ABSTRACT

PORTERFIELD, KALIE GRACE. Quantifying Consumer Sacrifice Gap for Product Optimization in Mass Customization Environments. (Under the direction of Dr. Scott Ferguson.)

Mass customization combines the seemingly contradictory ideas of customized goods and services with prices consistent with mass production. The distance between the current market environment and what is possible under mass customization has been referred to as the customer sacrifice gap, the difference between what a customer wants and what is currently available. Minimizing sacrifice gap is said to benefit both the firm and the consumer. Although narrative definitions of this term exist, a process for obtaining a quantitative measure of sacrifice gap is absent. This thesis investigates two research questions that aim to bring a hypothetical market closer to mass customization by minimizing sacrifice gap. The first question develops a method for empirically defining and quantifying customer sacrifice gap in the market. The second research question explores how this metric can be used in mass customization product line design problems to maximize value to the firm and consumer. The results of this investigation show that sacrifice gap is a useful tool in product design and assessment for mass customization, and that it has significant potential for use in product line optimization problems.

Quantifying Consumer Sacrifice Gap for Product Optimization in Mass Customization Environments

by
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BIOGRAPHY

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CHAPTER 1: INTRODUCTION AND MOTIVATION

This chapter provides context for the work in this thesis by discussing tools in the engineering and marketing domains that look to enable a practical application of mass customization in real markets. The motivation for this work comes from identification of knowledge gaps in the formulation and application of these tools. The motivation is translated into two research questions that address the need for greater integration of engineering and marketing research in the pursuit of mass customization. The chapter concludes with an outline of this thesis.

1.1. MOTIVATION

Individual customers are, by nature, unique in their product preferences. Person A may prefer a blue sedan with leather seats and a manual transmission, while Person B may prefer a black SUV with cloth seats and an automatic transmission. Person C, meanwhile, may prefer some mix of both vehicle configurations. In choosing how to approach this heterogeneous market, a vehicle company will choose a design strategy that represents a point lying somewhere between mass customization (everyone is different) and the one-size-fits-all extreme of mass production (everyone is the same). Mass production provides the firm and consumer with the greatest opportunity to capitalize on efficiency and cost savings, but at the expense of fully meeting all of an individual customer's needs and/or preferences.

Mass customization (MC), on the other hand, is based on the idea that each customer will get "exactly what they want when they want it", but at additional costs that come with the loss of production efficiencies and additional design considerations [1]. The more

practical definition adapted from Pine and used by Ferguson et al. (2011) is the "concept of MC is to provide consumers with custom goods and (services) at prices consistent with mass production" [2], [3]. Taken from Ferguson et al. and Davis' ideas, mass customization is defined by the following two tenets:

1) goods and services that maximize customer value by giving them "exactly what they want", and

2) providing these goods and services at "prices consistent with mass production"

One can think of mass production and mass customization in their purest form as opposite ends of a spectrum, where market conditions such as globalization and external competition are pushing design approaches from the one-size-fits-all mass production pole towards the theoretical mass customization pole [2]. This evolution is a positive one for both the customer and the firm. Customization allows firms to create products that better address the wants and needs of the customer, differentiate their products from other firms, and charge a price premium for the added value [2]. This concept is depicted in Figure 1.1 below.

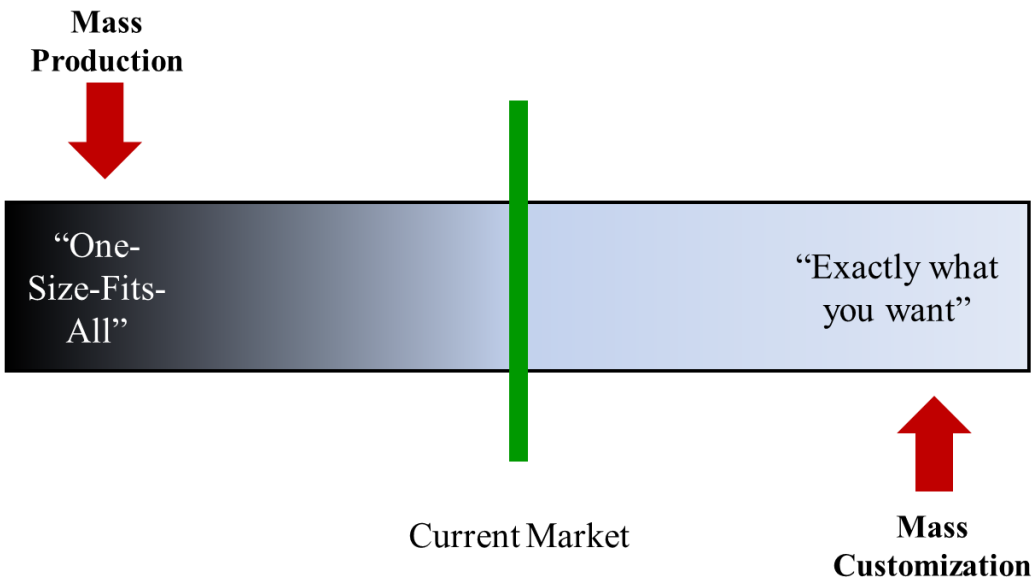

Figure 1.1: Product Design Strategy Spectrum

Since its conceptualization 25 years ago, engineering and marketing disciplines have developed methods to bring mass customