involving disciplines of marketing, operations management, organizational management and engineering design each focusing on critical decisions (Krishnan and Ulrich, 2001). These critical product design decisions are ultimately realized as product attributes and features that are important to the market and must compete against other products along multiple attribute dimensions, including price. The realization that the decision for many of these attributes and features are made early in the design stage and cannot be changed significantly to help the marketability of the product or its economic success, has led to cross-disciplinary approaches in many of these related fields (Ulrich and Eppinger, 2004). To that end, many approaches have been developed in recent years to collect and integrate customer preferences in the early stages of design to provide the manufacturer flexibility in designing products that are market-focused. Some of them focus on the information sharing and coordination aspects across disciplines (see e.g., Terwiesch et al., 2002); others propose specific design methodologies that consider cross-disciplinary impact and synergies (Morgan et al., 2001). As mentioned in Chapter 3 with respect to the engineering design literature, the cross disciplinary methodologies developed have been improvements in engineering design aspects but assume that the manufacturer or producer interacts directly with the consumer in the marketplace. These recent approaches rely on the estimation of customer utility for high level product attributes that

are the result of engineering design decisions. High level product attributes are translated into market share and profit with implications focusing on competitive draw or market expansion using a discrete choice model and generally a cost model (see, for example, Ramdas and Sawhney, 2001).

While the above methodologies are suitable for contexts where manufacturers sell products directly to consumers, their efficacy is seriously compromised in indirect channels where manufacturers have to go through retailers to reach their customers. With the emerging clout of these retailers in their channel relationships, manufacturers are already forced to take this retailer power into account in the area of pricing and marketing (Luo et al., 2007). In this chapter, we extend our analysis to consider strategic pricing in the overall product design approach. An integrated approach is proposed that considers not only customer preferences in the early stages of the engineering design process but also the retailer pricing decisions and assortment compatibility (i.e., is the product good for the assortment) so as to account for the gatekeeper role these powerful retailers play in the market.

Retailers are primarily interested in vastly different metric than the customers in evaluating a new product to carry. While strong overall customer preference for the product is expected, it is the revenue per square foot that will determine whether a retailer will carry the product – it has to maximize overall category profit. For example, Home Depot will only carry the five out of twenty available drills that generate the greatest revenue for the drill category. This revenue, in turn, depends on the assortment of drills that is available at the store for customer to buy. The retailer puts together these assortments in such a way to maximize the chance that customers will buy a product (and

spend more) on any visit to the store. Given that the retailer's shelf space is limited, manufacturers, therefore, have to carefully consider the attributes and features of their product vis-à-vis the assortment the retailer carries, and competitors product features and attributes, all at the early design stage so as to maximize the chances of the product being carried by the powerful retailers and being successful in the market.

In considering the gate-keeper role of retailers and the competitive products and their designs, the manufacturer cannot afford to take a "myopic" perspective in the design decisions by considering only their design and its impact on the market. Because engineering design decisions determine product cost and attribute positioning at the foundation of the development process it is logical to conclude that engineering design decisions are transmitted to competitors and retailers as strategies to which they are forced to counteract. For example, just as a manufacturer considers retailers' assortment, profit criteria, and competitors' existing products in designing a new product, other competitors may anticipate this strategy and make their own move to influence the retailer. They might, for example, reduce their wholesale prices to the retailers to make the retailer margins more attractive. Or they may offer some additional features to their products to make them more appealing to retailers as well as consumers. Retailers, on the other hand, may also consider such strategic maneuvers in new product offerings and wholesale prices in making their own assortment decisions. Thus, these counteractions leading to a "game of moves and countermoves" in the marketplace call for the manufacturer to be "strategic" in their design decisions – that is, make design decisions by anticipating the moves of the competitors and retailers so that in equilibrium, none of the competitors or retailers have any incentive to change the status-quo.

This chapter seeks to integrate the strategic decision perspective with engineering design, manufacturing cost and marketing in a quantitative manner. The strategic design of the firm depends upon the projected market share of a new product offering as well as manufacturing costs estimated in the engineering design phase considering the anticipated moves of competition and the retailers. Marketing relies upon engineering design to produce customer desired product attributes. Engineering design and manufacturing are charged with the complex task of developing cost-efficient products for uncertain customer preferences and competitive environments. Using a strategic approach the designer will be able to develop a scenario that if a product is designed with engineering design variables x, that result in product attributes y, an equilibrium price P will result in the retail environment as a result of strategic interactions by competing retailers and manufacturers. The retail price P determines market share m and manufacturer profitability Π of the design which is the overall objective of the manufacturer. The extant approaches in the integrated design-manufacturing-marketing literature have not endogenized the important pricing process in engineering design.

With respect to the extant literature in the product development area, our approach focuses on the impact of downstream channel strategies on product design decisions, an area of limited focus thus far (see Krishnan and Ulrich, 2001). Additionally, this chapter proposes a framework for marketing and product strategy within retail channels which is an area identified as requiring additional research (Krishnan and Loch, 2005). From a pure analytical viewpoint, a number of game theoretic frameworks have been developed to understand strategic interactions with monopolies (Dewan et al., 2003), duopolies (Savin and Terwiesch, 2005, Balsubramanian, 2004, Klastorin and Tsai,

2004) and oligopolies (Naik et al., 2005) which are commonly observed in modern manufacturing and retail environments. The issue of multi-tiered strategic interactions (e.g., manufacturer duopoly, retailer duopoly) which is critical for modeling channel player behavior has been studied for simple and pre-existing product wholesale and retail pricing decisions (e.g., pricing of detergents) (Basuroy et al., 2001). The multi-tier structure has been rarely extended to competing along multiple dimensions. For example, Tsay and Agrawal study a single manufacturer/product with duopolistic retailers competing along two dimensions: service and price (Tsay and Agrawal, 2000). However, none of the previous approaches focus on the design of products. The one exception is the work of Luo et al. (2007) who empirically determine the high level product attributes for a manufacturer in an oligopolistic setting interacting with a monopolistic retailer. Luo et al. (2007) have analyzed the econometric and marketing portion of the product pricing and attribute decisions without delving into the feasibility of any engineering design which is the focus of our approach along with a generalization of the approach to a retail duopoly.

This chapter presents a multidisciplinary approach to product design that includes multiple player interactions (retailers and manufacturers), heterogeneous consumer marketing models, and integrated engineering design models and cost models. The strategic interaction considered is broad (retailer duopoly or oligopoly), which has not been explored in conjunction with engineering design and manufacturing costs in the extant research. We prove that a multi-product price equilibrium exists in the retail space for differentiated products under the multinomial logit (MNL) model and use this result to develop a methodology for optimal engineering designs for both monopoly and

duopoly retail channels structures. This proof allows the manufacturer to anticipate the potential price reactions to any change in design and therefore to evaluate the profit potential of any candidate design under the MNL demand model. Not only do we take into account price reactions by retailers to design introductions but also the reactions of competing manufacturers.

4.2   MARKET STRUCTURE AND PROPOSED FRAMEWORK

The product-market that we consider in this chapter is one characterized by manufacturers reaching out to customers indirectly through retail channel consisting of powerful retailers (monopoly or duopoly). The manufacturers differentiate themselves with strong brands in a mature market and compete with other manufacturers for retail shelf-space. When they introduce new products, they set wholesale prices for the retailers, who choose to either carry the product or not carry the product. Retailers set their own retail prices, which along with the wholesale price is taken into account for the carry-not carry decision. This product-market is characteristic of many consumer durables that are engineered and marketed to customers through retailers (e.g., power tools, household appliances, electronics, etc.). The multi-level strategic design framework is shown in Figure 4.2.1. From the bottom to the top, the framework includes the consideration of engineering design criteria for the focal manufacturer (bottom level), consideration of strategic criteria with respect to the manufacturer's competitors and dominant retailers (middle level), and the consideration of customer segments and preferences (top level). This problem will be analyzed from the perspective of the manufacturer firm (i.e., the perspective of a product designer in the firm) who is interested in maximizing profit. The general framework is shown in Figure 4.2.1 for a

retailer duopoly with four manufacturers and four consumer segments. This model can be simplified to the monopolistic channel by removing one retailer.
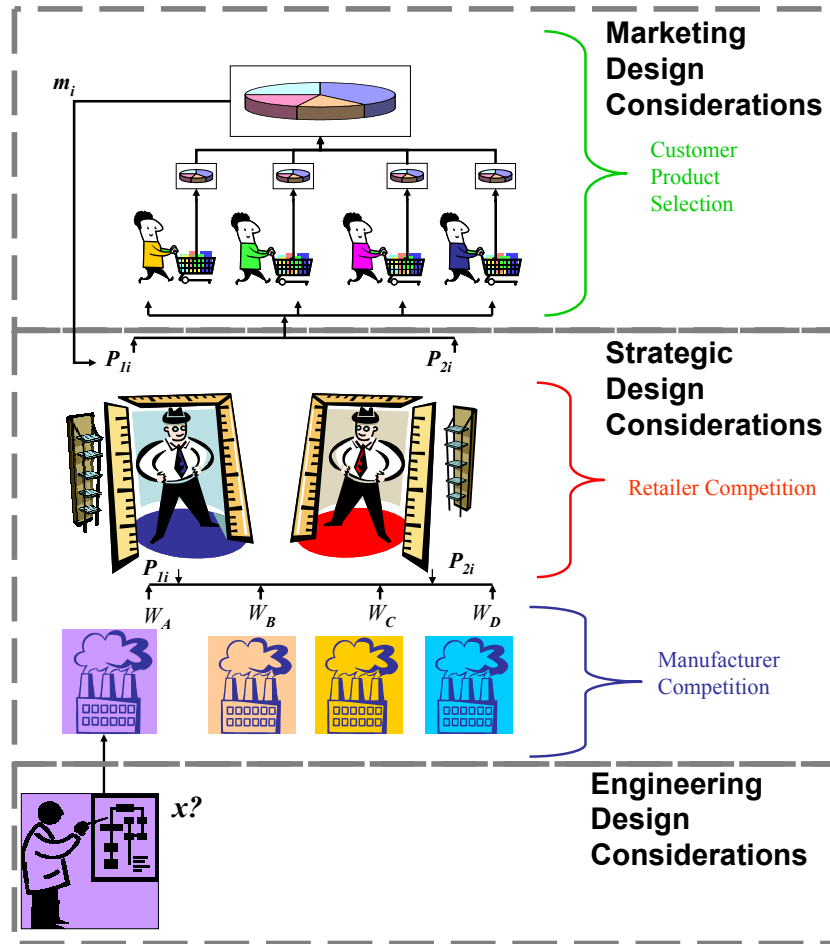
Figure 4.2.1: Strategic Design Framework

The product design problem can be described as follows (see Figure 4.2.1). In a competitive market of i products, Manufacturer A (the focal manufacturer) designs a candidate product with engineering design variables x where in it must take into account the strategic response of other manufacturers. We assume that the other manufacturers B, C and D have only the strategic move of altering their wholesale prices W_B, W_C and W_D, respectively. This is a standard assumption (Luo et al., 2007) as other responses in attributes are difficult to achieve in the short-term (Hauser, 1988, Horsky and Nelson,

1992). In order for manufacturers to set wholesale prices they must know the effect on

market share which can only be determined after retailers set their retail prices (e.g., P_{ri}

$=P_{1i}$, $P_{2i},...,P_{Ri}$ where i is index for the retailer's assortment and r is the index for the

retailer). We assume that both retailers and manufacturers are fully informed about

customer preferences (top level), which is a valid assumption in mature markets (e.g.,

Villas-Boas and Zhao, 2005). The market provides feedback to the retailers' actions in

the form of product market shares m_i. The retailers choose their retail prices to maximize

profits in the monopoly case or to reach price equilibrium in duopoly/oligopoly case.

Once retail prices are fixed at the retail level, manufacturers can determine equilibrium

wholesale prices. Given price equilibrium at the two levels (manufacturing and retail

levels) the manufacturer is able to determine the efficacy of any candidate design x. The

focal manufacturer can, thus, perform a strategic scenario analysis with retail profits and

manufacturer profits as outcomes given any design candidate. Thus the framework

provides a much richer and realistic environment for evaluating engineering design

decisions since it accounts for the power of retailers and the strategic responses available

to competitors. We expand on the links between engineering design, strategy and

marketing in the next few sections.

4.3   FROM PRODUCT DESIGN TO MARKET SHARE

Before discussing the strategic interactions in any design evaluation, we present

the mapping process for turning engineering designs x into product attributes y which are

then used to determine market share m_i while highlighting where the pricing process

affects market share. This process is depicted in Figure 4.3.1 for a hand-held power tool

– a right angle drill. We assume that market information – competition and their offerings – is already available, through shelf surveys of assortments at the channel dominating retailers. In the short term, we assume that the physical attributes of competitor products, $\bar{y}$, are fixed The three right angle drills at the right of Figure 4.3.1 are an example of existing assortment in the focal retailers in the application we consider. Each power tool's attributes in the assortment are recorded as the existing competitor's attributes which are critical to the positioning of any new design. Customer preference data can be in the form of survey data or choice-based conjoint data or point-of-sale data. For our application, we collect preference data through conjoint analysis where customers are presented with product prototypes for direct comparison. The customer preference data is analyzed using finite mixture estimation techniques to identify distinct latent class segments to capture the heterogeneity in customer preferences (Kamakura and Russell, 1989)[5]. This latent class approach along with the shelf survey allows our design approach to search for gaps in the competitive landscape that are weak in terms of competitive offerings as well as find customer segments whose preferences are currently underserved. The integration of this information with a bottom-up cross disciplinary translation of engineering designs into customer relevant product attributes is presented in Figure 4.3.1.

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[5] Alternatively, heterogeneity can also be captured using Hierarchical Bayesian estimation methods.
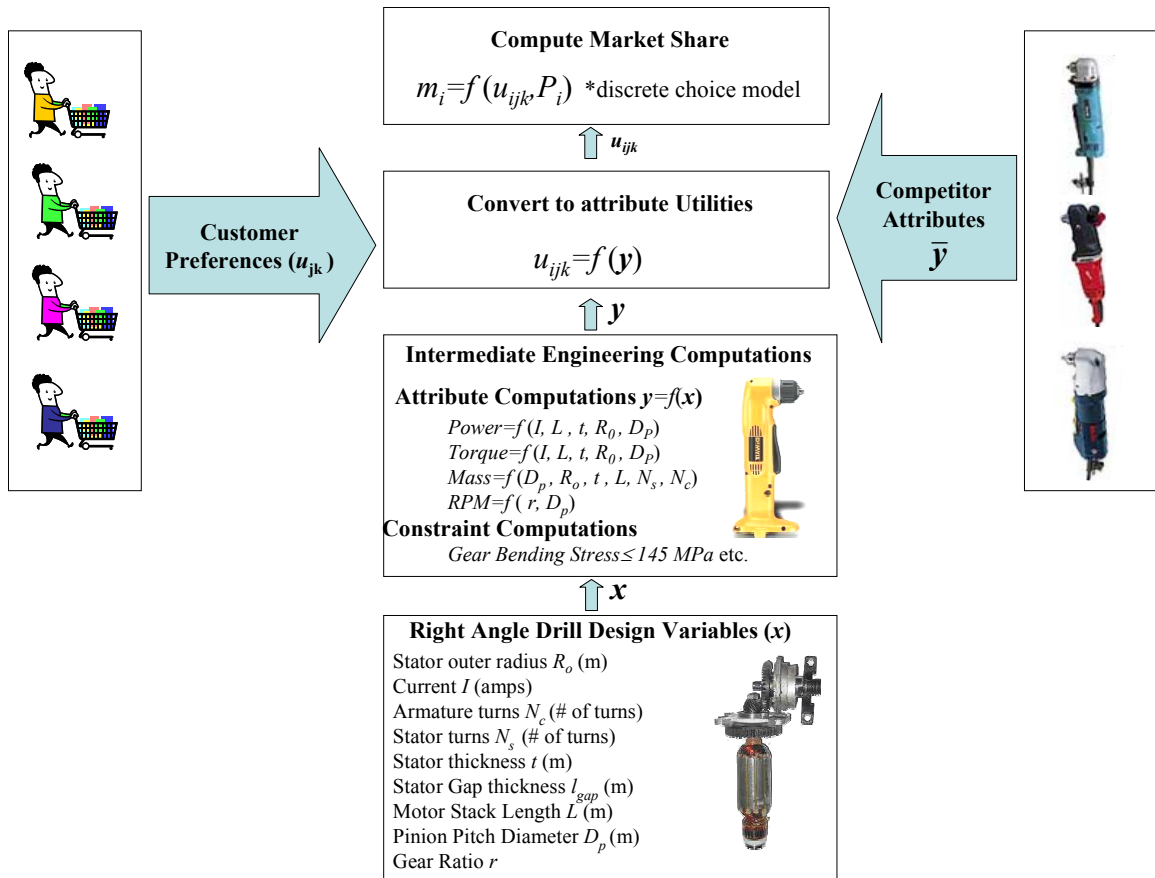
Figure 4.3.1: Product Design to Market Share

The design process starts with an instance of design variables x, which are then transformed to intermediate variables y through appropriate engineering computations (See bottom two blocks in Figure 4.3.1). For example, the weight of product is calculated from the density and volume of its constituent components. Similarly, power and torque of a product will be functions of gear ratios, current and voltage. Engineering constraints such as gear stresses, heat flux, armature velocity and others are calculated at this point to determine if the candidate design is feasible before proceeding to market share estimate determination. Design variables and engineering functions (constraints or attribute functions) need not be continuous as we will employ a genetic algorithm to find optimal designs (Deb, 2001) It is worth noting that the marketing and engineering should

collaborate (e.g., Morgan et al., 2001) to determine which product attributes are most relevant in investigating for optimization (i.e., they must matter to customers or affect the production cost). For example, the marketing communicates to engineering that weight is one of the important evaluation criteria to customers and should be an output of the design model.

Similarly, if engineering and manufacturing have determined that revolutions-per-minute *RPM* is an important driver of cost in the past due to higher stresses and heat dissipation requirements it should be communicated to marketing for inclusion in the conjoint study in an appropriate way. Even if customers place little value on *RPM*, this knowledge will be important to the overall design optimization as designers can therefore relax preconceived notions for minimum *RPM* values (a constraint) and possibly reduce production costs without affecting overall product performance and utility. Thus, an early concurrent consideration of all the relevant criteria (engineering design and customer preference) by the product development team gives a significant advantage in avoiding the costly mistake of performing customer studies that do not contain all of the relevant attributes that are cost or performance drivers in the engineering model (see Loch and Terwiesch, 1998).

Once product attribute variables *y* are determined from intermediate engineering design computations, one can estimate the utility of each attribute *y* (with a piecewise interpolation of utility values assigned to attribute levels, if needed) based on the conjoint analysis estimates for each segment by summing the utilities u_{jk}, in segment *k,* of all attributes *j* that appear in product *i*. This effort allows one to estimate market share as demonstrated in Section 3.3.4 using Eq. (3.15) to Eq. (3.17) with the one distinction that

pricing no longer remains constant and is continually adjusted at the top of Figure 4.3.1 in response to any new design entering at the bottom of Figure 4.3.1.

Given that retailers have increasingly consolidated power and control of the retail channel (i.e., access to consumers), evaluating the manufacturer's design in the context of the effect it has on retailer profit is an important consideration although our primary objective is to maximize the manufacturer profit. Clearly, if the manufacturer is concerned with possibility of being denied shelf space by the retailer he/she would prefer to select a design that is much more profitable for the retailer than the existing assortment it carries. At the same time the manufacturer's profits and the retailer's profits are competing objectives so a manufacturer would benefit from being able to choose from an optimal set of designs with respect to each of these objectives. The formulation presented in this chapter is such an approach to setting the manufacturer's design strategy given a specific channel structure. As such in addition to maximizing manufacturer profit we add a constraint to our formulation where the manufacturer also wishes to increase retailer profitability so as to ensure market access. Thus, the manufacturer's objective (which is our focus) (when facing a monopolist retailer) can be stated as:

$$
\begin{aligned}
\max_{x_i} : \quad & \Pi_i = m_i \left(W_i - C_i \right) \\
\text{s.t. } & g(x) \leq b \\
& \sum_{i=1}^{n} \pi_i^{new} \geq \sum_{i=1}^{n} \pi_i^{old} \\
& C_i, m_i = f(x)
\end{aligned}
$$

(4.1)

In section 4.5.1 we extend this formulation to multi-objectives for several other cases of channel markets (e.g., duopololistic retailers). Initially we present a single objective

(maximize manufacturer profit) to facilitate understanding of the pricing framework that will be presented in the subsequent section.

The manufacturers profit Π_i is maximized by altering engineering design variables $\boldsymbol{x}$ to satisfy engineering constraints $g(\boldsymbol{x}) \leq b$, realizing that market share m_i is largely a function of $\boldsymbol{y}$ and therefore $\boldsymbol{x}$. In addition to focusing on optimizing retailer profit we constrain the design search space to only those designs that improve the retailer's profit (i.e., $\sum_{i=1}^{n} \pi_i^{new} \geq \sum_{i=1}^{n} \pi_i^{old}$) just as we did in Chapter 3. This channel profit constraint is deterministic unlike the stochastic or "chance constrained" approach present in Chapter 3. Production costs C_i can be modeled as a function of the engineering design variables $\boldsymbol{x}$ or can be estimated from product attributes, $\boldsymbol{y}$, like those shown in Figure 4.3.1 (D.O.D., 1999, Boehm, 1981, Scanlan, 2002). We again use the latter approach in our application, which is based on historical prices of products in a category. The formulation presented above may appear simple until one considers that market share is also significantly dependent on retail price P_i (as shown in Figure 4.3.1) which is also dependent upon the wholesale price W_i which is not entirely under the manufacturer's control. Predicting the equilibrium retail and wholesale price of the products will be discussed in the next section along with the engineering optimization interface.

4.4 APPROACH TO STRATEGIC INTERACTIONS

A pricing framework that analytically captures the strategic interactions of Figure 4.2.1 is presented in Figure 4.4.1 for both monopoly (1 retailer) and duopoly (2 retailers) channels with an oligopoly of manufacturers competing with the focal manufacturer. The framework incorporates the layers of strategic pricing moves available to competitors and will be referred to repeatedly in the remainder of this section. It should also be noted that

we approach strategic interactions under the classical game theory assumptions (Osbourne and Rubinstein, 1994) that players are rational and fully informed of each others possible strategic moves (i.e., perfect information).

4.4.1 PRICING FRAMEWORK

The focal manufacturer (Manufacturer A) develops a new product A in the assortment $i=1,2,...,n$ that has engineering design variables x (bottom layer of Figure 4.4.1) with an objective to maximize profit. In the short term (one quarter to one year) the competing manufacturers will be unable to change product designs because of the manufacturing line and supply contract modifications that would be necessary. However, they can alter their wholesale prices and do so under the assumption that their competitors will attempt to make a "best response" to any W_i decision (manufacturer layer, Figure 4.4.1). The retailers also select retail prices P_{ri} that will maximize their profit under a "best" response assumption from their competitive retailer (in the case of a duopoly retail channel) or simply maximize profit (in the case of the monopoly channel). The retail prices and product designs affect each consumer segment depending on its specific preference structure, which the finite mixture latent class model estimates based on the conjoint analysis. These determine the segment sizes and the market shares (top layer of Figure 4.4.1).

Monopoly Channel	Duopoly Channel

Market Share Analysis: MSA1
- For each product

$$m_{ik} = \frac{\exp(U_i)}{\sum_{i=1}^{N} \exp(U_i)}$$

$$m_i = \sum_k S_k \cdot m_{ik}$$

Market Share Analysis: MSA2
- For each product

$$m_{rik} = \frac{\exp(U_{ri})}{\sum_{r=1}^{R}\sum_{i=1}^{n} \exp(U_{ri})}$$

$$m_{ri} = \sum_k S_k \cdot m_{rik}$$

$m_i \downarrow$ $\uparrow P_{1i}$ $m_{ri} \downarrow$ $\uparrow P_{ri}$

Retail Pricing Level: RPL1

$$\max_{P_i} : \sum_{i=1}^{n} \pi_i$$

Retail Pricing Level: RPL2

$$\begin{bmatrix} \dfrac{\partial \pi_{11}}{\partial P_{11}} & \dfrac{\partial \pi_{12}}{\partial P_{12}} & \cdots & \dfrac{\partial \pi_{1n}}{\partial P_{1n}} \\ \dfrac{\partial \pi_{12}}{\partial P_{12}} & \dfrac{\partial \pi_{22}}{\partial P_{22}} & \cdots & \dfrac{\partial \pi_{2n}}{\partial P_{2n}} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$m_i \downarrow$ $\uparrow$ W_{1i} $m_{ri} \downarrow$ $\uparrow W_i$

Wholesale Pricing Level: WPL1

$$\left[\frac{\partial \Pi_1}{\partial W_1}, \frac{\partial \Pi_2}{\partial W_2}, \dots, \frac{\partial \Pi_n}{\partial W_n} \right] = 0$$

Wholesale Pricing Level: WPL2

$$\left[\frac{\partial \Pi_1}{\partial W_1}, \frac{\partial \Pi_2}{\partial W_2}, \dots, \frac{\partial \Pi_n}{\partial W_n} \right] = 0$$

$m_i \downarrow W_{1i}$ $\uparrow x$ $m_{ri} \downarrow W_i$ $\uparrow x$

Engineering Design Level:EDL1
-

$$\max_{x} : \quad \Pi_i = m_i(W_i - C_i)$$
$$\text{s.t. } g(x) \le b,$$
$$\sum_{i=1}^{n} \pi_i^{new} \ge \sum_{i=1}^{n} \pi_i^{old}$$
$$C_i, m_i = f(x)$$

Engineering Design Level: EDL2

$$\max_{x} : \quad \Pi_i = m_i(W_i - C_i)$$
$$\text{s.t. } g(x) \le b,$$
$$\forall r \ \sum_{i=1}^{n} \pi_{ri}^{new} \ge \sum_{i=1}^{n} \pi_{ri}^{old}$$
$$C_i, m_i = f(x)$$

Figure 4.4.1: Pricing Framework

The game theoretic aspects of retailers and manufacturers selecting retail and wholesale prices based on Nash equilibria or "best response" functions makes the problem of optimizing product design computationally intensive. We solve the layered equilibrium situation as a nested algorithm where the retail pricing level (RPL) optimization is the selection of retail prices P using the Nash equilibrium of profit for retailers. The first order condition for a Nash Equilibrium must be met for each

retailer/product profit combination π_{ri} which is essentially requires solving a system of equations where the derivative of profit with respect to price P_{ri} is set to zero:

$$\frac{\partial \pi_{ri}}{\partial P_{ri}} = 0 \qquad (4.2)$$

In the duopoly case this becomes:

$$\begin{bmatrix} \dfrac{\partial \pi_{11}}{\partial P_{11}} & \dfrac{\partial \pi_{12}}{\partial P_{12}} & \cdots & \dfrac{\partial \pi_{1n}}{\partial P_{1n}} \\ \dfrac{\partial \pi_{12}}{\partial P_{12}} & \dfrac{\partial \pi_{22}}{\partial P_{22}} & \cdots & \dfrac{\partial \pi_{2n}}{\partial P_{2n}} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \qquad (4.3)$$

In practice, to solve Eq. 4.2 and Eq. 4.3 we use an optimization routine to minimize the square of the sum of the first derivatives of retailer profit with respect to each of the retail prices.

For the monopoly case we simply find the set of prices P_i that maximize monopoly profit:

$$\max_{P_i} : \sum_{i=1}^{n} \pi_i \qquad (4.4)$$

The existence and (preferably) uniqueness of the Nash equilibrium for retail prices for the multinomial logit (MNL) demand function is necessary to guarantee an equilibrium at the retailer where each of the retailers offer multiple products. Unlike the Nash equilibrium existence theorem (Caplin and Nalebuff, 1991) for a single product (competitors carry one product), to date a multi-product price equilibrium existence proof does not exist (Anderson et al., 1992). The multi-product environment is far more common in the retail environment as each retailer generally carries an assortment of products and thus deserves consideration.

THEOREM 1 – *Retailers' multi-product Nash equilibrium: A unique Nash equilibrium in prices exists for a retailer carrying an assortment of n products in a category of N products carried by all retailers.*

Proof is given in Appendix B.

The next layer for consideration in the pricing framework is setting of wholesale prices which are also based on the concept of Nash equilibrium. Similar to retail prices, we minimize the sum of the squares of the first derivatives of manufacturer profit functions with respect to wholesale prices W_i to solve Eq. 4.5 for each of the manufacturers $i=1,2,..n.$

$$\left[\frac{\partial \Pi_1}{\partial W_1}, \frac{\partial \Pi_2}{\partial W_2}, \ldots, \frac{\partial \Pi_n}{\partial W_n} \right] = 0 \qquad (4.5)$$

THEOREM 2 – *Manufacturer's single product Nash equilibrium: A unique Nash equilibrium in wholesale prices exists for a manufacturer selling products through a differentiated-retail-duopoly.*

Proof is given in Appendix B.

This structure creates a vertical Nash Equilibrium for the manufacturers and retailers in setting prices, which is an assumption that has ample support in actual practice (see Choi, 1991 and Kadiyal et al., 2001). A review of each of the proofs presented in the Appendix shows that the existence of global maximizing strategies for both the retailers and manufacturers requires that each of them to consider prices set by the other. While we cannot guarantee convergence of wholesale and retail prices considered simultaneously for all situations, we have observed convergence empirically without difficulty for all the cases we have considered in the application. The last layer of the optimization is the setting of engineering design variables by the focal

manufacturer. The engineering design problem is clearly not convex with many discontinuous and discrete variables. As such we use a genetic algorithm (Deb, 2004) to optimize the design.

The sequence for the pricing framework for monopoly and duopoly (shown in Figure 4.4.1) can be thought of as proceeding through the following steps for each design considered during the optimization:

1. Start with a population of engineering design alternatives at the Engineering Design Level (EDL).

2. Set initial wholesale prices W_i at the Wholesale Pricing Level (WPL) for each design alternative:

    a. Monopoly (WPL1): One set of wholesale prices is initialized

    b. Duopoly (WPL2): Two sets of wholesale prices are initialized at WPL2

3. Set initial retail price at the retail price level (RPL) for each design:

    a. Monopoly: One set of retail prices is initialized at RPL1

    b. Duopoly: Two sets of retail prices are initialized at RPL2

4. Calculate market shares (m_i and m_{ri}) based on utility of the engineering designs and retail prices and returned to the RPL.

    a. Monopoly (MSA1): Return markets shares m_i for the monopolist

    b. Duopoly (MSA2): Return market share m_{ri} for each retailer.

5. Adjust retail prices in the RPL until:

a. Monopoly (RPL1): monopolist profit is maximized in RPL1. Due to the no-choice option in the latent class model and a downward sloping demand function the problem is quasiconcave.

b. Duopoly (RPL2): a Nash equilibrium is reached for logit models by minimizing the first partial derivatives of retail firm profit.

6. Pass equilibrium retail prices (RPL) back to step two. Wholesale prices are adjusted (as a short term strategic response) until Nash equilibrium is reached (i.e., no manufacturer can alter the wholesale price and capture more profit). Once a Nash equilibrium (Eq. 4.5) is reached proceed to step 7.

7. Estimate profit from engineering design variables (cost), market share (step four), and equilibrium wholesale price (step six).

8. Stop if optimal profit is found. (Note: it is possible to implement additional objectives in this step for a multi-objective problem).

4.4.2 STRATEGIC CASES

We present four cases of varying channel structure to show the effect of taking into account the channel's competitive landscape on optimal engineering design based on an actual product-market. We consider 4 manufacturers (A to D) and 2 retailers (1, 2).

Case 1: Retailer Monopoly/Manufacturer Oligopoly

This is the simplest case of the four as there is no strategic interaction between retailers. The retail optimization layer is simply a profit maximization problem that depends upon the wholesale inputs of the manufacturers and of course the consumer characteristics. Strategic interactions occur at the manufacturer level in setting wholesale

prices which impact the engineering optimization. This is the baseline case that extends the prior work (Luo et al., 2007) to include engineering design optimization.

Case 2: Retailer Duopoly/Manufacturer Oligopoly: Identical Retailers

Here a retailer duopoly exists but consumers are indifferent across all segments as to which retailer to buy from so the retailer's only compete on price. This case is more complex than Case 1 due to the nature of the strategic interactions at the retailer level, though both cases require an inner optimization at the retailer layer. The formulation for the setting retailer prices takes into account wholesale prices as before but now is formulated as an equilibrium optimization where retail prices are adjusted to minimize the square of the first derivatives of the duopoly retailers' profits with respect to price. We assume that consumers are indifferent toward the retailers and that each retailer carries the same assortment. While somewhat unrealistic, such a case should demonstrate downward pressure on retail prices and therefore wholesale prices relative to the monopoly case. This will also serve as a baseline to examine Case 3 and Case 4 results.

Case 3: Retailer Duopoly/Manufacturer Oligopoly: Differentiated Retailers

A more realistic approach would account for the preference of consumers for the retailers themselves. It is well documented that specific retailers target specific consumer segments and therefore logical to assume that they have achieved differentiation in that regard. For example, Lowes targets female customers with wider, brighter isles and a greater emphasis on decorating (Pittman, 2005). A conjoint study can easily include samples where product i is offered at retailer r and then assess the value that consumers place on the "retailer attribute". Because the value of the product will vary with each retailer, the equilibrium prices at the retail level should be at least marginally different. If

manufacturers can predict outcomes for this scenario with our methodology they should be able to develop more profitable designs and wholesale price negotiations at the other optimization levels. In Table 3.5.1 of the previous chapter we show that 3 out of four customer segments prefer one retailer over the other.

Case 4: Retailer Duopoly/Manufacturer Oligopoly: Exclusive retailer strategy

Numerous examples exist in a variety of markets where manufacturers and retailers seek exclusive reseller relationships (Moner-Coloques, 2006). This is done as a means to secure access to market (manufacturer's perspective) and as a means differentiate an assortment for greater profits (retailer's perspective). We model this arrangement in a manner similar to Case 2 except that the focal manufacturer decides to go to the market through only one of the two identical retailers as an exclusive retailer strategy. This approach where one retailer is allowed to fulfill all demand "Referral to Reseller" has been shown to theoretically improve profits[6] for both parties in the exclusive channel (Tsay and Agrawal, 2004). Our method is similar to previous analyses (Trivedi, 1998) where the manufacturer is integrated with only one retailer except that we allow the retailer to carry additional differentiated products from the original assortment which reflects market reality of our shelf surveys. The retailer chosen for the exclusive relationship will carry the new product offered by the manufacturer as long as its profits improve relative to the original assortment just as in the previous cases. The competing retailer not chosen for exclusivity with our manufacturer simply offers the original assortment.

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[6] For example, Apple and AT&T sold 270,000 iPhones in under 30 hours in an exclusive channel relationship which boosted both firms profitability (Hartley, 2007).

4.5   CASE STUDY

We chose to apply Cases 1-4 to the engineering problem problem developed in Chapter 3, Section 3.5. This detailed engineering design structure and marketing data (conjoint analysis) (Luo et al., 2007) were available for common small angle grinders and an ideal candidate application for the case studies as they are typically sold in a strong retailer channel environment as presented in Chapter 3.   A brief shelf survey of the channel controlling retailers Lowes and Home Depot would reveal an assortment similar to that shown in Table 4.5.1.

Tool	A	B	C	D
Brand	W	X	Y	Z
Price ($)	$79.00	$99.00	$129.00	$79.00
Amps	6.00	9.00	12.00	6.00
Life (hrs)	80	110	150	110
Switch	Paddle	Trigger	Side	Side
Girth (in)	2	3	3	2.25
Weight (lbm)	5.00	9.00	16.00	5.00

Table 4.5.1:   Example Assortment at a Retailer

For the first four strategic cases from Section 4.4.2 our model replaces Tool A with a new product whenever the channel constraint is met in Eq. (4.1). The assortment is the same for the retailers under the monopolist and duopolist cases in that they carry the new product and products C-D. For the fourth (exclusive retailer channel) we assume that retailer one carries the new product and that the competing retailer carries the existing product (i.e., Product A from Table 4.5.1).

4.5.1   OPTIMIZATION APPROACH

We used Matlab's Genetic Algorithm and Direct Search Toolbox (GADS) (Matlab User Manual, 2007) to develop a multi-objective genetic algorithm (MOGA) to simultaneously optimize focal manufacturer profit (Manufacturer A) and retailer profit. While our focus is to maximize the focal manufacturer's profit while ensuring that retailer makes at least as much profit as he was making with the existing assortment, determining the Pareto solutions for manufacturer and retailer profits would help us understand the trade-off better, as we show subsequently. Additionally, one might think of increasing the retailer's profitability above the prior assortment profit as strengthening the manufacturers case to obtain shelf space. We formulate the manufacturer's decision as two objectives: (1) maximizing his own profit, and (2) maximizing the channel partner's profit (monopolist, duopolist, or exclusive retailer). This can be described mathematically by adding the second objective to the optimization formulations as shown in Figure 4.5.1:

Monopoly	Duopoly	Exclusive
$\max\limits_{x,W_i} :\quad \Pi_i = m_i(W_i - C_i)$	$\max\limits_{x} :\quad \Pi_i = m_i(W_i - C_i)$	$\max\limits_{x,W_i} :\quad \Pi_i = m_i(W_i - C_i)$
$\max\limits_{x,W_i} :\quad \sum\limits_{i=1}^{n}\pi_i$	$\max\limits_{x} :\quad \sum\limits_{r=1}^{2}\sum\limits_{i=1}^{n}\pi_{ri}$	$\max\limits_{x,W_i} :\quad \sum\limits_{i=1}^{n}\pi_{1i}^{new}$
s.t. $g(x) \le b,\ \sum\limits_{i=1}^{n}\pi_i^{new} \ge \sum\limits_{i=1}^{n}\pi_i^{old}$	s.t. $g(x) \le b,\ \forall r\ \sum\limits_{i=1}^{n}\pi_i^{new} \ge \sum\limits_{i=1}^{n}\pi_i^{old}$	s.t. $g(x) \le b,\ \sum\limits_{i=1}^{n}\pi_{1i}^{new} \ge \sum\limits_{i=1}^{n}\pi_{1i}^{old}$
$C_i, m_i = f(x)$	$C_i, m_i = f(x)$	$C_i, m_i = f(x)$
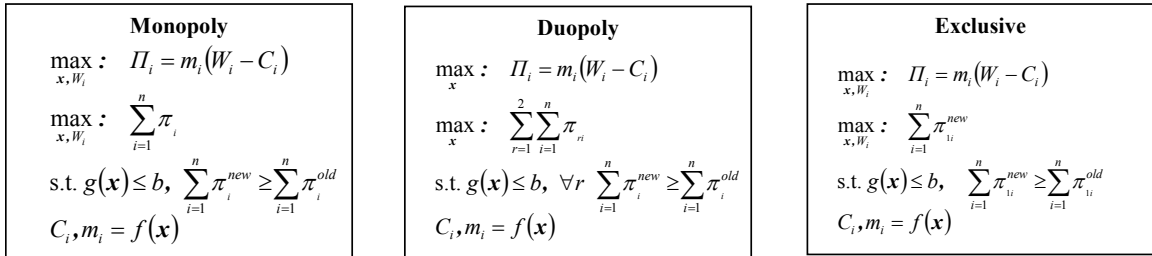
Figure 4.5.1: Optimization Formulations

A non-dominated sorting algorithm (Deb, 2001) is employed to find a Pareto frontier for each strategic situation (Monopoly, Duopoly with identical retailers, and Duopoly with differing retailers, and the Exclusive retailer). The 9 design variables were encoded in a binary format with lower and upper bounds specified in accordance with

Table 3.5.3. The wholesale prices were allowed to increase up to $100, which is higher than the maximum wholesale prices encountered in practice. The design variables were encoded as 200 bit binary strings and run with a population size of 100 for 200 generations. Additionally, the MOGA was set to terminate if objective function values change less than 1×10^{-6} over 50 generations or change less than 1×10^{-6} for a time period of 10,000 seconds. Constraints were handled using the "Feasible Over Infeasible Approach" (Deb, 2001) where violated designs are set equal to the worst function call plus a penalty. Additionally, a crossover fraction of 0.6, a mutation rate of 0.1 and an elite fraction of $1/3^{rd}$ were used. The inner optimizations for retail price setting and wholesale price setting are strictly quasi-concave for monopoly and duopoly price setting (See proofs in Appendix B) and as such are amenable to gradient based optimizers such as Matlab's fmincon (Matlab User Manual, 2007). The computational issues involved in our methodology are discussed at length in Appendix B.

4.6   DISCUSSION OF APPROACH AND CASE STUDY

4.6.1   INTERPRETATION OF MANUFACTURER VS. RETAIL PROFITS

The results focus on Manufacturer A's design strategy in developing a new design to replace the existing Product A design in the market under different channel structures, with the assumption that the competitor products remain in the market with their existing attributes, which is taken into account in developing the new design scenarios. The competitors can however change their wholesale prices of their products in the short-term. As expected the strategic cases present varying levels of profitability for the manufacturers and retailers highlighting the impact of the varying market power of the two types of players under different channel structures (monopoly and duopoly).

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In Figure 4.6.1 we present an optimal set of designs for four strategic cases where the focal manufacturer is able to manipulate a design (Tool A) to achieve maximum profit for himself and the retailer (monopoly) or retailers (duopoly). All the design solutions satisfy a constraint that the retailers' profits exceed those with preexisting assortment and thus achieve channel acceptance under the proposed decision framework. The profit level of the existing assortment for each of the strategic cases is shown as a dashed horizontal line in Figure 4.6.1. The great variety of optimal designs are shown in Figure 4.6.1 to highlight the importance of the strategic case and how designs can change as one transitions between manufacturer profitability and retailer profitability along the Pareto set of designs. Initially we focus on explaining equilibrium prices for the strategic cases and will return to the variety of designs present in the next section.

Consider the retailer monopoly case in Figure 4.6.1. Design A3 is the optimal design from the focal manufacturer's (Mfr A) viewpoint which maximizes A's profit while ensuring that retailer makes more profit than what he makes with the existing assortment. The other design solutions along the Pareto frontier from Design A1 to Design A3 increase retailer profit at the expense of the manufacturer profit. If Manufacturer A is greatly concerned about being rejected by the retailer due to the uncertainty in the retailers own decision framework he might select a design between Design A3 and Design A1 along the Monopoly Pareto frontier. Any design between these two points clearly increases the manufacturer's value proposition to the retailer which motivates the retailer to carry the product.
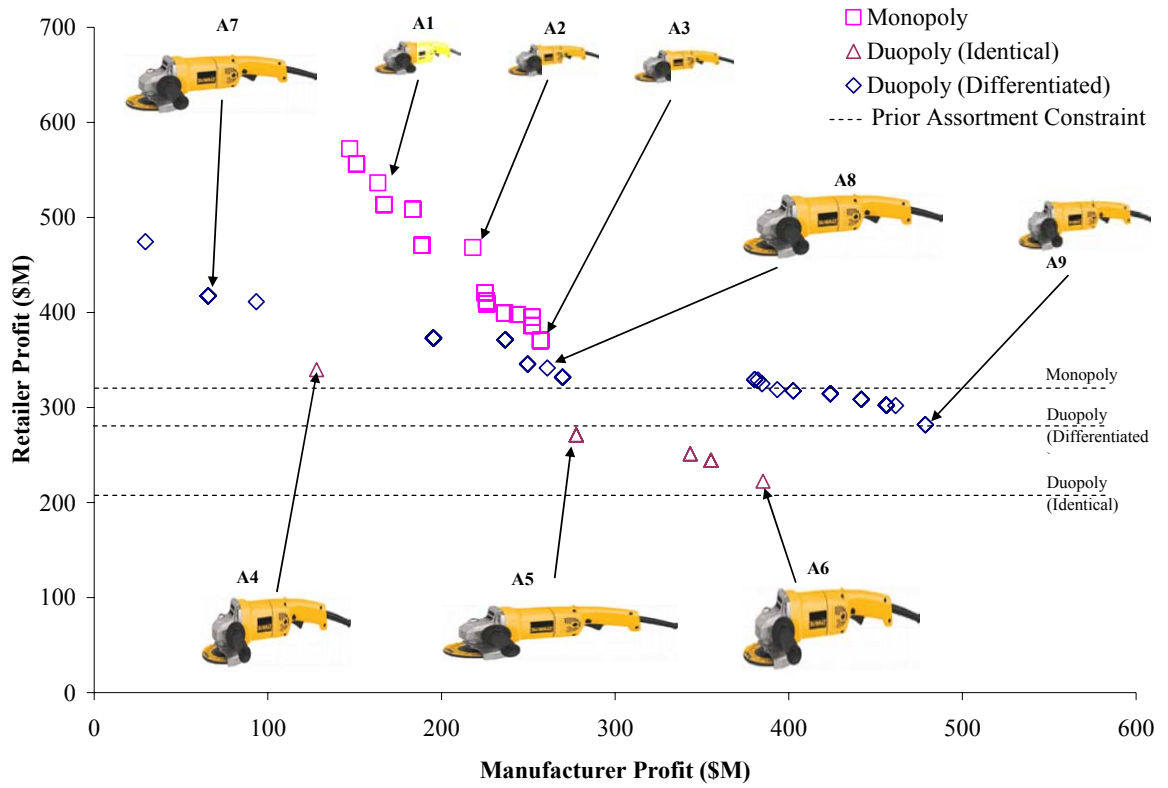
Figure 4.6.1: Strategic Environment Comparison

4.6.2 COMPARISON OF STRATEGIC ENVIRONMENTS: CASES 1-3

The solution set of each of the strategic cases presented Figure 4.6.1 are unique and depend on the specific channel structure. The monopoly Pareto frontier is the least profitable situation for manufacturers as both duopoly cases have acceptable solutions that have higher profits than the monopoly solution with the greatest manufacturer profit. In addition, monopoly retailer profits exceed any of the duopoly cases which consistent the extant literature (Gibbons, 1992), (Anderson et al., 1992) given that the monopolist does not have competition to shift prices lower. The increased price competition in the two duopoly retailer situations (identical and differentiated) allow for the possibility of greater manufacturer profits as prices in the retail space a lower resulting in fewer customers preferring the no-choice option. The reasons for this are clear when we look

closer at the retail prices that are the outcomes under the various situations (See Table 4.6.1 to Table 4.6.3). In each of the tables, we present the optimal new design for Manufacturer A as the third row which is preceded by other Pareto designs that increase retailer profits at the expense of manufacturer profits. The last row in each of the tables presents the wholesale prices and retailer prices for the pre-existing assortment (Table 4.5.1).

Overall, the results are consistent with the general economic model predictions for monopoly and duopoly structures. For example, in the optimal solutions (Designs A3, A6, and A9) the retail margins are much higher for the monopoly retailer ($72 to $84) as compared to the margins in the duopoly situations ($26 to $50). This is to be expected when one player in the channel controls access to consumers. Additionally, manufacturers receive lower wholesale prices at strategic equilibrium under the monopoly situation ($25 to $50) versus the duopoly ($39 to $70). The retailer obviously enjoys much higher profits as a monopoly (note that duopoly profits are sum of the two retailer's profits in Figure 4.6.1).

New Design ID	Equilibrium Wholesale Prices				Equilibrium Retail Prices				Mfr A Profit ($Million)	Retailer Profit ($Million)
	Tool A	Tool B	Tool C	Tool D	Tool A	Tool B	Tool C	Tool D		
A1	$43.23	37.46	$25.01	$25.33	$118.89	$113.12	$100.65	101.53	$167.00	$523.40
A2	$46.21	$38.27	$38.45	$25.67	$118.40	$110.46	$110.64	$97.86	$218.00	$468..34
A3	$50.03	$41.10	$32.95	$31.81	$128.46	$119.53	$111.38	$110.24	$257.1	$370.5
Equilibrium Prices with Existing Design	$29.78	$42.70	$29.78	$52.01	$89.93	$102.85	$90.75	$112.16	Current Mfr A Profit $30.38	Current Retailer's Profit $313.77

Table 4.6.1: Designs for Monopoly Retailer

In Table 4.6.1, we observe that the wholesale price of the optimal new design (A3) for manufacturer A is much higher than the existing design in the market due to the

greater utility of the new design. In this scenario, Manufacturer B and D also lower their wholesale prices as a reaction to the new design A3 which improves the retailer's profit. However, Manufacturer C raises the wholesale price. This is consistent with predictions in extant literature (Hauser and Shugan, 1983) who show that incumbent manufacturers may find raising wholesale prices as a defensive strategy to be optimal for them depending on the distribution of consumer tastes and which segment the tool is targeted. In the monopoly case, the retailer does pass on the decrease in wholesale prices to consumers in the form of lower retail prices except for Tool C (compare the existing retail prices in the last row with the equilibrium retail prices for Pareto optimal design A1 in the first row). Another interesting result is that if Manufacturer A chooses to introduce Design A1, with a much lower wholesale price, it leads to pricing by other manufacturers which are also very low, even though the other attributes of their design remain the same. At some of these wholesale prices, these manufacturers may actually be selling below costs; however this reaction is to be expected as they would try to stem the loss of market share to Manufacturer A (similar to airlines matching cut-rate prices of competitors even though it might result in losses for everyone). However, the optimal design A3 (from MFR A's perspective) does not suggest any such possibilities.

Another interesting result in the monopoly case is how much market share the monopolist retailer gives up to the "no choice" option. Summing the market shares for the four tools for each case A1, A2, and A3 yields total market shares of 72%-75% implying that 25% to 28% of consumers will opt to purchase none of the tools based on the high price. This is readily observed in the retail prices for the monopolist being $20 to $50 higher than the in the duopoly cases. In contrast, the customers purchasing a tool

under duopolistic competition are in the 95% to 98% range which is consistent with the notion that competition is better for consumers.   The differentiated duopoly has a slight edge in penetration relative to the identical duopoly (i.e., closer to 98% for many of the Pareto designs) as each retailer can focus on preferred segments.

New Design ID	Equilibrium Wholesale Prices				Retailer	Equilibrium Retailer Prices				Mfr A Profit ($Million)	Sum of Retailer Profits ($Million)
	Tool A	Tool B	Tool C	Tool D		Tool A	Tool B	Tool C	Tool D		
A4	$55.89	$48.67	$50.00	$49.99	R1	$83.52	$76.31	$77.63	$77.62	$128.1	$339.8
					R2	$83.52	$76.31	$77.63	$77.62		
A5	$39.07	$62.32	$39.34	$56.69	R1	$67.58	$90.83	$64.86	$85.20	$277.70	$271.20
					R2	$67.58	$90.83	$64.86	$85.20		
A6	**$66.25**	**$62.50**	**$42.50**	**$46.25**	**R1**	**$92.69**	**$88.94**	**$68.94**	**$72.69**	**$385.21**	**$222.40**
					R2	**$92.69**	**$88.94**	**$68.94**	**$72.69**		
Equilibrium Prices with Existing Design	$50.35	$55.96	$46.16	$50.38	R1	$76.53	$82.14	$72.33	$76.54	Current Mfr A Profit	Current Retailers' Profit
					R2	$76.53	$82.14	$72.33	$76.54	$226.10	$206.68

Table 4.6.2:   Designs for Duopoly Identical Retailers

Interesting results can also be found when comparing the two duopoly cases. As was expected, when the retailers are differentiated the results lead to different retail margins and identical retailers lead to identical retail margins.   The pricing model that we employ offers each retailer the same wholesale price and retail prices are subsequently selected. When retailers are identical it appears that price competition is particularly fierce with the lowest retail margins observed for all cases. Differentiation by retailers in terms of which segments they appeal to the most allows both retailers to retain higher margins than the identical case (Table 4.6.2 and Table 4.6.3).

New Design ID	Equilibrium Wholesale Prices				Retailer	Equilibrium Retailer Prices				Mfr A Profit ($Million)	Sum of Retailer Profits ($Million)
	Tool A	Tool B	Tool C	Tool D		Tool A	Tool B	Tool C	Tool D		
A7	$50.70	$40.02	$45.14	$59.86	R1	101.85	91.14	96.29	111.01	$65.6	$304.12
					R2	$105.89	$95.31	$100.43	$115.15		
A8	$46.95	$55.77	$45.78	$53.47	R1	$92.39	$101.22	$91.22	$98.91	$269.74	$332.00
					R2	$93.74	$102.57	$92.57	$102.27		
A9	$57.49	$55.00	$55.01	$57.50	R1	$101.44	$98.96	$98.95	$101.46	$478.61	$281.90
					R2	$84.87	$82.39	$82.39	$84.89		
Equilibrium Prices with Existing Design	$57.80	$44.84	$44.42	$48.81	R1	$111.44	$98.49	$98.06	$103.45	Current Mfr A Profit	Current Retailers' Profit
					R2	$103.39	$90.43	$90.01	$95.40	$223.61	$273.53

Table 4.6.3:   Designs for Duopoly Differentiated Retailers

4.6.3   ANALYSIS OF EXCLUSIVE STRATEGY

In addition we have developed strategic case for the exclusive retail channel arrangement that is growing increasingly frequent.   This is especially appropriate for our case study as exclusivity is common in the tool industry where, for example, Home Depot exclusively sells Husky hand tools and Ryobi power tools (Han Shih, 2005). To set up the exclusive retail channel we selected one of the two retailers as a "channel partner" who has exclusive rights to carry the new tool (Tool A) along with Tools B to D. The remaining retailer or "competing retailer" in the subsequent figures carries the original assortment (Tools B-E). Tool E is the design in place prior to optimization. We selected retailer one as a fixed choice for the exclusive relationship although in principal the selection of the retailer could easily be made a design variable with the use of binary variable.

The exclusive channel (Case 4) is compared to the most relevant example from the previous cases, duopoly with identical retailers (Case 2), which included optimal

designs A4 to A6. For this comparison all retailers are considered equal in attractiveness to each segment. They only differ by the content of their assortment.   The previously termed Duopoly (identical) case will now just be referred to as the "Non-exclusive Case".

New Design ID	Equilibrium Wholesale Prices					Equilibrium Retailer Prices						Mfr A Profit ($Million)	Channel Partner Profits ($Million)
	Tool A	Tool B	Tool C	Tool D	Tool E	Retailer	Tool A	Tool B	Tool C	Tool D	Tool E		
A10	$41.03	$54.97	$39.29	$62.52	$57.72	R1	$84.13	$98.07	$82.39	$105.63		$216.1	$248.6
						R2		$95.90	$80.22	$103.46	$98.65		
A11	$54.65	$50.03	$49.63	$54.95	$49.88	R1	$95.45	$90.93	$90.53	$95.65		$270.07	233.0
						R2		$89.13	$88.73	$93.85	$89.88		
A12	$62.76	$69.99	$41.93	$50.03	$56.70	R1	$102.76	$110.00	$81.93	$90.03		$298.0	$218.1
						R2		$109.50	$81.43	$89.53	$96.20		
Equilibrium Prices with Existing Design	$54.97	$49.93	$49.99	$54.99	$51.05	R1	$123.20	$118.16	$118.22	$123.22		Current Mfr A Profit	Current Retailer's Profit
						R2		$112.84	$112.90	$117.90	$113.90	$135.53	$217.74

Table 4.6.4:   Designs for Exclusive Case (Identical Duopoly)

In comparing the two cases we see that the under the exclusive channel the channel partner (retailer selected to carry the optimized tool) benefits greatly as the profits for the entire Pareto Set dominate those of the non-exclusive case. In contrast the manufacturer loses the possibility of achieving the highest profit (Figure 4.6.2). If we compare the manufacturer's optimal design under the non-exclusive case (A6) to the optimal design under exclusivity (A12) we see potential profits erode by $80M.   In contrast the channel partner's profits rise from $111.4M (recall Table 4.6.2 is the sum of 2 identical retailers) to $218.1M or increase by $106.7M.   Thus $26.7M in net value has been added to the channel which anecdotally explains the existence of exclusive retail relationships. Given that the retailer's still have strategic dominance in this situation due to their control of market access, one can consider the exclusive offering as an incentive

to a retailer to achieve shelf space similar to a slotting allowance. For a cash-strapped or risk-averse manufacturer the exclusive offering may be much more attractive than a slotting allowance. This risk is due to the high outflow of cash for a slotting allowance in the present period with no guarantee of sales volume. The profits of the model are still a prediction whereas a slotting allowance is an immediate deterministic outflow of cash. In addition the exclusive contract can provide greater manufacturer profit than some of the non-exclusive Pareto designs. For example, A12 is preferred by the manufacturer to A5 and A4. A12 is also preferred by the channel partner, which in effect coordinates the two channel member's objectives.
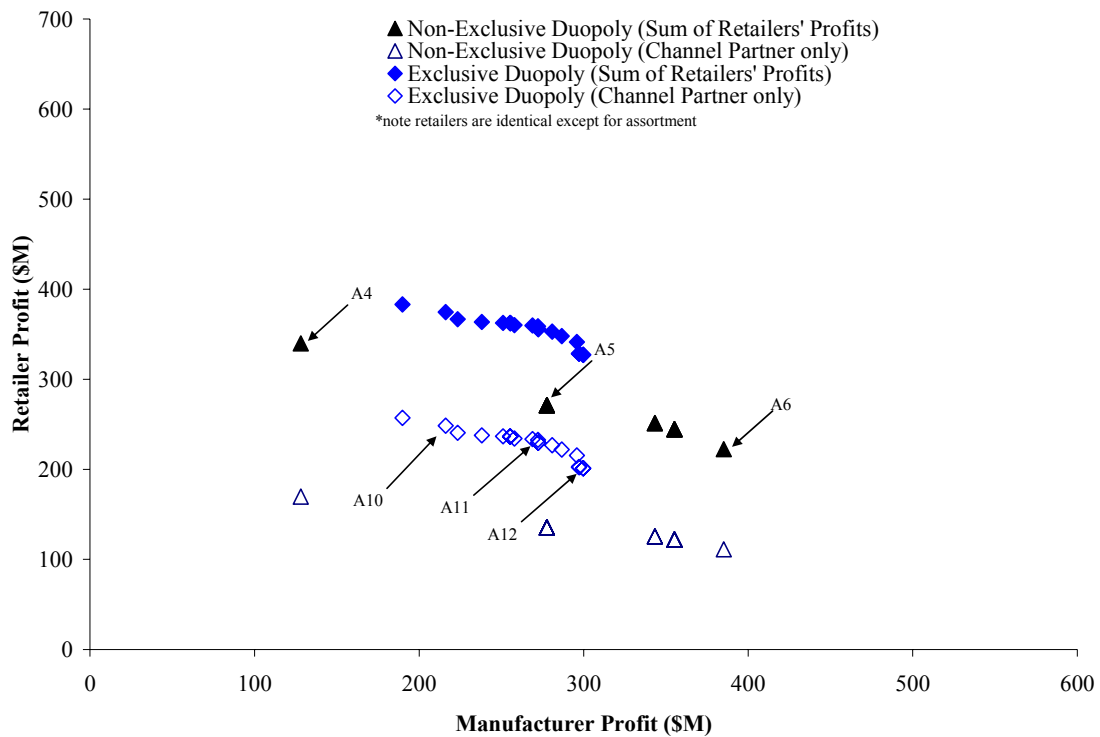
Figure 4.6.2: Exclusive Channel Comparison

4.6.4 OPTIMAL ENGINEERING DESIGNS

There are some trends that can be observed in the designs themselves in comparing the channel structures and location along the Pareto frontier. First, the most profitable designs for the focal manufacturer (A3, A6, A9, A12) are in general less powerful than their less profitable counterparts. It is costly for the manufacturer to produce a tool with greater power to weight ratio yet the consumers value this attribute. Regardless of the strategic case analyzed this appears to be the case. In comparing the strategic environments we see that along the entire Pareto frontier the manufacturer develops lighter tools for the monopoly (5.15 to 5.33lbm) with a smaller girth (1.79 to 1.82 in). As global observation we see that the designs under a monopoly channel are also far less diverse than the other channel structures. For example, weight under the differentiated duopoly case varies by nearly 5 lbm and only varies by a few ounces under the monopoly. We believe this is a facet of the monopoly being able to dictate which attributes will best fit the current assortment as defined by the segment utilities. The lighter tool is more costly to produce based on our cost predictions which significantly erodes the manufacturer profit as shown in Figure 4.6.1. Still the amperages for the monopoly tools are in the lower quality range. This has important implications for manufacturers as it may not be possible to design high quality tools, (as perceived by customers with regard to amperage) for the monopolist, that have positive wholesale margins.

The differentiated duopoly appears to offer the highest wholesale prices and allows the manufacturer to design the highest amperage tools. Because the retailers are not competing entirely on price in the differentiated case, retail prices can be adjusted higher for segments that prefer a particular retailer. These higher retail prices provide the

manufacturer with the opportunity to search a larger design space and provide a more diverse set of designs (including higher performance models) that still generate the greatest profits (Figure 4.6.1). Thus the manufacturers would prefer the differentiated case to persist in reality. Finally, in the exclusive case we see the manufacturer again isolates his strategy to a relatively narrow set of product attributes in terms of weight and amperage. This is similar to the monopoly case where it appears that the retailer is better able to dictate acceptable model design for the assortment. Of course a fifth tool is present under this case so it may be that this is also the best position to compete against the original assortment (now including Tool E.)

		Monopoly			Duopoly (Identical)			Duopoly (Differentiated)			Exclusive		
	New Design ID	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
Design Variables	**Units**												
Armature wire turns	N_c (# of turns)	196	205	205	204	205.6	208	216	171	172	259	259	263
Stator wire turns	N_s (# of turns)	110	139	110	160	177.7	154	144	179	176	143	149	132
Stator outer radius	R_o (m)	0.01	0.01	0.01	0.022	0.018	0.024	0.016	0.017	0.017	0.019	0.017	0.020
Stator thickness	t (m)	0.012	0.012	0.012	0.005	0.005	0.005	0.026	0.007	0.028	0.002	0.002	0.003
Gap thickness	l_{gap} (m·10^{-4})	4.6	1.8	4.6	3.9	5.0	14.8	26.4	20.5	8.0	29.2	20.1	23.7
Current	I (amps)	5.01	6.15	5.06	6.69	6.73	5.62	8.72	6.67	5.20	5.92	6.01	5.41
Stack Length	L (m)	0.072	0.081	0.09	0.146	0.198	0.155	0.162	0.169	0.139	0.147	0.141	0.197
Gear Ratio	r	2.87	2.17	2.87	4.98	3.36	3.47	3.09	4.54	2.96	2.88	3.07	3.12
Pinion Pitch Diameter	D_p (cm)	0.012	0.012	0.012	0.013	0.015	0.012	0.023	0.047	0.049	0.019	0.019	0.019
Girth	(cm)	4.62	4.55	4.55	6.96	6.12	7.39	5.66	5.84	5.84	6.50	6.17	6.55
	(in)	1.82	1.79	1.79	2.74	2.41	2.91	2.23	2.30	2.30	2.56	2.43	2.58
Weight	(kg)	2.34	2.38	2.42	4.60	4.32	5.03	3.56	5.66	4.36	4.36	4.09	4.48
	(lbm)	5.15	5.24	5.33	10.14	9.53	11.08	7.84	12.48	9.62	9.62	9.02	9.87

Table 4.6.5:   Pareto Designs

The important take-away from the above table is that the optimal designs are quite different for the different channel structures considered. Virtually none of the Pareto Designs predicted by this model would have been developed by a traditional engineering model which would search for different objectives: lowest cost, highest amperage and lightest tool for example. The fatal flaw for such an approach is that some consumers prefer heavier tools (Table 3.5.1) which would allow the manufacturer to design less costly, Eq. (8), yet optimal tools in some cases (e.g., 7.8 to 12.48 lbm for the Duopoly

cases). Additionally, ignoring pricing changes by competitors within segments might result in negative revenue if profitable wholesale prices are unachievable because of the strategic landscape.

Additionally, there are significant variations in the design variable values for the manufacturer's optimal designs A3, A6 A9 and A12 most importantly with respect to stack length, stator radius, current, gear ratio and pinion pitch. These variables in turn impact the performance and cost (price) of the tool, which the market is concerned with. While, from a qualitative perspective this difference is to be expected given the intuitive pricing pressures from different channel structures, our methodology provides a systematic manner to incorporate the impact of channel structures and strategy into the product design process. Overall we observe a tendency for the manufacturer to fill a niche in the lower cost, low to medium amperage and heavier (except for the monopoly situation) category which is currently underserved by the assortment (Table 4.5.1). The manufacturer appears able to capture a significant market share (30% to 40%) with all Pareto designs due to the weakness of the competing products. This, of course, is a function of the attributes of the competitive offerings that we have considered in the case study. However, it is clear from the results our methodology provides a very efficient way to consider the competitive positions in the market, their potential reactions and the retailer reactions.

4.7 SUMMARY

Considerable effort in the design community has produced methodologies that significantly improve customer satisfaction and quality. These methods frequently ignore the reality that customers interact principally with dominant retailers for many product

categories and have no access to the manufacturer. The approach presented in this chapter takes into account these channel dominating retailers through a game theoretic price setting model at the wholesale and retail level. Several cases of channel structures are presented and we observe that the optimality of designs vary markedly as the structure changes and as the threat of shelf space denial goes up. Under a heightened threat of shelf space denial our approach provides a Pareto set of designs to choose from that can mitigate this risk. In addition to the variance in designs, channel structures appear to affect retail and wholesale margins to a great deal. The monopolist retailer is able to drive wholesale prices to the lowest level while differentiated retailers and exclusive arrangements are able to improve profitability for both members of the channel. Additionally, our approach shows that manufacturers may be able to make their offer significantly more attractive with an exclusive contract. Our results provide anecdotal evidence that while the manufacturer is limited to lower profits under an exclusive relationship the exclusive relationship provides significant motivation for channel acceptance and may be preferable to choosing a higher retailer profit under the non-exclusive arrangement. The strategic dominance of retailers presented here may provide some insight as to the recent large migration of manufacturing operations to less expensive and arguably lower quality workforces such as those in China. Facing a monopolist retailer a manufacturer would have little choice but move off shore if a competitor does so as well. The downward pressure on wholesale prices demands it.

In the next chapter, design of product bundles is modeled with its impact on multiple product categories. That is, several products are designed simultaneously with the possibility of selling two or more for a single price. Additionally, a preliminary

probing of the assumptions of pricing equilibrium (Nash Equilibrium) is investigated along with other sources of uncertainty to determine their affect on optimal (robust) design for channel markets.

CHAPTER 5:   MULTI-CATEGORY DESIGN OF BUNDLED PRODUCTS FOR RETAIL CHANNELS CONSIDERING DEMAND DEPENDENCIES AND UNCERTAINTY IN COMPETITIVE RESPONSE

In this chapter, multi-category and bundled product design is explored as well as an approach to designing for uncertainty in the channel structure. A prevalent approach to increasing both retailer and manufacturer revenues is to improve the attractiveness of a product offering by bundling related items together for one price. To be most effective, bundled products should be developed with an integrated design approach that seeks to achieve utility for the end customer as well as cost efficiencies through measures such as using common parts. We propose a bundled product design approach that endogenizes the profit maximizing prices set by the channel controlling (monopolist) retailer similar to the monopolist framework of Chapter 4. The approach extends the previous chapter to account for demand dependencies between the product categories and thus the impact of the bundle and cross-category competition on proposed engineering designs is known.

Additionally, an approach that simultaneously considers uncertainty in engineering design tolerances, competing manufacturer product attributes, customer preferences, to ensure acceptable product profitability and market share under interval uncertainty is presented in this chapter. A bundled product design case study is presented for two complimentary power tools which rely on the case study developed in Chapter 3 along with the modifications necessary to make the tools cordless. Manufacturer profit and market share are optimized both deterministically and under uncertain intervals. We

find that considering demand dependencies can create optimal bundle and individual product designs that increase profits for both retailers and manufacturers.

The rest of the chapter is organized as follows. After the introduction in Section 5.1, an overview of the proposed framework along with model assumptions and justifications is provided in Section 5.2. In Section 5.3, we provide the specific case study modifications necessary for the bundled product design relative to that presented in Chapter 3. Section 5.4 details the optimization approach used with the results presented in Section 5.5 and a summary in Section 5.6.

5.1   INTRODUCTION

In this chapter, we narrow the focus to the increasingly pervasive practice of product bundling in the retail sector which has been studied by economists and marketing researchers (Salinger, 1995), (Mulherne and Leone, 1991), (Pierce and Winter, 1996), (McAfee et al., 1989). Bundling is a practice where value is added to the product offering by combining multiple complimentary products for a single price which directly impacts any demand model used to design the product. Two sub-categories of bundling exist: (1) price bundling and (2) product bundling (Stremersch and Tellis, 2002). Price bundling is simply the offering of two or more separate and possibly independent products for one price. Product bundling, on the other hand, requires some level of product integration and dependency. Price bundling can be easily achieved by retailers while product bundling requires action on the part of manufacturers to integrate the products at the design stage. Researchers generally agree that product bundling provides the greatest opportunity for increased profits (Mulhearne and Leone, 1991), (Stremersche and Tellis, 2002) and is therefore a prime candidate for design consideration.

Extant literature has addressed coupling engineering design for a single product category with discrete choice models such as the multi-nomial logit (Besharati et al., 2006), (Luo et al., 2007). Because bundled products present a new category in and of themselves we extend these approaches to investigate competing product category designs within a Nested Multi-Nomial Logit (NMNL) formulation (Anderson et al., 1992), (Kannan and Wright, 1991). The NMNL formulation for large choice sets (e.g., multiple categories) helps avoid violations of the irrelevant alternatives (IIA) assumption (Ben-Akiva, 1973) (McFadden, 1978). This assumption essentially requires that original pair wise decisions remain in tact as additional alternative choices are added (Lourviere et al., 2004). Bundle choice models (BCM) fall under the larger genre of multi-category models (Seetharman et al., 2003) and thus the evaluation of high level bundle attributes with choice models is not without precedent (Chung and Rao, 2003). Kopalle et al., (1999) have shown that pure bundling (offering a bundle only) is never the equilibrium strategy (profit maximizing for multiple players) under the NMNL formulation. As such, we investigate a mixed bundling strategy within NMNL formulation as a significant improvement in accuracy is possible over previous approaches where cross category effects are ignored (Williams et al., 2006) or when bundles are simply evaluated within existing product categories (Williams et al., 2007).

Although examples abound in the retail marketplace, the extant literature has not considered the role of bundling early in the product design process. Ideally, a design process would take into account the possibility of bundling by incorporating efficiencies of quantity and scope (i.e., costs) from the bundle as well as any market share gained from the added value to customers. Less obviously, the design approach should also take

into account the effects of design integration on the individual products design, the cannibalization of sales between products, and the effect of the bundle on the retailer's profit. Finally, regardless of the bundling strategy a retailer chooses to use, if products are made more complementary in the design stage itself both manufacturers and retailers can benefit from higher sales, which may make it easier for the manufacturer to convince the retailer to carry its products.

Additionally of concern, retailers now exert significant pressure on manufacturer wholesale prices as the largest retailers (e.g., Wal Mart) strive to continuously provide value to customers through price reductions (Fishman, 2006). Realizing that manufacturers do not interact directly with end customers but rather propose product offerings to retailers who price the product and might accept or reject the design based on their own objectives, a new methodology is needed. Retailers wish to maximize profit (see e.g., Simpson et al., 2001, Wagner et al., 1989, and Shipley, 2001) which is an objective that does not necessarily align with the manufacturers profit maximization objective (i.e., the retailer and manufacturer do not necessarily cooperate). Some recent and relevant work in the engineering literature has sought to analyze non-cooperative behaviour (objectives are not aligned) between engineering disciplines within a manufacturing firm (Chanron and Lewis, 2005), (Xiao et al., 2005) (Marlar and Arora, 2004). The new approach proposed here will consider a non-cooperative externality: the retailer. In that vain, the profit maximizing objective of the manufacturer has been modelled simultaneously with the retailer's objective of maximizing category profits (Luo et al., 2007) (Williams et al., 2006) but in this work we extend approach to the multi-category assortment that includes the possibility of product bundles. In our

approach the retailer is essentially an important stakeholder (Donaldson et al., 2004) who makes decisions on prices and shelf space while the manufacturer makes decisions on the rest of the product attributes. We limit our scope to a monopolist pricing model, from the retailer's point of view, for multi-category profitability.

While the *manufacturer-monopolist retailer* relationship can be readily modeled as a non-cooperative game, the relationship between the focal manufacturer and competing manufacturers is much more complicated. Game theoretic approaches to modeling simultaneous competitor reactions require strict-quasiconcavity of all competitor profit functions with respect to their own strategies in the case of deterministic games (Osborne and Rubinstein, 1998) and the super-rationality of players in the case of Bayesian games (Harsanyi, 1967). These are rather strict criteria and difficult to prove for a multidisciplinary engineering design problem with discrete variables, and non-convex objective functions. Additionally, players have repeatedly proven to be irrational (i.e., make responses that are not best responses to a competitors action, see e.g., Binmore et al., 2001) and incapable of identifying the Nash Equilibrium (Nash, 1951), (Haruvy and Stahl, 2005). These aspects make it difficult to incorporate manufacturing competitor actions in a game theoretic framework. Rather than focusing on the question of "which designs are optimal for our focal manufacturer given all manufacturers converging to a competitive equilibrium?" we reframe the question as "which designs are optimal for a bundle given that all competitor strategies and uncertain events (within an interval of uncertainty) conspire against him?" Therefore, the one of the objectives of this paper is to develop a flexible design methodology that allows

manufacturers to manage uncertainty in the design, pricing and marketing of multiple products.

5.2   APPROACH TO MULTI-CATEGORY DESIGN WITH BUNDLES

We approach this problem from the perspective of the manufacturer who is considering the design of multiple individual products and their possible bundle. Each individual product and the bundle of all products are modeled as product categories. The approach is formulated to evaluate demand for an engineering design in light of the possibility of substitution between product categories. Our approach is formulated with four key goals in mind: (1) the effect of bundled product designs should be accounted for in calculating all product category market shares and profits (e.g., cross category effects), (2) the approach should be capable of optimizing product designs for multiple manufacturer firm objectives (e.g., profit and market share), (3) the design should take into account retail prices dictated by the monopolist retailer, and (4) designs should be robust or have acceptable objective variation under uncertainty (e.g., uncertainty in competitor product attributes, uncertainty in wholesale price, or uncertainty in an engineering parameter like material's property).

Our framework is aimed at addressing these goals and is built up in a multilayered fashion where design decisions, retailer reactions, and consumer choices are sequenced in an order that mimics reality as shown in Figure 5.2.1.
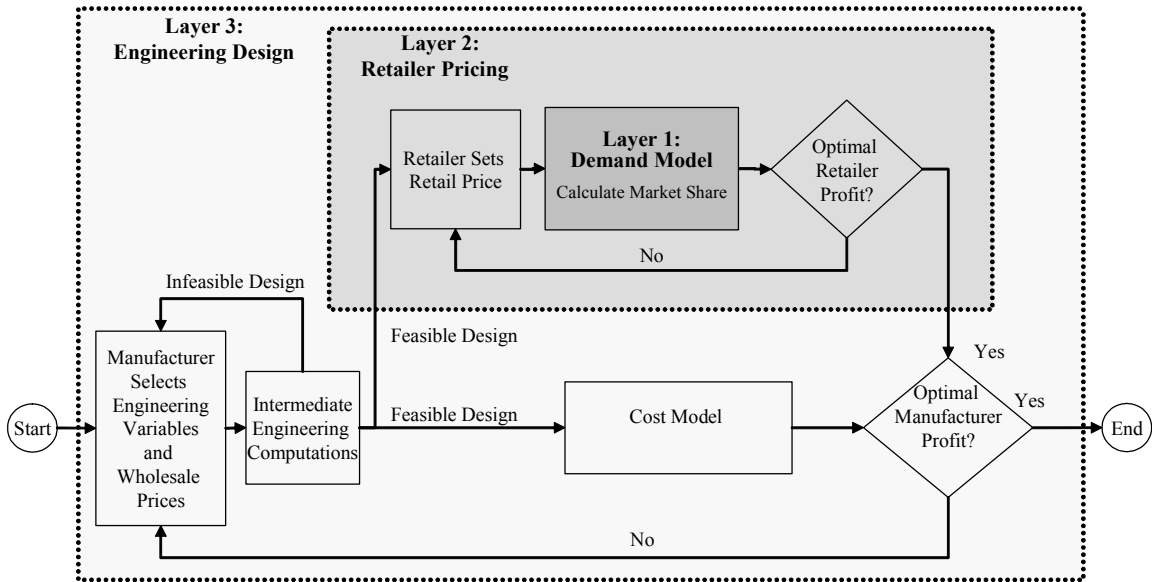
Figure 5.2.1: Multi Layered Design Framework

As shown Figure 5.2.1, the innermost layer, Layer 1, is for the determination of the market shares for each product as designed (see the darkest block). Market shares can only be determined once the retail price for the assortment in each category is set since price is a major component of customer utility. The demand model (Layer 1) we employ will be presented in Section 5.2.1. The next layer, retailer pricing layer (Layer 2), will be explicated in Section 5.2.2. This layer of the model is depicted as the medium grey toned region allows the retailer to set prices that maximizes profits across all product categories. Finally, engineering design (Layer 3) is the outermost layer (light grey tone) and must ensure the feasibility of the designs while simultaneously predicting monopolist price setting at the retail level (see Section 5.2.3). This basic model provides the basis for the more detailed aspects of the remainder of Section 5.2.

5.2.1 LAYER 1: DISCRETE CHOICE MARKETING MODEL

Manufacturers are concerned with profit which is a function of production costs, wholesale price, and market share. In the context of a bundled product the manufacturer is concerned with the profit generated by the original unbundled products as well as that of the bundle which can be addressed with the NMNL formulation. In our implementation of the NMNL formulation we use a nest for each product category. For example for two products there would be a nest for product 1, a nest for product 2 and then a nest for a bundle of the two products.

The NMNL approach is very flexible and capable of analyzing multiple categories along with the no-choice option which is presented in Figure 5.2.2.
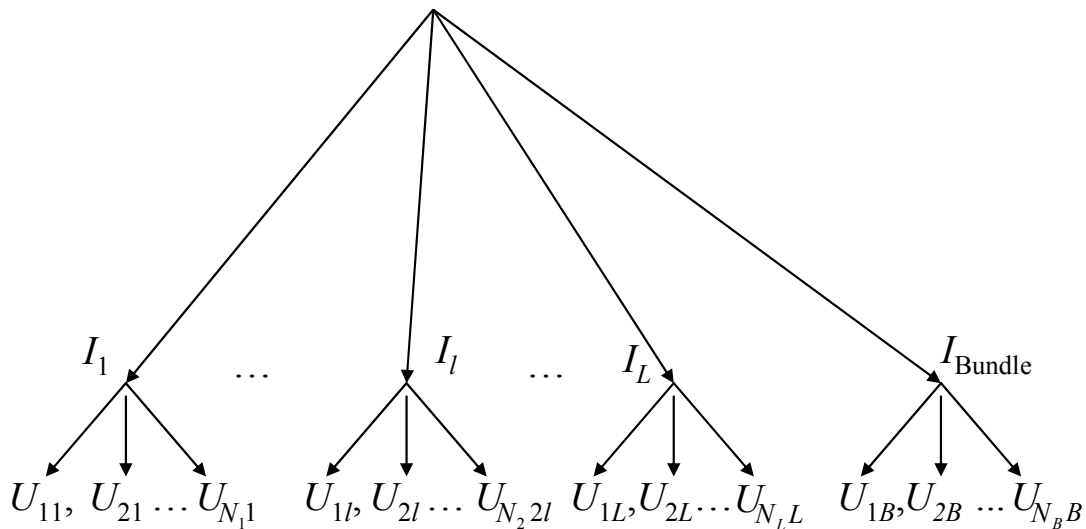
Figure 5.2.2: Discrete Choice Design for Product Bundling

Each of the $l=[1,2,\ldots,L,B]$ nests or categories has an attraction or *inclusive utility, I_l* that determines the overall market share of the product category. *B* represents the bundle nest while individual product competition is represented with $(1,2,\ldots,L)$. This representation in Figure 5.2.2 assumes that any bundle *B* must be made up of all individual products $[1,2,\ldots,L]$ for a manufacturer offering a bundle. That is one product

from each individual nest must make up the bundle. To analyze the situation where n of L individual products are offered as bundles requires an additional bundle nest for each combination of categories.

The inclusive utility I_l of nest l is essentially a function of the utilities U_{il} for each of $i=1,2,\ldots,N_l$ products within the lth category G_l, as shown in Eq. (5.1) (Anderson et al., 1992):

$$I_l = \mu_2 \ln \sum_{i \in G_l} \exp\left(\frac{U_{il}}{\mu_2}\right) \qquad (5.1)$$

where μ_2 is a scaling parameter within the nest which is estimated using conjoint analysis of consumer surveys. The probability of a consumer selecting the category nest G_l is approximated with the nest scaling parameter μ_1:

$$P(G_l) = \frac{\exp\left(\dfrac{I_l}{\mu_1}\right)}{\displaystyle\sum_{l=1}^{L} \exp\left(\dfrac{I_l}{\mu_1}\right)} \qquad (5.2)$$

In the second stage conditional probability of selecting the ith product given the category nest G_l is:

$$P(i \mid G_l) = \frac{\exp\left(\dfrac{U_{il}}{\mu_2}\right)}{\displaystyle\sum_{i \in G_l} \exp\left(\dfrac{U_{il}}{\mu_2}\right) + \exp\left(\dfrac{U_{nc}}{\mu_2}\right)} \qquad (5.3)$$

Thus the probability at the outset of selecting any one product competing within such a cross category environment is a function of product utilities in all of the categories. The market share m of product i in category G_l is then:

$$m_{il} = P(G_l)P(i \mid G_l) = \frac{\exp\left(\dfrac{I_l}{\mu_1}\right)}{\displaystyle\sum_{l=1}^{L} \exp\left(\dfrac{I_l}{\mu_1}\right)} \cdot \frac{\exp\left(\dfrac{U_{il}}{\mu_2}\right)}{\displaystyle\sum_{i \in G_l} \exp\left(\dfrac{U_{il}}{\mu_2}\right) + \exp\left(\dfrac{U_{nc}}{\mu_2}\right)} \qquad (5.4)$$

This NMNL market share calculation forms the cornerstone for rest of the bundle design approach as the innermost layer but relies on some preparatory work including shelf surveys (i.e., what are the competitor attributes?) and consumer surveys for each category (i.e., what do consumers want in terms of product attributes?).

To perform this task, we assume that first, manufacturers will collect customer preference data from likely users using a conjoint analysis (Green and Srinivasan, 1990) based on the alternatives in each of the two categories and the bundles (e.g., 1, 2, and the bundle). Customers are provided choice sets, each with an alternative from product category 1, an alternative from product category 2, and an alternative from the bundle category. Each choice set also has a no-choice option. Based on the choice data from customers across the many choice sets, customer value or utility that customer places on the various attributed of the products and the bundle are estimated. Recent estimation techniques allow estimation of utilities at the individual level using Bayesian techniques (Rossi and Allenby, 2003, or at the segment level using finite-mixture model techniques (Kamakura and Russell, 1989). Based on the conjoint data, customer's probability estimates for choosing one or the other category or the bundle can be estimated at the segment level. Commercially available marketing software (e.g., Sawtooth Software Market Research Tools) (Sawtooth, 2001) can be used to perform these conjoint utility estimates for each market segment and is a suggested methodology to support this framework. The customer choices from the conjoint survey are decomposed into j

attribute utilities using maximum likelihood estimation and ultimately used to calculate

market share. Attribute utilities $u=[u_1,u_2,\ldots,u_j]$ are functions of high level customer

relevant product attributes $y=[y_1,y_2,\ldots,y_j]$. To estimate the total utility U_{il} for a product i

within a category G_l, we sum the attribute utilities u_{ijl}:

$$U_{il} = \sum_j u_{ijl}$$ (5.5)

The market share calculations presented in this section culminate in a monopolist retailer

setting retail prices so as to maximize profit of all categories. When products in a

category within the NMNL formulation have market shares of less than an arbitrarily

small number, 0.5%, due to low utility we can interpret such a situation as the product

being denied shelf space. The setting of retail prices is presented in the next subsection.

5.2.2 LAYER 2: RETAIL PRICING MODEL

At this point we expand the original framework to demonstrate the internal

workings of the retailer pricing model to calculate retailer profit π as he/she sets profit

maximizing prices for all categories given a set of product designs, as shown in Figure

5.2.3.
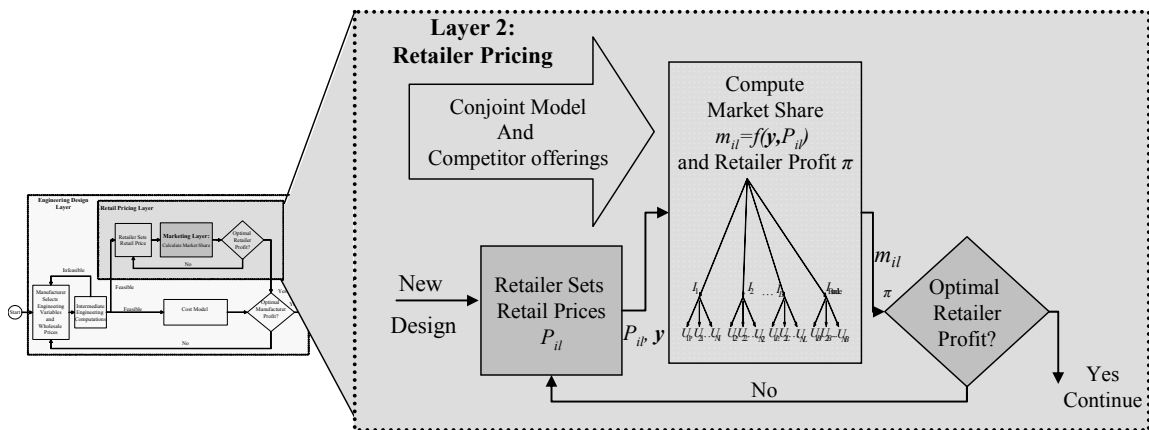
Figure 5.2.3: Retailer Pricing Layer

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In the expanded section of Figure 5.2.3 the retailer pricing model is presented. The retailer observes the attributes of his own assortment and has a conjoint model of customer utilities before setting retail prices for each product, i, in the multiple categories, l:

$$
P_{il} = \begin{matrix}
P_{11} & P_{12} & \cdots & P_{1L} & P_{1B} \\
P_{21} & P_{22} & & & \vdots \\
\vdots & & \ddots & & \vdots \\
P_{N_{1}1} & \cdots & \cdots & P_{N_{L}L} & P_{N_{B}B}
\end{matrix}
\tag{5.6}
$$

P_{11} signifies the retail price of the first product in the first nest/category. Each nest has N_l products and thus the retail price matrix may not necessarily be square or symmetric. These retail prices will be iteratively set to maximize the profit of the retailer. Each iteration consists of setting a retail price, calculating market share and retailer pricing, and then determining if retail profit is optimal as shown in Figure 5.2.3. If profit is optimal the retail price is then known and the algorithm can proceed to the engineering layer. To implement this we must first fully characterize the retailer's profit function within the context of multiple categories, bundles and NMNL. Given that there are a corresponding set of wholesale prices W_{il} assumed in the model for every retail price P_{il} and the possibility consumers may prefer not to select any product (i.e., no choice) U_{nc}, the retailers profit objective becomes:

$$
\max_{P_{il}} : \quad \pi = \sum_{l=1}^{L,B} \sum_{i=1}^{N_l} \left((P_{il} - W_{il}) \cdot \frac{\exp\left(\dfrac{I_l}{\mu_1}\right)}{\displaystyle\sum_{l=1}^{L} \exp\left(\dfrac{I_l}{\mu_1}\right)} \cdot \frac{\exp\left(\dfrac{U_{il}}{\mu_2}\right)}{\displaystyle\sum_{i \in G_l} \exp\left(\dfrac{U_{il}}{\mu_2}\right) + \exp\left(\dfrac{U_{nc}}{\mu_2}\right)} \right)
\tag{5.7}
$$

It is important to note that I_l and U_{il} are functions of retail price which is a customer level product attribute (i.e., $P_{il} \in y$). Utility for a product is downward sloping in price which means that customers (given two identical products) prefer the less expensive alternative. As such the utility for the retail price attribute takes the form: $u_{j=R} = -P_{il} / \beta_R + \beta_o + \varepsilon$, where the price elasticity (i.e., customer response to price increases) is estimated in terms of a negative slope $-1/\beta_R$, an intercept β_o and an error term ε. In turn U_{il} is a function of this $u_{j=R}$ as well as ultimately the attractiveness of the nest I_l. Thus the retailer (regardless of monopoly power) cannot freely increase retail prices. As retail prices approach infinity the market share of all products drops to zero and customers turn to the no purchase or no choice option U_{nc}. Thus even a monopolist must strategically select prices for customer evaluation.

Under certain conditions (i.e., strictly quasiconcave profit functions in a manufacturers own wholesale prices) W_{il} can be estimated using a game theoretic framework (see, e.g., Luo et al., 2007) but a reasonable approximation can also be found by observing actual retail prices and reducing the price by the retailer's gross margin estimated from annual reports. The latter interpretation is used in this work as the strict quasi-concavity of profits cannot be guaranteed for multiple manufacturers whose profit functions we discuss in the next section.

Ultimately, this pricing model allows the retailer to maximize profits across related categories and to take into account the cross category effects of cutting prices on one manufacturer's product to see the relative inclusive utility altered for all products and categories. We believe such an approach more accurately models the decision framework of modern channel controlling retailers as department managers will

inherently seek to maximize departmental profit (multiple related categories) rather than each individual category.

5.2.3 LAYER 3: MANUFACTURING ENGINEERING AND PRICING MODEL

We limit our decision model to a single focal manufacturer and as mentioned previously estimate wholesale prices at competing manufacturers from annual reports and shelf surveys. We make no assumption on wholesale prices for the focal manufacturer and rather allow wholesale price to be a design optimization variable. The manufacturer assumes the static wholesale prices of his competitors from retail prices discounted by a margin approximated from annual reports and then tries to maximize profit by setting optimal wholesale prices. If he sets wholesale prices too high the monopolist retailer reacts by raising prices to the point of negligible market share for the focal manufacturer's products. The optimization algorithm ensures that the manufacturer sets prices with foresight of the retailer's reactions.

Even after bounding our pricing framework in this manner a sizeable problem remains due to the nature of the multidisciplinary decisions that must take place for the manufacturer to optimize profit. The complexity of product category dependencies in bundles along with the strategic response from the monopolist retailer requires that manufacturers develop their product line very carefully.   In our approach, the manufacturer begins by developing engineering models with inputs x. These models serve two purposes: (1) high level product characteristics (e.g., weight, power) valued by customers are estimated through engineering design computations, and (2) product design feasibility in terms of design constraints such as maximum temperatures and stresses in a gear box are estimated.   In the extant methods that consider demand models only one

product's design variables need to be generated since only one category exists. In our approach we are tackling multiple categories/products at once with design dependencies amongst the products due to bundling. As such, more design variables are required. We concatenate the design variables for the different products which are then passed in to the intermediate computations as shown in the lower left of Manufacturer's Bundle Design Framework (Figure 5.2.4).

$$x = \left[\left(x_{G_1}, x_{G_2}, \ldots x_{G_L}\right), x_{Shared}, x_{G_B}\right]$$

Figure 5.2.4: Manufacturer's Bundle Design Framework

When L individual product categories are incorporated into the engineering design simulation, each product category set G_l will have a set of design variables x_{G_l} and wholesale prices W for the focal manufacturer. The manufacturer also develops a set of bundle design variables x_{G_B} if the bundle is to differ from the individual product designs. Finally, the manufacturer can specify which design variables must be common or shared amongst the individual products and/or the bundle with the vector x_{Shared}. This is key to achieving a *product bundle* as opposed to simply offering two products for one price

since some level of product integration is imposed by the shared variables. For each category that the manufacturer wishes to consider in the design optimization wholesale prices $W=[W_1, W_2,...,W_L,W_B]$ should be selected as well. When x and W are sent to the next stage we refer to these vectors together as a candidate design.

The next step is performed in the "Intermediate Engineering Computations" block of Figure 5.2.4. Here engineering design model takes inputs from the lowest level design variables x and simulate higher level (customer relevant) product attributes y. The functions that take place in this stage can be anything from simple mathematical functions that predict an attribute like horsepower to highly detailed finite element simulations that predict stiffness of a power tool's housing. Additionally, the engineering simulations are responsible to check the limitations of the design. That is a function $g(x)$ is calculated and measured relative to a maximum value b. If $g(x)>b$ then the candidate design is rejected and a new design selected.

If the design is feasible, the customer level product attributes y and wholesale prices W are passed to the retail pricing layer and demand model after which ultimately emerges the market share m_{il} of each product which is a critical component of the manufacturer's profit objective and obviously any market penetration objective. Thus the manufacturer is able to influence market share in a couple of different ways. Design variables can be tuned (through optimization) to better address customer preferences in light of the assortment or the manufacturer can reduce wholesale prices to encourage the retailer to reduce retail prices on the focal manufacturer's product.

The last key to the manufacturer's design selection is computing production costs which are of course a critical component of the profit function and takes place in

"Compute Production Costs" block of Figure 5.2.4. Competitor wholesale prices and production costs for all manufacturers are estimated using the parametric approach detailed in Chapter 3. That is wholesale prices and production costs are estimated from wholesale and retail margins found in annual reports and a multi-regression of product attributes currently found in the dominating retailers' assortments.

The estimation of market share, production costs, and proposed wholesale price culminates for the manufacturer at the decision node in Figure 5.2.4 "Optimal Manufacturer Profit?" We can write the manufacturers profit function as the sum of profits derived from each of the product categories (including the bundle category). For the first objective, first we sum the profit in each nest G_l but of course only those i products belonging to the focal manufacturer's (*FM*) offering $i \in G_l^{FM}$. As before (see retailer profit Eq. 5.7) we sum the profit across all nests (See Eq. 5.8.1). Several researchers (see, Stremersch and Tellis, 2002, for a comprehensive summary) have pointed out that in addition to profit, market share (or market penetration) may be equally important in new product introductions. Therefore, we sum the market shares of the manufacturer offerings and determine market penetration Φ (Objective 2, Eq. 5.8.2) as a second objective:

Objectives:

(1) $\displaystyle \max_{x,W}: \Pi = \sum_{l=1}^{L,B} \sum_{i \in G_l^{FM}} \left((W_{il} - C_{il}) \cdot \frac{\exp\left(\dfrac{I_l}{\mu_1}\right)}{\displaystyle\sum_{l=1}^{L} \exp\left(\dfrac{I_l}{\mu_1}\right)} \cdot \frac{\exp\left(\dfrac{U_{il}}{\mu_2}\right)}{\displaystyle\sum_{i \in G_l} \exp\left(\dfrac{U_{il}}{\mu_2}\right) + \exp\left(\dfrac{U_{nc}}{\mu_2}\right)} \right)$

$$(5.8.1)$$

(2) $\displaystyle \max_{x,W}: \Phi = \sum_{l=1}^{L,B} \sum_{i \in G_l^{FM}} \left(\frac{\exp\left(\dfrac{I_l}{\mu_1}\right)}{\displaystyle\sum_{l=1}^{L} \exp\left(\dfrac{I_l}{\mu_1}\right)} \cdot \frac{\exp\left(\dfrac{U_{il}}{\mu_2}\right)}{\displaystyle\sum_{i \in G_l} \exp\left(\dfrac{U_{il}}{\mu_2}\right) + \exp\left(\dfrac{U_{nc}}{\mu_2}\right)} \right)$

$$(5.8.2)$$

Subject to: (1) $\quad g(x) \leq b$ $\hspace{4cm}$ (5.8.3)

$\hspace{2.4cm}$ (2) $\quad \pi_{old} \leq \pi_{new}$ $\hspace{3.7cm}$ (5.8.4)

Initially it is not obvious that the two objectives are competing because their forms are similar. The greatest difference between the two lies in the fact that if wholesale prices are set below production costs profit (Objective 1) will be negative and market share (Objective 2) may be extremely high as the retailer senses an opportunity to increase profit by directing consumers to the low wholesale price product through incentives such as low retail price. While counterintuitive, these negative margins have been observed for several product introductions (see, e.g., Hesseldahi, 2005, who examines the X-box video game console) where maximum market share was the primary consideration. This so called "loss leader" approach is implemented in anticipation of future profits on accessory sales (e.g., software/games). The optimal design for this loss-leader strategy can be found using our multi-objective approach. These profit and penetration formulas Eq. (5.8.1-5.8.2) are flexible in that a manufacturer can offer multiple products within a nest/category as we sum over $i \in G_l^{FM}$ and also the cross

category effects are taken into account with the NMNL calculation. Thus the manufacturer has the ability to assess changes in design variables as they impact the entire product line. Moreover, as discussed previously, the manufacturer faces physical constraints Eq. (5.8.3) and highly consolidated retailer power Eq. (5.8.4) that requires that the retailers new profit π_{new} be greater than the old π_{old} in order to achieve access to consumers. So, in essence, the previous methods (e.g., Williams et al., 2006) have been extended to multiple categories and bundles through an initial calculation of Eq. (5.7) that determines the retailer profit with the existing assortment or π_{old} as shown in Figure 5.2.5.

Design Layer $\Rightarrow$

$$\max_{x, W_{il}} : \Pi$$
$$\max_{x, W_{il}} : \Phi$$
$$\text{Subject to} : g(x) \le b$$
$$\pi_{old} \le \pi_{new}$$

y, W_{il} P_{il}, π_{il}

Retail Pricing Layer $\Rightarrow$

$$\max_{P_{il}} : \pi$$
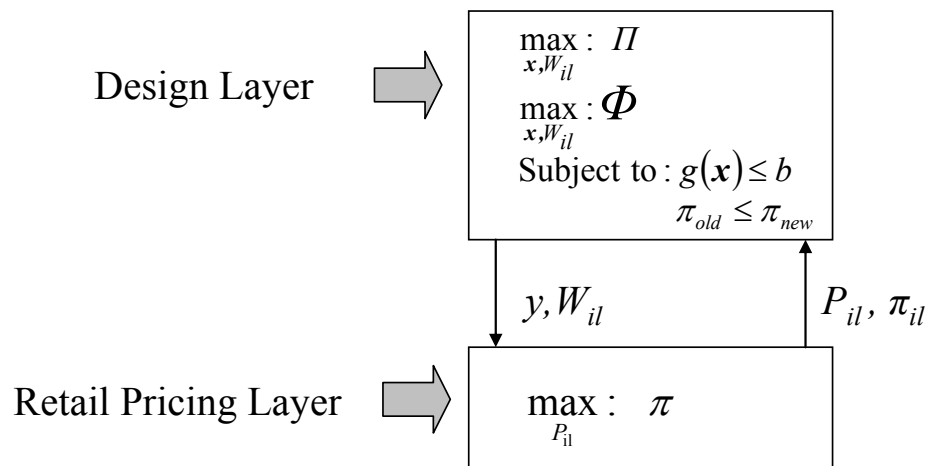
Figure 5.2.5: Nested Optimization

Any proposed set of new products (individual products and bundles) must increase the retailers profit or the manufacturer faces rejection. Thus we provide an additional constraint for the multi-category model that constrains the new retailer profit to being higher than the retailer's prior profit, see Eq. (5.8.4). If the model were extended to consider multiple retailers one would simply add additional constraints for those retailers but the pricing layer becomes much more complicated as multiple retailers must reach a competitive equilibrium in pricing rather than a simple maximization.

In total, Figure 5.2.5 makes up the mathematical formulation of the engineering layer shown in Figure 5.2.4 as well as the retail pricing layer. Given that many design variables are discrete and the desire to find a global optimum for objectives that may not be convex we recommend a genetic algorithm and specifically a multi-objective genetic algorithm (see, e.g., Deb, 2001) to optimize the engineering layer. The retailer profit can be found through a gradient based algorithm because of the quasi-concavity of the NMNL formulation.

5.2.4   MULTIDISCIPLINARY UNCERTAINTY

We propose robust optimization as a method to solve for a focal manufacturer's strategy under uncertainty. Robust optimization, pioneered by Taguchi (1978), seeks to find designs with minimal variation in design's (objective) performance due to variation in uncertain parameters. Although robust optimization has principally been applied to models with variation in engineering parameters (e.g., dimensional tolerances) we believe it is equally amenable to multi-disciplinary sources of uncertainty (e.g., consumer preferences, wire thickness etc.) as demonstrated in (Besherati et al., 2006). We extend the scope of uncertainty to included strategic sources such as competitor reactions in choosing product attributes that might not be strictly quasi-concave (in own profit) decisions.

Uncertain intervals can be constructed from defined probability distributions based on confidence intervals (Besharati et al., 2006) or the decision maker can specify an interval range of uncertainty for parameters before optimization. This can be used to model strategic options of a competitor as an uncertain interval whereby we believe that a competitor might select a product attribute between some lower and upper limits of the

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attribute. In the context of bundling one can specify a range that the bundle product attributes might deviate from the existing individual product attributes since the cost function for retooling the bundled product is unknown. These strategic options are essentially modeled as uncertain parameters which can be accounted for in robust optimization as will be discussed subsequently.

While not computationally trivial, the Multi-Objective Robust Optimization (MORO) technique developed by Li et al. (2006) has many properties that are amenable to finding solutions that are optimal given an acceptable level of objective variation. This approach is capable of finding designs that are *multi-objectively robust* (i.e., the uncertainty considered does not cause variation outside of a range specified for each objective). This range is called the Acceptable Objective Variation Range (AOVR) and is defined by the decision maker. The MORO approach has convenient properties in that objective functions need not be convex in parameter uncertainty since a genetic algorithm is used to probe the candidate design for robustness.

MORO is most easily described graphically but first a few definitions are in order. Uncertain input parameters $\boldsymbol{p}=[p_1, \ p_2,...,p_G]$ are assumed to vary by an amount $\pm\Delta\boldsymbol{p}=[\pm\Delta p_1, \ \pm\Delta p_2,...,\pm\Delta p_G]$ around a nominal parameter value of $\boldsymbol{p_0} =[p_{0,1}, \ p_{0,2},...,p_{0,G}]$ and form a parameter tolerance region as shown in the left of Figure 5.2.6(left).
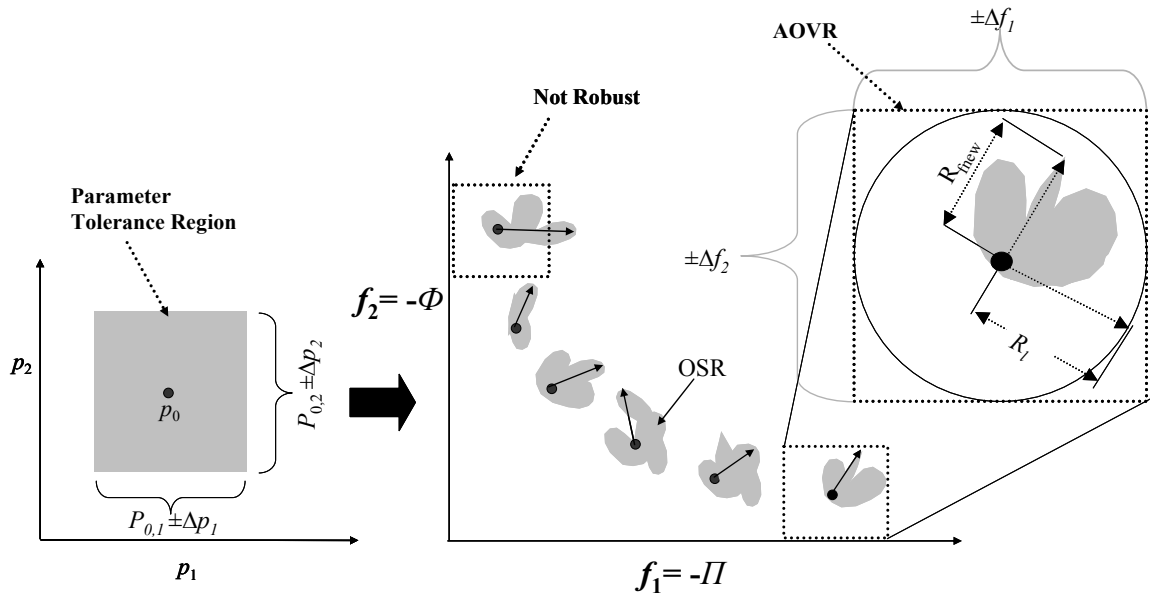
Figure 5.2.6: MORO: Robust Optimization

If the parameter tolerance region were exhaustively mapped to objective space we would see regions of uncertainty surrounding each design which is called the objective sensitivity region (OSR) (grey areas on the right side). In this case we present a set of designs that are multi-objectively optimal with respect to profit and market share on the right side of Figure 5.2.6. In order to define robustness we must first define a range of objectives that the decision maker would find acceptable. The approach has the decision maker define ranges $\pm\Delta f = [\pm\Delta f_1, \pm\Delta f_2, ..., \pm\Delta f_M]$ for each of the objective functions $f = [f_1, f_2, ..., f_M]$ which are first normalized. These ranges make up a hypercube termed the AOVR. The simplest definition for robustness is to say that if AOVR encloses OSR then the design is robust as is the one in the exploded view shown in Figure 5.2.6. Equivalently if we find the Euclidian distance to the worst case of the OSR R_{fnew} is less than the normalized distance to the tangency of the AOVR (R_I) then the design is also robust. For completeness a design that is multi-objectively optimal in a nominal sense yet is not robust per this definition is shown at the top of Figure 5.2.6. This design would

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be rejected for excessive uncertainty. A simplified inner-outer optimization approach is shown in Figure 5.2.7 to accomplish the task of robust optimization. In cases where robust optimization is unable to find a feasible solution (including the robustness constraint) the decision maker can expand the AOVR incrementally. The reader is directed to Li et al., (2006) for further details and detailed comparisons with other approaches.

$$\begin{aligned} \min_{x} &: f_1(x, p_0) = -\Pi \\ \min_{x} &: f_2(x, p_0) = -\Phi \\ \text{s.t.} & \\ & g(x, p_0) \leq b \\ & R_{fnew} - R_I \leq 0 \end{aligned}$$

x R_{fnew}

$$R_{fnew} = \max_{p} : \left[\sum_{m=1}^{2} |\Delta f_m(\Delta p)|^2 \right]^{\frac{1}{2}}$$

$$p_o - \Delta p \leq p \leq p_o + \Delta p$$
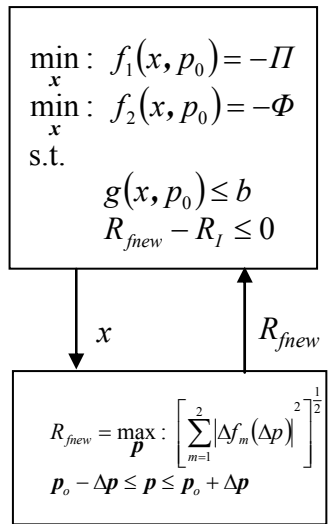
Figure 5.2.7: Robust Optimization Topology

In Section 5.3 this approach will be applied to a case study with multi disciplinary sources of uncertainty that are of consequence to the design of bundled products.

5.3   CASE STUDY: CORDLESS ANGLE GRINDER AND RIGHT ANGLE DRILL

5.3.1   NESTED LOGIT DEMAND MODEL

A bundled product engineering design for notional customer segments was developed based on historical data as a case study for our approach. A *product bundle* of a cordless angle grinder and a cordless right angle drill is proposed as a bundle that is

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likely of interest to customers. The customer preferences for these products and the bundle are estimated using the NMNL model (see Table 5.3.1 and Table 5.3.2). The grinder and drill are each treated as categories (Table 1) that compete with the bundle category (grinder plus drill in Table 5.3.2) within the NMNL model. Each product comes with a battery pack and charger when sold separately and share a battery/charger when sold together in a drill/grinder bundle. Segment specific product attribute utilities u_{ijl} are given in tables one and two along with the nest scaling parameter μ_l.

Grinder Category Utility Estimates					Drill Category Utility Estimates				
Segment	One	Two	Three	Four	Segment	One	Two	Three	Four
Share	37.8%	24.8%	12.1%	25.3%	Share	22.4%	21.2%	34.4%	22.0%
μ_1	0.82	1.02	0.85	1.10	μ_1	0.92	0.94	1.06	0.89
Price					Price				
$99.00	4	3	2	2	$99.00	2	3	2	3
$199.00	0.1	0.1	0.1	0.1	$199.00	0.1	0.1	0.1	0.1
$299.00	-4	-3	-2	-2	$299.00	-2.1	-3.1	-2.1	-3.1
Volts					Volts				
10	-1.25	-0.45	-1.5	-0.5	10	-2.25	-1.45	-2.5	-2.5
25	0.13	0.1	-0.65	-0.38	25	-0.13	-0.1	-0.65	-0.38
40	1.2	1	2.13	2.82	40	2.38	1.55	3.15	2.88
Life (min)-operating time					Life (min)-operating time				
4	-1.4	-1.12	-1.71	-0.8	4	-0.8	-0.5	-0.7	-1.2
10	0.5	-0.47	-0.82	0.74	10	-0.3	-0.5	0.2	0.3
16	0.9	1.57	2.53	1.54	16	1.1	1	0.5	0.9
Girth					Girth				
Small	-2.5	0.7	1.5	-0.6	Small	1.5	1.4	0.5	-0.8
Large	2.5	-0.7	-1.5	0.6	Large	-1.5	-1.4	-0.5	0.8
Weight					Weight				
16lbs	-0.3	-1.2	-0.5	-1.5	16lbs	-2.3	-1.8	-2.5	-1.5
9 lbs	-0.5	0.4	-0.1	0.5	9 lbs	-0.5	-1.2	-1.5	-0.5
6 lbs	0.8	0.8	0.6	1	6 lbs	2.8	3	4	2
No Choice	-2	-2	-2	-2	No Choice	-2	-2	-2	-2

Table 5.3.1:   Grinder and Drill Category Utilities

For motivation it is worth explaining that, an angle grinder is a tool commonly used in many trades for removal of material or cutting while a right angle drill is frequently used for drilling in cramped spaces due to its reduced horizontal clearance. A bundle of these tools would be especially attractive to plumbers, electricians, or even the

weekend hobbyist and requires design integration of the common battery and voltage specifications. The user can expect to receive a reduced price by using the same supporting components (battery pack and charger in Figure 5.3.1).

This complicates the design optimization as the battery pack design must consider the preferences of the shoppers of all three categories (drill, grinder, and drill+grinder) Cordless angle grinders are operated for long periods (minutes at a time) at high RPM (10,000 RPM) while drills are operated for much shorter periods at higher torque (up to 600 in-lbs) and lower RPM (less than 1,750). Due to the nature of these two operating environments one can expect the voltage requirements (directly impacts torque) for each tool and battery capacity (amp-hrs) to be somewhat different for each tool. For example, buyers of angle grinders want longer battery life due to the high RPM and longer tasks while the users of drills are particularly interested in light weight designs.

Bundle Category Utility Estimates

Segment	One	Two	Three	Four	Segment	One	Two	Three	Four
Share	24.7%	21.5%	35.5%	18.3%	Share	24.7%	21.5%	35.5%	18.3%
μ_1	1.26	1.04	1.09	1.01	No Choice	-2	-2	-2	-2

Combined Attributes

Price	One	Two	Three	Four	Bundle Weight	One	Two	Three	Four
$99.00	1	2	1	2	26lbs	-0.3	-1.2	-0.5	-0.5
$199.00	0.1	0.1	0.1	0.1	16 lbs	-0.5	0.4	-0.1	-0.5
$299.00	-1	-2	-1	-2	8 lbs	0.8	0.8	0.6	1
Volts									
10	-1.75	-1.45	-1.48	-2.00					
25	0.00	-0.10	-0.28	-0.52					
40	1.75	1.55	2.08	2.51					

Pure Attributes (bundle context)

Drill Life (min)-operating time	One	Two	Three	Four	Grinder Life (min)-operating time	One	Two	Three	Four
4	-0.80	-0.46	-0.67	-1.18	4	-1.37	1.17	-1.66	-0.76
10	-0.25	-0.48	0.22	0.35	10	0.55	0.48	-0.77	0.76
16	1.05	0.94	0.45	0.83	16	0.82	-1.65	2.43	0.00
Drill Girth					Grinder Girth				
Small	1.52	1.42	0.52	-0.77	Small	1.25	0.98	0.75	-0.61
Large	-1.52	-1.42	-0.52	0.77	Large	-1.25	-0.98	-0.75	0.61
Drill Weight					Grinder Weight				
16lbs	-2.27	-1.80	-2.46	-1.46	16lbs	-0.29	1.21	-0.48	-1.48
9 lbs	-0.46	-1.19	-1.47	-0.49	9 lbs	-0.47	-0.36	-0.07	0.51
6 lbs	2.74	2.98	3.93	1.95	6 lbs	0.76	-0.85	0.55	0.97

Table 5.3.2:   Bundle Category Utilities

We assume that all three categories make up a market size of 20 million units although the exact size of each category is unknown until the shares of the nests are calculated in the NMNL model. The focal manufacturer updating his offering of 1 of 3 drills in the monopolist retailer's assortment as well as 1 of 3 grinders and 1 of 3 bundles in the retailer's assortment. The new offering must be more profitable than the assumed assortment pre-existing on the retailer's shelf. The conjoint analysis of bundle attributes contains more product attributes because each of the tools in the bundle will be evaluated in the context of the nest or category. In addition, the bundled tools have combined attributes such as voltage, price, and combined weight because the bundle has one less battery and will be evaluated as a whole when one considers the contractor who must

carry the tools to and from the jobsite as a set. The grinder and drill individual product weight will each be evaluated with the battery attached.

The differing values placed by the product category segments on product attributes will be important in selecting an optimal design since the nests do not value attributes equally. For example a tension exists between the grinder category that wants long battery life and the tool category that prefers light weight. The engineering design must take this into account in providing all three category designs since the battery design will affect all three categories differently. Product attributes from the left side of Table 5.3.1 and Table 5.3.2 will be computed in the next section.

5.3.2   ENGINEERING PERFORMANCE MODEL

The general universal motor and bevel gear design methodology from Chapter 3 was adapted for the cordless right angle drill and angle grinder. In designing the two individual tools and the bundle the proposed approach was restricted offering the individual tools as a bundle a logical cost savings approach through commonality of components. In the design of electric power tools we have identified 9 design variables that impact higher level attributes that are then translated into utility. Because we are designing two different motors (one for each the grinder and the drill) we have 18 design variables related to motor and bevel gear (Figure 5.3.1). There are also two shared design variables that affect all category offerings from the manufacturer: voltage (volts) and battery size (amp-hrs). Finally, three wholesale prices were also set as design variables, one for the grinder, drill and bundle.

Drill Design Variables (9)	Grinder Design Variables (9)
Stator outer radius R_o (in)* Current I (amps)* Armature wire turns N_c (# of turns)* Stator wire turns N_s (# of turns)* Stator thickness t (in)* Stator Gap thickness l_{gap} (in)* Motor Stack Length L (in)* Pinion Pitch Diameter D_p (in)** Gear Ratio r**	Stator outer radius R_o (in)* Current I (amps)* Armature wire turns N_c (# of turns)* Stator wire turns N_s (# of turns)* Stator thickness t (in)* Stator Gap thickness l_{gap} (in)* Motor Stack Length L (in)* Pinion Pitch Diameter D_p (in)** Gear Ratio r** **Bevel Gear* *Universal Motor*
Battery/Charger Design Variables (2) Voltage V (volts) Battery Size Cap (amp-hrs)	**Wholesale Price Design Variables (3)** Grinder/Drill Bundle Price ($) Grinder Price ($) Drill Price ($)

Note: motor variables *, bevel gear variables **

Figure 5.3.1: Design Variables

The engineering design variables were transformed to intermediate customer relevant variables that are then transformed to utility using linear interpolation of the customer level attributes utilities in Table 5.3.1 and Table 5.3.2 just as we did for one tool in Chapter 3. One of the simplest examples of this transformation is the operating time or battery life of the tool:

$$Life(\text{min}) = 0.7 \times \frac{Cap}{I} \qquad (5.9)$$

where I is the design variable for motor current and Cap is the Battery size and an efficiency factor of 0.7 is applied (Hurricks, 1994). Similarly the girth attribute G of the design is :

$$G(in) = 2 \times (R_o + .5) \qquad (5.10)$$

where R_o is the outer radius of the stator in inches and ½ inch is added to the radius to account for the plastic body of the tool and an air gap for cooling the motor. The weight of the tool is a somewhat more complicated approximation from the design variables and

is presented in Table 5.3.3. This intermediate attribute also has a complicated affect on

market share as it affects each category's overall utility differently.

Density Steel ρ_s (lbm/ in^3)	$\rho_s = 0.283(lbm/ in^3)$
Density of Copper ρ_{copper} (lbm/	$\rho_{copper} = 0.297(lbm/ in^3)$
Face Width b (in)	$b = 0.3$ in
Gear Pitch Diameter D_g (in)	$D_g = D_p \cdot r$
Armature Diameter l_r (in)	$l_r = 2(R_o - t - l_{gap})$
Wrap length l_{rw} (in)	$l_{rw} = 2l_r + 2L$
Stator Mass M_s (lbm)	$M_s = (\pi(R_o)^2 - \pi(R_o - t)^2) \cdot L \cdot \rho_{steel}$
Armature Mass M_a (lbm)	$M_a = A_r \cdot L \cdot \rho_s$
Windings Mass M_w (lbm)	$M_w = l_{rw}(N_c + 2N_s)A_w \cdot \rho_{copper}$
Motor Mass M_m (lbm)	$M_m = M_s + M_a + M_w$
Pinion Mass M_p (lbm)	$M_p = (\pi \cdot D_p^2 \cdot b \cdot \rho_{steel})/4$
Gear Mass M_g (lbm)	$M_g = (\pi \cdot D_g^2 \cdot b \cdot \rho_{steel})/4$
Bevel Gears Mass M_{bg} (lbm)	$M_{bg} = M_p + M_g$
Battery Mass M_{bat} (lbm)	$M_{bat} = Cap + 0.5$
Fixed Mass M_f (kg)	$M_f = M_{commutar} + M_{Arbor} .... = 1.2(lbm)$
Total Mass M_t (kg)	$M_t = M_{bg} + M_m + M_f + M_{bat}$

Table 5.3.3:   Cordless Tool Mass Computations

The mass of the battery M_{bat} is an approximation based upon a survey of

commercially available replacement batteries for power tools. It is important to note that

the battery capacity impacts two performance attributes in the design (weight and battery

life) which affect each category differently as shown in Table 5.3.1 and Table 5.3.2 utility

estimates.

Integer Turns	$N_c, N_s = \text{int}$
Length to Diameter Ratio	$L/G \le 5$
Flux Density armature B_r (Tesla)	$B_r = \phi/((\pi \cdot l_r^2)/4) \le 1.5 Tesla$
Flux Density Stator B_s (Tesla)	$B_s = \phi/(2 \cdot L \cdot l_r) \le 1.5 Tesla$
Flux Density Air Gap B_g (Tesla)	$B_g = \phi/(L \cdot l_r) \le 1.5 Tesla$
Armature Heat Flux K_s (A/m)	$K_s = \dfrac{N_c \cdot I}{\pi \cdot l_r} \le 10000$
Stator Heat Flux K_s (A/m)	$K_s = \dfrac{N_s \cdot I}{\pi (l_r + t)} \le 10000$
Contact Stress σ_f (Pa)	$\sigma_f = Z_H Z_e \sqrt{\dfrac{K_a K_m F_i (d_v + D_v)}{(d_v D_v)}} \le 720 MPa$
Bending Stress σ_b (Pa)	$\sigma_b = (K_a K_m F_i)/(m \cdot J) \le 145 MPa$
Armature Tip Velocity v_a	$v_a = \pi \cdot N_{motor} \cdot l_r \le 10000\,(ft/s)$

Table 5.3.4: Common Constraints

A set of constraints is implemented for each class of power tool though the universal motor and bevel gear overall design is general in nature. This is because the usage scenario of each motor is far different (e.g., high torque necessary for drill, high RPM necessary for grinding). The common constraints (Table 5.3.4) are implemented for each design while Table 5.3.5 constraints are individual product specific. In total there are 24 constraints for the overall engineering design $(2 \cdot 10(common) + 2(drill) + 2(grinder)) = 24$. If the bundle products were not forced to follow the individual product category designs an additional set of engineering constraints would be necessary. Due to space constraints it was not possible to demonstrate all intermediate computations. For details on calculating the following intermediate design variables (flux ϕ, module (pinion) m, motor RPM N_{motor}, torque T, gear cone depth D_v, pinion cone depth d_v, tooth loading intensity F_i, zone factor Z_H) and selection of design constants (Z_e, K_a, K_m, J) see Chapter 3.

For the grinder, two unique constraints were implemented to ensure safe operating speeds and adequate grinding RPM. The range of output RPM was limited from 8000 to 10000. 10000 RPM is the upper limited allowed by the manufacturers of the grinding disks that are commonly sold for the angle grinder while 8000 RPM under no-load

conditions ensures adequate operation for material removal. Right angle drills are used to bore large holes through wall studs for routing plumbing and electrical services. The large drill bits require significant torque so the output was constrained to greater than 500 lbf-in which is appropriate for high quality consumer grade power tools. In addition, the no-load output RPM was limited to 1750 to ensure a reasonable operating range for drilling in wood.

Motor RPM N_{motor}	$N_{motor} \leq 40000$
Grinding Wheel RPM $N_{out\text{-}grinder}$	$8000 \leq (N_{out\text{-}grinder} = N_{motor}/r) \leq 10000$
Drill Torque T (lbf-in)	$T \geq 500 \ (lbf - in)$
Drill Output RPM $N_{out\text{-}drill}$	$N_{out\text{-}drill} = N/r \leq 1750$

Table 5.3.5:   Grinder and Drill Performance Constraints

Finally, a battery cost model was added to the motor-bevel gear cost model (Section 3.5) based upon a market survey of battery costs and a simple multi-regression of two coefficients: voltage and battery size.

$$BatteryCost(\$) = 1.51 \cdot V(Volts) + 10.3 \cdot BatterySize(Amp - hrs) \qquad (5.11)$$

The battery design (cost) is then very important and affects three attributes as the customer segments are sensitive to the performance (i.e., voltage and battery life) as well as have significant utility for lower prices. The tension between these performances attributes, engineering design constraints, and strategic interplay makes for an interesting case study and test bed for our proposed methodology.

5.3.3   CASE STUDY SOURCES OF UNCERTAINTY

For this case study, it is assumed that the manufacturer wishes that his profit, and market penetration be maximal but also wants the projected profit and penetration results to be insensitive to uncertainty. Using the MORO approach discussed previously we set the AOVR of the objectives $\pm\Delta\boldsymbol{f}_M$ to $\pm10\%$. That is, if the projected profit or market share of the candidate design varies by more than 10% the design is rejected. Some may argue that simply maximizing the expected value of profits and market share is sufficient but firms can be placed at a serious disadvantage if they under-perform earnings forecasts significantly. Our use of robust optimization helps ensure that forecasts are closer to targets under the uncertain parameter intervals considered. Additionally, one might question why an upper limit on profit or market share variation need be enforced. Consider the case of extremely strong demand where a manufacturer cannot fulfil orders due to capacity limitations. In such a case the powerful retailer may penalize the manufacturer by a degraded evaluation of ability-to-deliver for future product transactions or even through a contract instrument that financially penalizes non-performance. Thus both underestimating and overestimating performance have negative implications regardless of the expected value. The MORO is one approach to reducing the inaccuracy of objective estimates through engineering design.

As discussed in Section 5.2 we can use MORO to mitigate the affect of the multiple sources of uncertainty in a product design optimization. Sources of uncertainty in the case study come from 3 disciplines: strategic uncertainty (competitor attributes), manufacturing tolerances, and cost model projections. Since it is not possible to consider all sources of uncertainty we limit our focus to a few candidates from each discipline.

The first three parameters considered will endogenize the possibility that a competing manufacturer may cut his/her wholesale prices to suboptimal levels with respect to the firm's own profit. Thus the wholesale prices of the grinder, drill and bundle for a competitor ($WP_{grinder}$, WP_{drill}, and WP_{Bundle}) are allowed to vary during robust optimization by $\pm30\%$ from their nominal value. The nominal value of the wholesale price is estimated using multi-regression and annual reports as formulated in Section 3.5. The competitor might also change other important product attributes such as voltage and battery size. As such, we also allow these values to vary by $\pm30\%$ during robust optimization from the value observed for the competitor in the shelf survey. If the $\pm10\%$ variation in objective functions cannot be met the decision maker can reduce uncertainty in the model inputs or expand the scope of the acceptable variation and then rerun the robust optimization.

Next, we include considerations for manufacturing tolerance uncertainty. The stator outer radius R_o and the stack length L were allowed to vary for the focal manufacturer by $\pm1\%$ which is a considerable tolerance region. This uncertainty impacts strategic positioning by affecting the mass of the tools but also the ability of the tool to carry voltage and current or to stay within pre-defined operating limits (i.e., motor RPM in Table 5.3.4). Thus the method insures that constraints are met under uncertainty and that changes in attributes do not cause too great of variation in profit or market share. Additionally, these attributes impact the production cost function as weight impacts the cost function significantly. Lastly, we address uncertainty in the cost function estimate itself by assuming that the power/weight ratio cost coefficient in (Williams et al., 2006) is allowed to vary within its 95% confidence interval estimated during the multi-regression.

These uncertain intervals (5 strategic, 2 manufacturing, and 1 cost = 8 total) that make up the parameter tolerance region can be expanded or contracted along with the AOVR in accordance with the risk aversion of the decision maker for the focal firm. In addition, the number of sources of uncertainty considered can be expanded as the risk aversion of the firm increases. Ultimately though, a balance must be struck between the size of the AOVR and the uncertainty intervals as no feasible results can be found with an extremely small AOVR and large uncertainty intervals.

5.4   OPTIMIZATION APPROACH

We used Matlab's Genetic Algorithm and Direct Search (GADS) Toolbox to develop a MOGA to simultaneously optimize market share and profit for the subject manufacturer using a non-dominated sorting algorithm for design ranking (Deb, 2004). The 23 design variables were encoded in a binary format with lower and upper bounds specified. The wholesale prices were allowed to increase to $2,000 each as a method to eliminate any unprofitable product from the manufacturer's product line. Such a price would result in a miniscule market share that would be truncated from consideration by a decision maker. The design variables were encoded as 12 bit binary strings and run with a population size of 200 for 200 generations. Additionally, the MOGA was set to terminate if objective function values change less than 10^{-6} over 50 generations or change less than 10^{-6} or a time period of 600 seconds. Constraints were handled using the "Feasible Over Infeasible Approach" (Deb, 2001) where violated designs are set equal to the worst function call plus a penalty. Additionally, a crossover fraction of 0.6, a mutation rate of 0.1 and an elite fraction of $1/3^{rd}$ were used. The inner optimization in Figure 5.2.5 for retail price setting is strictly quasi-concave (Anderson et al., 1992) for

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monopolies. As such, we implemented this in Matlab's minimization routine "fmincon" where retail prices were constrained to being greater than wholesale prices. As mentioned previously, the robust optimization approach used was MORO and implemented as described in Li et al., (2006) which has an inner optimization that uses a genetic algorithm to find the expected global solution.

5.5   RESULTS AND DISCUSSION

One case was run for both the nominal or non-robust monopoly case and the robust-monopoly case for bundled product design. Figure 5.5.1 shows Nominal Pareto Design frontier (non-dominated solutions) with squares and the Robust Pareto Design frontier as diamonds. Robust solutions are plotted at the uncertain parameter's nominal value so one can think of the position on the graph as being unable to move greater than 10% in any direction under the tolerance region considered. Both results show that a wide range of optimal market penetration and profit results are possible along the Pareto frontier although a much larger range of possibilities exists for the robust design approach. These plots confirm that a tension exists between market share and profit as objectives as suspected. Market share can be gained at the expense of profit and vice versa. We also see that market share and profit can only be traded against one another to a limited extent by varying the product design.

Interestingly, the practice of offering products at a loss to achieve market penetration (e.g., X-box, inkjet printers) is confirmed in the negative profit regions of the Robust Pareto Designs on Figure 5.5.1 where the market share realized nearly reaches 60% or 12M units at a $272M loss This result is possible because the customers are sufficiently elastic (sensitive) to price and the wholesale pricing was allowed to reach

values far below marginal cost which encouraged the retailer to lower prices and direct market share to the focal manufacturer. This result can also be achieved by designing extremely high quality goods (i.e., greater utility) and offering these goods at below cost. It need not be a situation where a mediocre good is offered at an extremely low price. Both types of solutions exist along the Robust Pareto Designs. This is a business model akin to that employed for the X-box and inkjet printers where manufacturers accept losses to achieve future revenue streams on software and ink.

Finally, we are able to see the impact that the decision making structure has on the profitability of designs along the Pareto Frontier by overlaying the Pareto curves on Figure 5.5.1. By virtue of the fact that robust design optimization requires an additional robustness constraint relative to the original problem it is observed that the robust solutions are dominated by the nominal solutions.
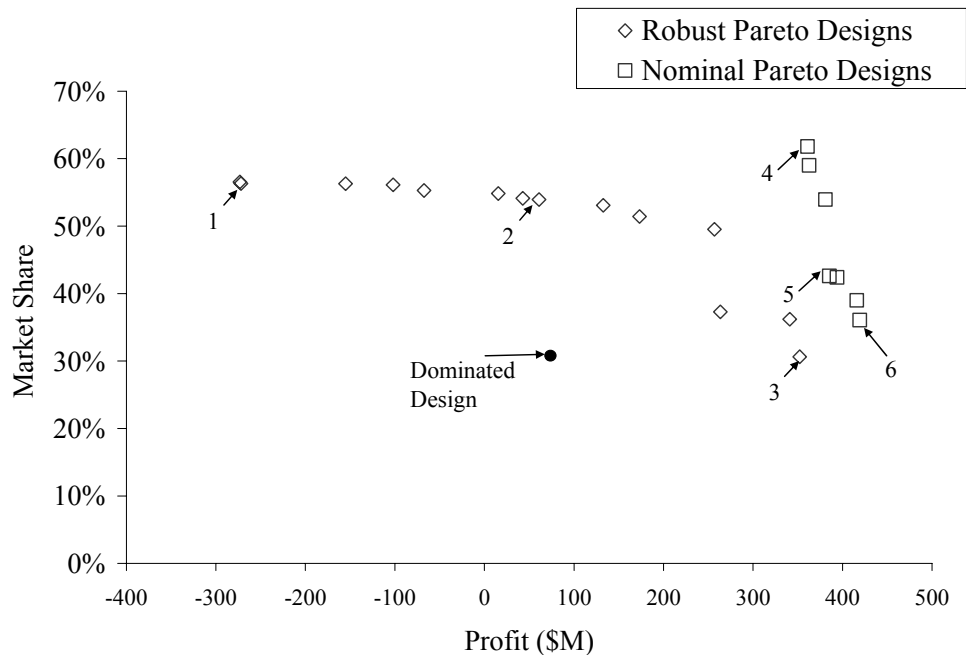

Figure 5.5.1: Robust/Nominal Pareto Comparison

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To demonstrate how designs along the Pareto curve can be achieved we present 6 designs (as indicated on Figure 5.5.1) in Table 5.5.1. Design 1 is highly unprofitable yet captures high levels of market share by offering better attributes at higher production costs yet with low wholesale prices or a negative margin. The profitable designs (2, 3, 4, 5 and 6) have much lower voltages and lower battery capacities in general which results in a lower production cost. It appears that given consumer price elasticity from the conjoint estimates that low cost/lower performance strategies are better for the focal manufacturer given the assumed strategic framework (monopoly) and competitor assortment.

	Robust Monopoly						Nominal Monopoly					
	Design 1		Design 2		Design 3		Design 4		Design 5		Design 6	
	Grinder	Drill	Grinder	Drill	Grinder	Drill	Grinder	Drill	Grinder	Drill	Grinder	Drill
N_c (turns)	130.73	118.43	130.00	121.24	118.96	133.99	101.01	92.08	110.19	96.30	98.90	114.58
N_s (turns)	42.33	15.30	38.86	15.77	39.04	15.06	28.23	16.71	26.48	16.82	43.24	16.72
R_o (in)	0.59	0.62	0.59	0.62	0.59	0.61	0.64	0.44	0.53	0.45	0.47	0.44
T (in)	0.22	0.28	0.22	0.28	0.28	0.32	0.14	0.14	0.17	0.18	0.13	0.14
l_{gap} (mil)	3.78	2.28	3.27	2.76	1.69	2.87	0.12	3.19	0.24	3.19	0.35	3.15
L (in)	2.68	2.57	2.67	1.89	2.60	2.06	2.79	2.73	2.78	1.66	2.80	2.73
r (ratio)	1.99	2.56	2.65	2.62	2.66	2.07	2.01	4.37	2.01	3.39	2.01	4.37
D_p (in)	1.25	0.69	1.25	0.68	1.24	0.66	1.51	0.65	1.39	0.83	1.51	0.64
V (Volts)	41.79		31.13		17.07		23.75		21.58		15.44	
Cap (amp-hrs)	1.43		1.23		1.26		1.10		1.10		1.11	
Girth (in)	2.17	2.23	2.17	2.22	2.18	2.22	2.27	1.88	2.27	1.90	2.18	1.88
Mass (lbm)	5.87	5.54	6.41	5.37	6.21	5.27	6.84	5.76	6.11	5.40	6.22	5.79
Duration (min)	2.21	2.28	2.92	2.23	2.36	1.83	2.46	1.51	3.26	1.51	2.46	1.93
Prices												
Pure Price	$76.16	$98.18	$76.35	$92.13	$76.54	$90.81	$82.14	$96.91	$98.18	$90.91	$79.04	$96.88
Bundle Price	$115.44		$116.95		$129.10		$122.72		$110.22		$122.62	
Market Share												
Pure Share	5.92%	19.12%	5.30%	32.58%	8.10%	17.24%	38.03%	12.05%	24.94%	10.16%	22.17%	8.40%
Bundle Share	20.75%		16.40%		10.82%		11.57%		7.21%		5.50%	

Table 5.5.1: Sample of Optimal Designs

It is worth noting that retailer profits benefit from the design optimization of the product bundle. Otherwise the designs would be rejected by the retailer who can reject a design by raising the price to high levels and therefore eliminate market share. Further evidence of the improvements offered by bundle design optimization can be seen in the market shares estimated by the approach. The bundle products share significant market

share with the individual product categories for many of the optimal designs. Overall the robust offerings from the focal manufacturer tend to have more attractive bundles as evidenced by the higher market shares for the bundle versus the non-robust designs. This observation is an additional motivation for pursuing bundle design for manufacturers. Lastly, we see a slight shift from the manufacturer emphasizing the grinder design to the drill design as he/she attempts to make the designs more robust. The emphasis is shifted by reducing the wholesale price of the drill, reducing the weight of the Drill through engineering design changes, and most importantly by increasing the voltage which is highly valued by drill shoppers. This somewhat unexpected trend demonstrates the importance of considering the categories simultaneously in the NMNL formulation. Making these engineering design decisions without such a model would lead to suboptimal cross category profit cannibalization for the manufacturer which is of great concern considering the number of manufacturers offering bundles and products in multiple categories.

5.6 SUMMARY

This chapter has presented a new approach to developing bundled product designs within a retail channel setting. The NMNL approach considers demand dependencies amongst the product bundle and individual product categories while our nested optimization of retail prices accounts for the increasing clout of retailers in the market place. The case study demonstrates the effectiveness of this new methodology on a bundle-relevant product category in optimizing profitability and market share. Considering the bundle and individual products simultaneously has important design implications as shown in the power tool case study where each individual tool and bundle

relies upon the same battery pack and voltage that would likely be suboptimal for either tool in isolation. Additionally we have shown that robust optimization can account for multiple sources of uncertainty including the competitor strategies and that hedging against such strategies requires design consideration (i.e., optimal robust designs are different than nominally optimal designs). Our approach is distinct as a design methodology in that we take into account monopolist pricing as developed in Chapter 4 as well as a retailer acceptance criterion established in Chapter 3 which we demonstrate are important factors in calculating profit and market share.

This concludes the main body of this dissertation. In the next chapter, concluding remarks about all three research thrusts will be made. Additionally the primary contributions of this work will be discussed along with possible future areas of research and extensions.

CHAPTER 6:   CONCLUSIONS

This dissertation has focused on engineering design optimization of products for retail channels.   The powerful downstream position of retailers from manufacturers allows them to unilaterally make two decisions that greatly impact manufacturer profit. The two retailer decisions are: (1) whether to commit or deny shelf space to a product and (2) what prices should be set for the assortment. These are the fundamental issues of this dissertation as ultimately these decisions affect the success of any engineering design.

After introductory material and terminologies in Chapters 1 and 2, Chapter 3 (Research Thrust 1) is focused on developing a framework for answering the manufacturer's first decision: "will this design make it to market?" under myopic or non-strategic conditions which in reality means "does the profit improve the retailer's profitability?" If so, it the product is likely to make it to market. Additionally, marketing considerations such as slotting allowances and a switching cost threshold are considered in concert with engineering design. Chapter 4 (Research Thrust 2) extends the design methodology from Chapter 3 to consider retailer and manufacturer price setting to answer the manufacturer's second question: "what design will perform well assuming prices reach equilibrium at the wholesale and retail level?" under strategic considerations. This means that the focal manufacturer expects all other players (manufacturers and retailers) to play their best response to all other best response functions and his design should be optimal under that scenario. Chapter 5 (Research Thrust 3) addresses the first question but reframes the second question to "what design is optimal if uncertain strategies and outcomes go against me?" This means he wishes to consider in advance how other player's strategies and even events might make his design suboptimal. Additionally the

approach in Chapter 5, extends the prior approaches to multiple products sold separately and in a bundle. Robust optimization is applied as an approach to consider multi-disciplinary sources of uncertainty.

In this chapter, conclusions and highlights about each of the Research Thrusts are provided in Section 6.1. The main contributions of the dissertation are discussed in Section 6.2 and possible future research directions are presented in Section 6.3.

6.1 CONCLUDING REMARKS

A subsection is devoted below to concluding remarks for each of the Research Thrusts.

6.1.1 ENGINEERING PRODUCT DESIGN OPTIMIZATION FOR RETAIL CHANNEL ACCEPTANCE

In this first research thrust the dominance of the channel dominating retailer was established with significant evidence from news reports (Frontline, 2004), academic journals (Singh, 2006), annual reports (Annual Reports, 2006) and even books devoted to channel dominating retailers (Fishman, 2006). Although modern design methodologies do take into account the preferences of the end consumer the extant approaches have neglected the preferences of the retailer and in particular neglected the engineering design considerations. The strong evidence of channel control which dictates a need to develop designs that have a high probability of acceptance to the retailer was the impetus for this research thrust.

While typical design methodologies attempt to maximize customer utility they do not address the metric by which retailers measure a product: assortment profitability (Simpson et al., 2001). The impact of a new product design on retailer's assortment

determines its likelihood of acceptance. If the design provides significant profit improvements for the retailer one would expect that the design would readily have access to shelf space. This concept of requiring that designs improve retailer profitability or provide an improved value proposition is the basis of research thrust one.

The manufacturer can improve retailer profitability and gain access to the market in one of three ways: (1) providing low wholesale prices for improved retailer margin, (2) designing products with increased customer utility to allow increased retail prices or an alternative for those customers not currently purchasing a product, or (3) providing a slotting allowance to the retailer. The first method is obvious and directly reduces the profitability of the manufacturer's product which is our focus along with attaining channel acceptance. The second and third approaches are used simultaneously in this research thrust to increase profitability of the retailer while simultaneously ensuring channel acceptance.

To model retailer acceptance and increase profitability, a discrete choice model consisting of latent class segments is employed. This approach allows one to consider the preferences of like customers separately to determine how a potential design fits the market. This is key to assessing the impact on the retailer's assortment with regard to profitability and thus acceptability. Through a careful translation of engineering design variables into higher level customer relevant product attributes one can estimate the segment share attained by any given engineering design. This estimation of segment share leads to an estimate of market share which directly contributes to the manufacturer's profitability and along with retail margins determine retailer acceptance.

To model the retailer acceptance criteria a chance constraint is employed. This chance constraint takes into account the uncertainty in customer preferences along with the effect of slotting allowances which is added as a deterministic quantity. The chance constraint provides a convenient framework to assess the probability of acceptance of the design given uncertain segment preferences and allows the manufacturer to simultaneously tailor his slotting allowance to achieve a probability of retailer acceptance.

In this research thrust, it is demonstrated that both improved design and slotting allowances can increase manufacturer profitability and the probability of retail channel acceptance. Additionally, it is demonstrated that a wide variety of designs are optimal (in a multi-objective sense) depending upon the level of profit and probability of acceptance required by the manufacturer. Finally, this research thrust provided the groundwork for profit estimation, channel acceptance criteria, and the case study that were used heavily in the subsequent thrusts.

6.1.2   STRATEGIC ENGINEERING PRODUCT DESIGN FOR MONOPOLISTIC AND DUOPOLISTIC RETAIL CHANNELS

This research thrust extends the effort to considering pricing reactions at the retailer and manufacturer levels. Given that retailers attempt to maximize the profit of their assortment, one would expect them not to passively accept the manufacturers' suggested retail price and rather act strategically to optimize profits. This is, of course, another departure from the extant literature that assumes that the manufacturer interacts directly with the end customer.

To implement such an extension a strategic pricing framework is developed that allows manufacturers and retailers to anticipate the strategic moves of their competitors

and downstream channel partners under a variety of channel structures. The framework allows the focal manufacturer to generate and evaluate designs in the context of the channel structure and therefore optimize designs taking into account the strategic pricing of wholesale competitors as well as the ensuing price competition that takes place at the retail level. An existence proof for a unique Nash equilibrium is provided in Appendix B for the retailers and manufacturers. A unique equilibrium is necessary for the manufacturer to accurately assess the optimality of any of his/her engineering designs.

Several channel structures are investigated and compared in this research thrust. They include: manufacturer oligopoly – retailer monopoly, manufacturer oligopoly – non-differentiated retailer duopoly, manufacturer oligopoly – differentiated retailer duopoly, and manufacturer oligopoly - retailer duopoly with exclusive contracts. In all of the cases, a multi-objective genetic algorithm is used to simultaneously optimize manufacturer and retailer profit. This provides an alternative approach to ensuring channel acceptance. Designs on the Pareto frontier with high retailer profits would very likely achieve greater retailer acceptance than those only marginally better than the current assortment.

In comparing the various channel cases one can conclude that different designs are optimal dependent upon the channel case and the manufacturer's commitment to improving retailer profitability. Consistent with economic theory (Osborne and Rubinstein, 1994) the monopolist achieves the greatest profits for the retailer and the least profitability for the focal manufacturer. The manufacturer appears to be able to take advantage of the differentiated duopoly to specifically tailor products that better fit the two retailer's assortments than when the retailers are identical. The exclusive contract

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between manufacturer and retailer is becoming more common in industrial practice and for good reason. It appears that by creating a design specifically for his channel partner the manufacturer is able to raise that retailer's profits substantially. The downside is that the manufacturer loses access to the other retailer and forgoes significant profits through reduced market share.

Ultimately, this research thrust has demonstrated the need for manufacturers to not only take into account pricing reactions of competitors but also the channel structure itself. It also provides manufacturers with a framework to pursue exclusive contracts as an alternative to slotting allowances as they substantially improve the retail partner's profits.

6.1.3 MULTI-CATEGORY DESIGN OF BUNDLED PRODUCTS FOR RETAIL CHANNELS CONSIDERING DEMAND DEPENDENCIES AND UNCERTAINTY IN COMPETITIVE RESPONSE

This research thrust extends the analysis of retail channels to consider multiple product categories and the bundle of products from those categories. Because, to some extent, products from different categories can act as substitutions for products in other categories demand dependencies exist between the categories. Additionally, a product bundle acts as a substitution for any of the individual products. This is of concern to the retailer and manufacturer alike as cross category substation will affect category profit which is the metric that retailers use to accept or deny manufacturer product offerings.

Realizing these demand dependencies exist, a design optimization formulation has been demonstrated that allows a manufacturer to consider the impact of offering bundled products along side individual products. A NMNL formulation is used to estimate

market shares for all products from within the different product categories where bundles are treated as an additional nest along side the individual products. In this formulation, as a product design becomes more attractive it increases the utility of the corresponding nest. That nest or category increases in inclusive utility which increases the overall market share of the nest at the expense of other nests or categories. Using this approach the manufacturer is thus able to measure to the cross category effect and therefore able to optimize designs for profit across multiple categories.

Demand estimation is just a portion of the overall multi-category product optimization framework. Additionally, this approach considers that a design dependency exists between the products. A design dependency means that products from different categories must share design variables. In the example provided, the tools must share the same voltage level and battery pack. The approach used in this research thrust treats these design dependencies as common or shared design variables in the MOGA. That is the voltage and the battery capacity of the individual products and the bundle must be the same. The selection of shared variables in the multi-category framework then becomes extremely important as they impact the desirability of all individual products as well as the bundle.

Similar to Research Thrust 2, this research thrust considers that retailers will set profit maximizing retail prices after a manufacturer offers a design. Instead of assuming that wholesale prices shift to a Nash equilibrium as well this research thrust assumes that manufacturers have imperfect information, may not act rationally (maximize profit), or may have different objectives (market share for example). The uncertainty in manufacturer responses is treated similar to machine tolerances or environmental

uncertainty in formulating a robust optimization of the multi-category design framework. We assume intervals of uncertainty for these multi-disciplinary sources of uncertainty and show that all can be managed at one time using a deterministic robust optimization approach.

A case study is developed for two power tools that operate off of the same battery pack and optimized under the pricing framework of a monopolist retailer. A multi-objective optimization is performed for profit and market share which are shown to be competing objectives. Additionally, a robust optimization considering uncertainty in competitor response at the wholesale level, manufacturing tolerances and cost is performed. The nominal optimum solutions dominate the robust solutions as is to be expected considering the additional constraint imposed (profit and market share must vary by less than 10%). Most importantly, one can observe that the optimal design characteristics change depending upon the focal manufacturer's objectives and tolerance for uncertainty in the objective functions. Robust designs are significantly different than nominally optimal designs. For example, robust designs exhibit much higher voltages and lower wholesale prices. Finally, the retailer reacts favorably to the bundled products by pricing them in a way that it attracts significant market share in competing against the individual products. Ultimately, this effort has provided a much more rich and realistic framework for manufacturers to simultaneously design products and product bundles for multiple categories consistent with actual industrial practice.

6.2   MAIN CONTRIBUTIONS

Several new product design optimization approaches have been developed in this dissertation that specifically tailored for the emerging clout of channel controlling

retailers. Each of the research thrusts provides a step forward in terms of discipline integration with engineering design relative to the extant approaches.

In research thrust one several contributions are made that make the rest of the dissertation possible:

- A design acceptance criterion is established based upon the profitability of the retailer's assortment. This criterion mimics the reality of the retailer decision making process and is modeled in a chance constrained formulation that allows the manufacturer to gauge the probability of acceptance for any candidate design. This improvement allows manufacturers to simultaneously quantify profit and risk for a design decision.

- Slotting allowances are incorporated in an engineering design framework. This extends the engineering design approach to include a very realistic marketing consideration. Additionally, the approach mimics reality by having the manufacturer pay a deterministic quantity to offset the uncertainty in the retailer's profit. It is shown how a designer can use slotting allowances for any given design to achieve a probability of acceptance. This may be a good alternative to changing the design to improve acceptability since it is possible to achieve higher profits for a given level of acceptability by offering a slotting allowance as compared to changing the optimal design.

- Cost and market share are modeled and optimized simultaneously with respect to engineering design. Costs are predicted with financial analysis

and multi-variable regression while market share predicted through a discrete choice analysis that includes latent consumer segments.

- An optimization approach is presented to allow a manufacturer to trade profitability versus the probability of retailer acceptance. The approach uses the uncertainty in a conjoint estimate to develop a chance constraint that bounds the feasible region for engineering design. The objectives are traded against one another using the constraint epsilon approach.

Research Thrust 2 builds on the work of Research Thrust 1 with the primary focus on manufacturer and retailer strategies:

- The primary contribution of this research thrust was to integrate the pricing structure in retail channels in the design process. Prior approaches assumed that both manufacturer competitors and retailers were passive upon the entry of a new product.

- Several pricing structures are developed that allow the manufacturer to more accurately gauge the positioning of a design within the marketplace. These structures are the most common in channel environments and all assume that an oligopoly of manufacturers provides products at a price to: a monopolist retailer, identical duopolistic retailers, differentiated duopolistic retailers, and duopolistic retailers with exclusive contracts.

- Proof of a vertical Nash equilibrium is provided for multi-product retailers supplied by single product manufacturers.

- In this research thrust, profit of both the focal manufacturer and retailers is optimized simultaneously. This provides the manufacturer with a new

way to gauge retail acceptability of a candidate design. A risk-averse manufacturer can forego profit for the retailers sake to improve acceptability by choosing a design along the Pareto frontier.

- The approach allows us to quantify the value of providing an exclusive contract to a retailer which it turns out is substantial.

- Under each of the pricing structures a variety of optimal designs are demonstrated which provides credence to the belief that the channel environment should be taken into account by designers.

In Research Thrust 3 the overall approach is extended to consider multiple product categories (*including bundles*) *along with uncertainty in competitive response*:

- The extant engineering design literature has not considered demand modeling for multiple product categories which is the foundation of this thrust. Multiple product category demand is estimated using a NMNL formulation. This provides the means to evaluate any candidate design's affect on the in-category assortment as well as the related category assortments since some degree of substitutability exists across categories.

- Product bundles are increasingly pervasive in retail markets and the new approach offered in this thrust allows retailers and manufacturers to evaluate the attractiveness of product bundles to end consumers as well as the impact of the bundle on the individual product's profitability.

- The design of product bundles is formulated for simultaneous evaluation next to the manufacturer's individual products. The approach allows

manufacturers to create products that are both optimal when sold as a bundle and optimal when sold as individual products.

- Due to the fact that game theory cannot predict all strategic actions an alternative design framework is developed to consider the actions of competitors. Uncertainty in strategic actions is very large at the manufacturer level where production costs, varying objectives, and multiple strategic dimensions (price, quality, color weight for example) make it impossible to conclusively prove equilibrium in strategy amongst competing manufacturers. To overcome this, an established robust optimization technique is used to optimize multiple categories and bundles under uncertain intervals of model parameters in multiple disciplines. The approach is implemented for uncertainty in competitor strategies, focal manufacturer production costs and engineering design tolerances providing a mechanism to account for the wide berth of uncertainties in product design for retail channels.

6.3 FUTURE RESEARCH DIRECTIONS

The multidisciplinary nature of this dissertation provides many avenues to further research. Given that, the extensions and improvements with the greatest promise will be the focus of this section.

6.3.1 IMPROVEMENTS IN THE RETAILER ACCEPTANCE CRITERION

The chance constrained retailer acceptance criterion presented in Research Thrust 1 can be extended in many ways. First, the case of many channel retailers that must all be satisfied with multiple chance constraints can be investigated. One could require that

a subset of retailers be satisfied with use of binary variables to select retailers as channel partners. Thus the manufacturer could avoid developing products that satisfy retailers that are less appealing to a profitable customer segment than other retailers. Additionally, the formulation could be extended to include acceptance criterion for multiple products offered at one time or the option for the retailer to select n of N products in the lineup.

Simplifications allowed us to exclude the affect of time but future work under this framework could include changing consumer demand profiles through the use of the net present value and other emerging models including the use of an option theory (Hull, 2006). Changing consumer demand profiles or utilities might be approximated using a time series of conjoint data and linear regression or standard forecasting techniques. As an example, consider the case where customer preferences are changing rapidly in the automotive sector to prefer more fuel efficient cars or novel designs such as crossover vehicles. One could measure the affect of econometric data (e.g., current gasoline price) on these changing utilities and couple these observations with an econometric forecast (e.g., gasoline price forecast) to predict the changes in future customer segment utilities. Clearly these, changing preferences would affect the solution, especially when a relatively low discount rate is applied to future cash flows, and is an area open for research.

6.3.2 IMPROVEMENTS IN STRATEGIC INTERACTIONS

In the future it would be useful to extend the strategic actions of the methodologies developed in Research Thrust 2 to take into account competitor strategies in other attributes (amperage, weight etc.) as we have only considering reactions in the

short term which is limited to price. This would be a very difficult task as noted in the motivation for robust optimization in research Thrust 3. To do this it would be necessary to prove profit quasi-concavity in all competitor design variables.

Second, it would also be useful to consider that the manufacturer may have multiple products within channel segment. With slight modifications, the proof in Appendix B can be extended to a multi-product manufacturer in a differentiated retail monopoly, duopoly, or oligopoly. Under such a formulation the manufacturer could attempt to optimize a line of products competing within the same product category. Such an extension could also be used to optimize individual products competing with bundles in multiple product categories. A proof of existence of a vertical Nash equilibrium for the NMNL formulation would be useful for this extension.

Finally, our strategic interactions have not considered the possibility of the retailer offering an "in-house" brand. In-house brands can be outsourced to external manufacturers or developed by a division owned by the retailer. In either case, the retailer has strategic control over the product attributes beyond the pricing considering in this dissertation. More importantly, the retailer's profit function will change to include the wholesale margin when the product is produced within the corporation. This fact may change the solution to pricing equilibrium, as well as access to shelf space (see e.g., Amrouche and Zaccour, 2007) and adds additional strategy variables for the retailer making the problem more complex.

6.3.3 PRODUCT LINE FORMULATION

A product line refers to two or more products offered by a firm within a product category. Product lines and more specifically product families have recently received

attention in the engineering design literature (see e.g., Simpson, 1998) as manufacturers attempt to manage costs through commonality of design. Product families share common features or components and offer the greatest opportunity for extensions of the present work in retail channels. Commonality of design for the product family or line can produce economies of scope or scale which of course contributes to profits for a manufacturer. A flexible core design or designs for can increase agility in adapting to changing customer needs which would be a competitive advantage in retaining value through optionality (Jiao et al., 2006).

Given these attributes and the prevalence of product families in retail channels an extension to that end would be an appropriate application of the methodologies developed in this dissertation. First and foremost it would be important to understand the retailer's acceptance criterion in light of the entire product line or family. The retailer pricing and assortment selection decision has been theoretically modeled (Villas-Boas, 1998) for simple demand models where the retailer has discretion to select any portion of the product line to maximize profits for the assortment. Actual industry input is difficult to come by but it would be very useful to know whether or not retailers accept or reject entire product lines or fractions thereof. Absent this information it should still be possible to extend the present formulation to include several aspects relevant to product lines.

First the manufacturer can take into account the retailer acceptance criterion (Research Thrust 1) and pricing for his/her product line as it spans across multiple product categories (including bundles) using the nested logit formulation demonstrated in Research Thrust 3. This extended formulation could be used in concert with an improved

cost model that considers design commonality to optimize profits across the entire product line. Such a formulation should be able to capture design trends in improving retailer acceptance for the product line as well as profitability for a product line.

Additionally, the extent to which design integration between products contributes to product line success might be modeled as in the bundling approach presented in Chapter 5. For example, a manufacturer that offers a highly integrated or dependent product line that customers value might find greater success. An example might be how a power tool line that operates off of a common inexpensive battery and a proprietary quick change chuck system (portion of the tool that holds bits) might experience greater acceptance for the entire product line due to design integration. The end customers perceive value in the optional use of common parts for subsequent tool purchases for emerging requirements.

More obviously, the product line can be optimized to best fit the existing assortment and underserved customers which are of primary importance to the retailer. Villas-Boas (1998) suggests that manufacturers should increase product line diversity to mirror the targeting strategy of retailer. This would be accomplished again through the nested logit formulation with customer segments who are presently more or less served by the existing assortment.

APPENDIX

APPENDIX A

This is a regression of product attributes to predict cost of an Angle Grinder cited in Section 3.5.2.

SUMMARY OUTPUT						
Regression Statistics						
Multiple R	0.886063					
R Square	0.785107					
Adjusted R Square	0.759826					
Standard Error	9.405603					
Observations	20					
ANOVA						
	df	SS	MS	F	Sig F	
Regression	2	5494.5	2747	31.055	2.1E-06	
Residual	17	1503.9	88.5			
Total	19	6998.4				
	Coeff.	Std Err	t Stat	P-value	Low 95%	Up 95%
Intercept	-29.2941	9.3861	-3.12	0.0062	-49.097	-9.49117
Amps (A)	3.616034	0.6987	5.18	8E-05	2.14188	5.09019
P/W (watts/lbf)	0.186567	0.0416	4.48	0.0003	0.09873	0.2744

Multiple Regression of Angle Grinder Cost Predictors

APPENDIX B - PROOFS

B.1   PREPARATORY MATERIAL

LEMMA 1

If f is quasiconcave, then any strict local maximum is a strict global solution (Wolfe P., 1970)

Proof of Lemma 1 by Contradiction (WolfStetter, 2000)

Assume that the contrary is true, i.e., a strict local maximum x^* is not a global maximum for a quasiconcave function f. For x^* to not be a global maximum there must exist some point y where $f(y) \geq f(x^*)$ (see Figure B1).
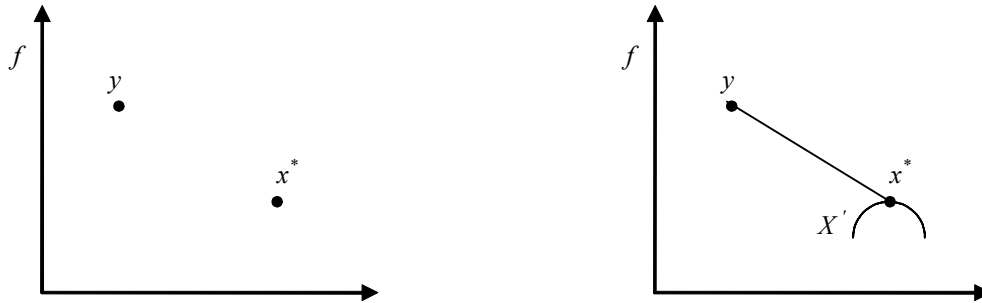

Figure   B1:   Lemma 1

All points X' in the local neighborhood of x^* must lie below $f(x^*)$ by the definition of a strict local maximum yet if the function is quasiconcave all points between x^* and y must be greater than $f(x^*)$ (the minimum of the two). A contradiction exists and $f(y)$ cannot lie above $f(x^*)$ for f to be quasiconcave. Thus all points of a quasiconcave function must lie below $f(x^*)$. A strict local maximum x^* of a quasiconcave function is therefore a global maximum.

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B.2   THEOREM 1 – RETAILERS' MULTIPRODUCT NASH EQUILIBRIUM

A Nash equilibrium in prices exists for a retailer carrying an assortment of n products in a category of N products carried by all retailers.

Proof of Theorem 1:

A retailer with n products seeks to maximize the sum of the n profits subject to similar profit maximizing responses from other retailers. For a Nash price equilibrium to exist the profit function must then be quasiconcave in the prices P_n. For a unique price equilibrium to exist the profit function must be strictly quasiconcave in prices. The general structure of the proof will be to first show that the profit function is quasiconcave and then to show that the stationary point(s) are strict local maximum (Lemma 1).

Nomenclature for Proof:

m_i Market Share of Product i in the focal retailer's assortment

m_j Market Share of Products $j=1,2,..n$ in the focal retailer's assortment

U_{tot} Represent e^U where U represents the total utility of all products at other retailers and the no choice option.

W_i Wholesale price of Product i

W_j Wholesale price of Products $j=1,2,..n$

P_i Retail price of Product i

P_j Retail price of Products $j=1,2,..n$

U_i Utility of non-price attributes Product i

U_j Utility of non-price attributes of Product j

μ Scaling factor for price utility

The multinomial market share variables are defined as:

$$m_i = \frac{e^{\left(-\frac{P_i}{\mu}+U_i\right)}}{\left(e^{\left(-\frac{P_i}{\mu}+U_i\right)} + \sum\limits_{j=1,j\neq i}^{n} e^{\left(-\frac{P_j}{\mu}+U_j\right)} + U_{tot}\right)}, m_j = \frac{e^{\left(-\frac{P_j}{\mu}+U_j\right)}}{\left(e^{\left(-\frac{P_i}{\mu}+U_i\right)} + \sum\limits_{j=1,j\neq i}^{n} e^{\left(-\frac{P_j}{\mu}+U_j\right)} + U_{tot}\right)} \quad \text{(B2.1)}$$

The profit for the focal retailer is then the sum of the two products

$$\pi_r = m_i(P_i - W_i)N + \sum_{j=1,j\neq i}^{n} m_j(P_j - W_j)N \quad \text{(B2.2)}$$

The first derivatives of market share that will be useful are:

$$\frac{\partial m_i}{\partial P_i} = \frac{m_i(m_i - 1)}{\mu} \quad \text{(B2.3)}$$

$$\frac{\partial m_j}{\partial P_j} = \frac{m_j(m_j - 1)}{\mu} \quad \text{(B2.4)}$$

$$\frac{\partial m_j}{\partial P_i} = \frac{m_i m_j}{\mu} \quad \text{(B2.5)}$$

Using the above simplifications the first derivative of π with respect to price of product i

is:

$$\frac{\partial \pi_r}{\partial P_i} = \frac{m_i(m_i - 1)}{\mu}(P_i - W_i)N + N \cdot m_i + \sum_{j=1,j\neq i}^{n} \frac{m_i m_j}{\mu}(P_j - W_j)N \quad \text{(B2.6)}$$

$$\frac{\partial \pi_r}{\partial P_i} = \frac{m_i N}{\mu}\left((m_i - 1)(P_i - W_i) + \mu + \sum_{j=1,j\neq i}^{n} m_j(P_j - W_j)\right) = 0 \quad \text{(B2.7)}$$

$$\left((m_i - 1)(P_i - W_i) + \mu + \sum_{j=1,j\neq i}^{n} m_j(P_j - W_j)\right) = 0 \quad \text{(B2.8)}$$

$$\left(m_i(P_i - W_i) - (P_i - W_i) + \mu + \sum_{j=1,j\neq i}^{n} m_j(P_j - W_j)\right) = 0 \quad \text{(B2.9)}$$

$$\left(\mu + \sum_{j=1}^{n} m_j(P_j - W_j)\right) = (P_i - W_i) \quad \text{(B2.10)}$$

Thus the retailer's margin (P_i-W_i) on product i can be determined in terms of all other products and the customer price scaling factor μ.

Now we look to see if by symmetry the absolute margin or markup is the same for any other product in the focal retailer's assortment n. We change the product index to any arbitrary value γ in the assortment where $\gamma \neq i$ to see if all products in n must have the same absolute margin at stationary points:

Replacing i with the arbitrary product γ in Eq. B2.1- B2.10 shows that the absolute markup on γ is also a function of all products in the retailers assortment (Eq. B2.10). Thus the absolute markup is equivalent and all products in n have equal markups at stationary points for the focal retailer:

$$(P_i - W_i) = (P_\gamma - W_\gamma) \tag{B2.11}$$

This result allows us to introduce the markup variable $\theta = P_i - W_i$ as a substitute for the multiple price variables P_i which we've shown is valid for all products at stationary points for the retailer of interest (Eq. B2.6). This new variable transforms the optimization to a single variable optimization. The constant markup assumption although not pervasive in the modeling literature is not without precedent (Sudhir, 2001). Our application of the single variable transformation is important because the more obvious approach of analyzing quasi-concavity for multiple variables with a bordered Hessian fails to guarantee quasi-concavity.

Additionally, for this assumption to be valid we only need to assume that profit is maximized at a stationary point as the set of constant markup solutions represents all stationary points. We know that profit function does not increase asymptotically at prices equal to infinity (market share goes to zero at the limit) or at prices at their lowest level

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(wholesale prices) and thus the maximum must at least be at a stationary point satisfying the first order condition. This does not prove quasi-concavity for the entire profit function though using the first derivatives and the second derivatives to create the bordered Hessian (sufficient condition) can show that the profit function is at least quasi-concave for large regions of price.

Instead, we use the result of constant markups at stationary points to transform the original problem and prove that the entire function is quasi-concave. The new profit function now becomes:

$$\pi_r = \frac{\displaystyle\sum_{i=1}^{n} e^{\left(-\frac{\theta+W_i}{\mu}+U_i\right)}}{\left(\displaystyle\sum_{i=1}^{n} e^{\left(-\frac{\theta+W_i}{\mu}+U_i\right)} + U_{tot}\right)} \theta N \tag{2.12}$$

Let k be the sum of the market shares for n products:

$$k = \frac{\displaystyle\sum_{i=1}^{n} e^{\left(-\frac{\theta+W_i}{\mu}+U_i\right)}}{\left(\displaystyle\sum_{i=1}^{n} e^{\left(-\frac{\theta+W_i}{\mu}+U_i\right)} + U_{tot}\right)} \tag{2.13}$$

The profit function simplifies to:

$$\pi_r = k\theta N \tag{B2.14}$$

The first derivative of the market share sum is:

$$\frac{\partial k}{\partial \theta} = \frac{-k}{\mu} + \frac{k^2}{\mu} \tag{B2.15}$$

Therefore the first derivative of profit with respect to markup is:

$$\frac{\partial \pi_r}{\partial \theta} = \frac{-\theta N k}{\mu} + \frac{\theta N k^2}{\mu} + kN \tag{B2.16}$$

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Solving the first derivative for stationary points yields:

$$\frac{\partial \pi_r}{\partial \theta} = \frac{-\theta Nk}{\mu} + \frac{\theta Nk^2}{\mu} + kN \qquad\qquad (B2.17)$$

$$\frac{\partial \pi_r}{\partial \theta} = Nk\left(\frac{-\theta}{\mu} + \frac{\theta k}{\mu} + 1\right) \qquad\qquad (B2.18)$$

$$\frac{\partial \pi_r}{\partial \theta} = Nk\left(\frac{-\theta}{\mu} + \frac{\theta k}{\mu} + 1\right) = 0 \qquad\qquad (B2.19)$$

$$\theta = \frac{-\mu}{(k-1)} \qquad\qquad (B2.20)$$

Interestingly, this result shows that as the retailer becomes nearly a monopolist (or dominates k) the margin will go up which seems to agree with overall economic interpretation of monopoly pricing and greater consolidation of power. Recall that the first derivative of profit with respect to markup is:

$$\frac{\partial \pi_r}{\partial \theta} = Nk\left(\frac{\theta(k-1)}{\mu} + 1\right) \qquad\qquad (B2.21)$$

Clearly if θ (markup) is increased from the solution to the first order condition Eq. (B2.20) then the slope is always negative (or profit is decreasing) because k-1 is always negative as the sum of market shares cannot exceed one (see Eq. B2.21). If θ (markup) which is non-negative is decreased then the slope is always increasing from zero and is thus positive (Eq. B2.21). Thus the profit function is at least quasi-concave in the non-negative markup variable.

Quasiconcavity proves that a Nash equilibrium exists but does not prove that a *unique* Nash equilibrium exists. It is necessary to prove that the function is strictly quasiconcave.

The second derivative of profit with respect to markup θ is computed as follows:

$$\frac{\partial \pi_r}{\partial \theta} = \frac{-\theta Nk}{\mu} + \frac{\theta Nk^2}{\mu} + kN \tag{B2.22}$$

$$\text{Let: } \alpha = \frac{-\theta Nk}{\mu}, \beta = \frac{\theta Nk^2}{\mu}, \phi = kN \tag{B2.23}$$

$$\frac{\partial \alpha}{\partial \theta} = \frac{-N}{\mu}\left(k + \frac{\partial k}{\partial \theta} \cdot \theta\right)$$
$$\frac{\partial \beta}{\partial \theta} = \frac{N}{\mu}\left(k^2 + \frac{\partial(k^2)}{\partial \theta} \cdot \theta\right) \tag{B2.24}$$

$$\frac{\partial(k^2)}{\partial \theta} = k\frac{\partial k}{\partial \theta} + k\frac{\partial k}{\partial \theta} = 2k\frac{\partial k}{\partial \theta} \tag{B2.25}$$

$$\frac{\partial \beta}{\partial \theta} = \frac{N}{\mu}\left(k^2 + \frac{\partial k}{\partial \theta} \cdot 2k\theta\right) \tag{B2.26}$$

$$\frac{\partial \phi}{\partial \theta} = \left(\frac{\partial k}{\partial \theta}\right)N \tag{B2.27}$$

$$\frac{\partial^2 \pi_r}{\partial \theta^2} = \frac{\partial \alpha}{\partial \theta} + \frac{\partial \beta}{\partial \theta} + \frac{\partial \phi}{\partial \theta} \tag{B2.28}$$

$$\frac{\partial^2 \pi_r}{\partial \theta^2} = \frac{-N}{\mu}\left(k + \frac{\partial k}{\partial \theta} \cdot \theta\right) + \frac{N}{\mu}\left(k^2 + \frac{\partial k}{\partial \theta} \cdot 2k\theta\right) + \left(\frac{\partial k}{\partial \theta}\right)N \tag{B2.29}$$

$$\frac{\partial^2 \pi_r}{\partial \theta^2} = \frac{N}{\mu}(k^2 - k) + \left(\frac{\partial k}{\partial \theta}\right)N\left(\frac{-\theta}{\mu} + \frac{2k\theta}{\mu} + 1\right) = N\left(\frac{\partial k}{\partial \theta}\right) + \left(\frac{\partial k}{\partial \theta}\right)N\left(\frac{-\theta}{\mu} + \frac{2k\theta}{\mu} + 1\right) \tag{B2.30}$$

$$\frac{\partial^2 \pi_r}{\partial \theta^2} = \left(\frac{\partial k}{\partial \theta}\right)N\left(\frac{-\theta}{\mu} + \frac{2k\theta}{\mu} + 2\right) \tag{B2.31}$$

$$\frac{\partial^2 \pi_r}{\partial \theta^2} = \frac{Nk(k-1)}{\mu}\left(\frac{-\left(\frac{-\mu}{k-1}\right)}{\mu} + \frac{2k\left(\frac{-\mu}{k-1}\right)}{\mu} + 2\right) = \frac{-Nk}{\mu} \tag{B2.32}$$

Evaluating the second derivative Eq. B2.32 at the solution to the first order condition (Eq. B2.21) shows that the profit function is negative definite at all stationary points and thus

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unique Nash equilibrium exists (Lemma 1). This solution takes nearly the same form as the single product per retailer equilibrium developed by Anderson, De Palma, and Thisse (1992).

The constant margin result of this proof can easily be shown numerically without enforcing the constant margin. For a wide range of utility inputs and wholesale prices we were able to reach first order solutions where the margin on the products within the retailers assortment was identical even though each price was considered a design variable in the numerical optimization of first derivatives. One cautionary note, is that it is possible for prices to diverge toward infinity as the first order conditions numerically satisfied when k falls extremely low due to high prices. This difficulty is easy to overcome though by constraining prices to less than some large unreasonable value (e.g., $10000 for an angle grinder)

B.3 THEOREM 2 – MANUFACTURER'S SINGLE PRODUCT NASH EQUILIBRIUM

A Nash equilibrium in wholesale prices exists for a manufacturer selling products through a differentiated-retail-duopoly.

Proof:

A manufacturer with 2 retailers seeks to maximize the sum of the profits from the 2 retailers subject to similar responses from other manufacturers. For a Nash price equilibrium to exist the profit function must then be quasiconcave in the prices W_{ri}. For a unique price equilibrium to exist the profit function must be strictly quasiconcave in

prices. The general structure of the proof will be to first show that the profit function is quasiconcave and then to show that the stationary point(s) are strict local maximum (Lemma 1). We assume that the retail margins θ_i are known from Theorem 1.

Nomenclature:

m_{ri} Market Share of Product i at retailer r

Π_i Manufacturer Profit

W_{ri} Wholesale price of Product i at retailer r

U_{ri} Utility of non-price attributes Product i at retailer r

The multinomial market share variables for two retailers are defined as:

$$m_{1i} = \frac{e^{\left(-\frac{W_{1i}+\theta_1}{\mu}+U_{1i}\right)}}{\left(e^{\left(-\frac{W_{1i}+\theta_1}{\mu}+U_{1i}\right)} + e^{\left(-\frac{W_{2i}+\theta_2}{\mu}+U_{2i}\right)} + U_{tot}\right)}, m_{2i} = \frac{e^{\left(-\frac{W_{2i}+\theta_2}{\mu}+U_{2i}\right)}}{\left(e^{\left(-\frac{W_{1i}+\theta_1}{\mu}+U_{1i}\right)} + e^{\left(-\frac{W_{2i}+\theta_2}{\mu}+U_{2i}\right)} + U_{tot}\right)} \quad (B3.1)$$

The profit for the focal retailer is then the sum of the two products

$$\Pi_i = m_{1i}\left(W_{1i} - C_i\right)N + m_{2i}\left(W_{2i} - C_i\right)N \quad (B3.2)$$

The first derivatives of market share that will be useful are:

$$\frac{\partial m_{1i}}{\partial W_{1i}} = \frac{m_{1i}(m_{1i}-1)}{\mu} \quad (B3.3)$$

$$\frac{\partial m_{2i}}{\partial W_{2i}} = \frac{m_{2i}(m_{2i}-1)}{\mu} \quad (B3.4)$$

$$\frac{\partial m_{2i}}{\partial W_{1i}} = \frac{m_{1i}m_{2i}}{\mu} \quad (B3.5)$$

Using the above simplifications the first derivative of π_r with respect to price of product i is:

$$\frac{\partial \Pi_i}{\partial W_{1i}} = \frac{m_{1i}(m_{1i}-1)}{\mu}(W_{1i}-C_i)N + N \cdot m_{1i} + \frac{m_{1i}m_{2i}}{\mu}(W_{2i}-C_i)N \qquad (B3.6)$$

$$\frac{\partial \Pi_i}{\partial W_{1i}} = \frac{m_{1i}N}{\mu}\left((m_{1i}-1)(W_{1i}-C_i)N + \mu + m_{2i}(W_{2i}-C_i)\right)=0 \qquad (B3.7)$$

$$(m_{1i}-1)(W_{1i}-C_i)+\mu+m_{2i}(W_{2i}-C_i)=0 \qquad (B3.8)$$

$$m_{1i}(W_{1i}-C_i)-(W_{1i}-C_i)+\mu+m_{2i}(W_{2i}-C_i)=0 \qquad (B3.9)$$

$$m_{1i}(W_{1i}-C_i)+\mu+m_{2i}(W_{2i}-C_i)=(W_{1i}-C_i) \qquad (B3.10)$$

Thus the manufacturer's margin (W_{1i}-C_i) at retailer 1 on product i can be determined in terms of the characteristics of both retailers (see m_{1i} and m_{2i}) and the price scaling factor μ.

Taking the 1st derivative with respect to the wholesale price for retailer 2 yields the same result:

$$m_{1i}(W_{1i}-C_i)+\mu+m_{2i}(W_{2i}-C_i)=(W_{2i}-C_i) \qquad (B3.11)$$

The left sides of Eq. B3.10 and Eq. B3.11 are equivalent and thus the markup of all products in are equal at all stationary points for the focal manufacturer:

$$(W_{1i}-C_i)=(W_{2i}-C_i) \qquad (B3.12)$$

This result allows us to introduce a wholesale markup variable $\omega_i=W_{ri}-C_i$ as a substitute for the multiple wholesale price variables W_{ri} which we've shown is valid for all products at stationary points for the manufacturer of interest (Eq. B3.12) . This new variable transforms the optimization to a single variable optimization similar to Theorem 1. We assume that the manufacturer's profit will be maximized at a stationary point and proceed with the now transformed single variable optimization. This constant markup for the manufacturer means that given identical production costs and transaction costs the

wholesale price charged to each of the retailers will be the same. If a retailer is more costly to work with (delays payments, many customer returns etc.) the assumption that C_i is not constant for all retailers can be changed to include the disparity in retailer performance.

The new manufacturer profit function now becomes:

$$\Pi_i = \frac{e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{1i}\right)} + e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{2i}\right)}}{\left(e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{1i}\right)} + e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{2i}\right)}+U_{tot}\right)}\omega N \tag{B3.13}$$

Let k be the sum of the market shares at the 2 retailers:

$$k = \frac{e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{1i}\right)} + e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{2i}\right)}}{\left(e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{1i}\right)} + e^{\left(-\frac{\omega+\theta+C_i}{\mu}+U_{2i}\right)}+U_{tot}\right)} \tag{B3.14}$$

The profit function simplifies to:

$$\Pi_i = k\omega N \tag{B3.15}$$

The first derivative of the market share sum is:

$$\frac{\partial k}{\partial \omega} = \frac{-k}{\mu} + \frac{k^2}{\mu} \tag{B3.16}$$

Therefore the first derivative of profit with respect to markup is:

$$\frac{\partial \Pi_i}{\partial \omega} = \frac{-\omega N k}{\mu} + \frac{\omega N k^2}{\mu} + kN \tag{B3.17}$$

Solving the first derivative for stationary points yields:

$$\frac{\partial \Pi_i}{\partial \omega} = \frac{-\omega N k}{\mu} + \frac{\omega N k^2}{\mu} + kN \tag{B3.18}$$

$$\frac{\partial \Pi_i}{\partial \omega} = Nk\left(\frac{-\omega}{\mu} + \frac{\omega k}{\mu} + 1\right) \qquad \text{(B3.19)}$$

$$\frac{\partial \Pi_i}{\partial \omega} = Nk\left(\frac{-\omega}{\mu} + \frac{\omega k}{\mu} + 1\right) = 0 \qquad \text{(B3.20)}$$

$$\omega = \frac{-\mu}{(k-1)} \qquad \text{(B3.21)}$$

Like Theorem 1, this result shows that as the manufacturer becomes nearly a monopolist (or dominates k) the margin will go up. Recall that the first derivative of profit with respect to markup is:

$$\frac{\partial \Pi_i}{\partial \omega} = Nk\left(\frac{\omega(k-1)}{\mu} + 1\right) \qquad \text{(B3.22)}$$

Clearly if ω (markup) is increased from the solution to the first order condition Eq. (B3.21) then the slope is always negative (or profit is decreasing) because k-1 is always negative as the sum of market shares cannot exceed one (see Eq. B3.22). If ω (markup) which is non-negative is decreased then the slope is always increasing from zero and is thus positive (Eq. B3.22). Thus the profit function is at least quasi-concave in the non-negative markup variable.

Quasiconcavity proves that a Nash equilibrium exists but does not prove that a *unique* Nash equilibrium exists. It is necessary to prove that the function is strictly quasi-concave. Because k and Π take the same form as Theorem 1 the rest of the proof is omitted for redundancy. Equation (B3.21) is therefore a strict global maximum.

APPENDIX C: COMPUTATIONAL ISSUES

The computation of the strategic cases as posed requires a tri-level optimization as shown in Figure 4.4.1.   Initially, the engineering module selects designs to populate the first generation of a Multi Objective Genetic Algorithm (Deb, 2001). Each design is sent to the wholesale pricing level where prices are selected using Matlab's gradient based constrained optimizer fmincon. At the third level retail prices are set using fmincon.

For the monopoly case each objective function call (profit maximization) at the retail level requires just one retailer profit calculation (RPC). Matlab's fmincon proceeds iteratively (RI=retailer iterations) to find the global maximum profit with respect to retail price through a typical gradient based optimization. Thus the time to find retail prices given a wholesale price is of the order ($RI{\times}RPC$). Retail prices can only be selected after each of the wholesale prices is known for the n manufacturers. It is assumed that manufacturers are operating as a small oligopoly with perfect information. As such we find wholesale prices by minimizing the sum of the square of profit derivatives for all manufacturers (Eq. 4.5). This requires a baseline function call of wholesale profits (Wholesale Profit Calculation) and a finite difference calculation for each manufacturer meaning that wholesale profits must be computed $n+1$ times for all iterations of the constrained minimization. Assuming the constrained minimization takes a number of iterations (WI=Wholesale iterations) the computational complexity at the wholesale level will be dependent upon the number of manufacturers and will thus be $(n+1) {\times}WI{\times}WPC$.

The WPC time is almost entirely dependent upon the retail price calculation. This is because the retail prices can take 30 to 40 seconds to converge for a monopoly but once known the market shares are trivial in comparison. Thus, the time complexity of

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WPC is of the order: *RI×RPC*.   The time complexity for the monopoly wholesale price equilibrium for each design is of the order $(n+1)$ *×WI× RI×RPC*. Given a generation of size *N* each generation in the genetic algorithm requires approximately:

Gen$_{monopoly}$=N (n+1) ×WI× RI×RPC

The time complexity of the duopoly is similar except that additional function calls are required to find the Nash equilibrium at the retail level. Each retailer *r* must set prices on the *n* products that are best responses to their competitor's prices. Much like the wholesale level we solve for retail prices by minimizing the sum of the squares of the first derivatives (Eq. 4.2). The computation of the first derivatives is performed with finite differences and therefore requires a baseline profit function call and *n* additional function calls for each retailer *r*. Thus, the time complexity at the retail level now becomes (1+*r×n*)*RPC*. In our case we investigate 4 manufacturers and two retailers so the retail level iterations take approximately 8 times longer than the monopoly case. The duopoly generations require a time approximation of: *Gen$_{duopoly}$=N (n+1) ×WI× RI×*(1+*r×n*)*RPC*.

Empirically, these approximations are born out by the evidence that each wholesale price for a given design required approximately 30 seconds for the monopoly case and 4 minutes for the duopoly case.

While the wholesale and retail profit functions are strictly quasi-concave it is numerically necessary to use constrained minimization because the slope of the multinomial logit (MNL) profit function approaches zero as prices approach infinity (See Figure   C1)
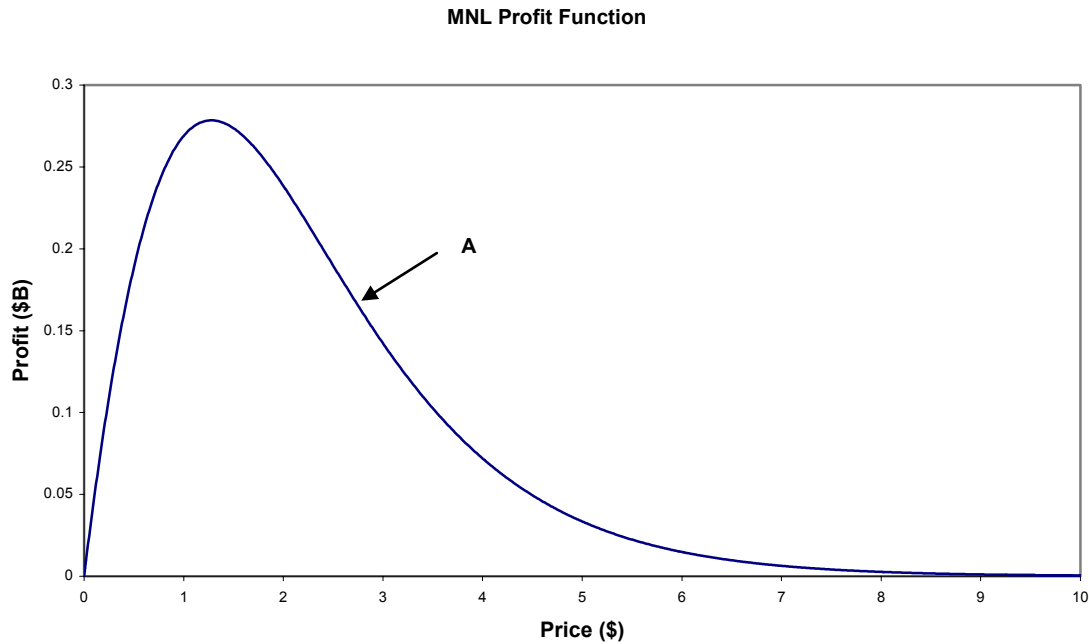
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MNL Profit Function

Figure   C1: MNL Profit Function

If one examines point A in Figure   C1 it is clear that a gradient based optimizer searching for stationary points (Eq. 4.2 and Eq. 4.5) is equally likely to find the maximum and the minimum of the MNL profit function if left unconstrained.   As such, we require the Nash equilibrium solutions for both the retail (Duopoly) and wholesale levels to satisfy the following constraints: (1) Hessian must be negative definite; (2) Price must be less than $X. ($2 for the example above). If characteristics of the MNL function are relatively stable across all designs considered it is possible to limit the required constraints to just constraint 2. For example, if the designer knows that the transition from a negative definite Hessian to a positive definite Hessian (approximately point A) is always greater than $X then constraint 2 can be used alone to eliminate the computational requirements of the Hessian.

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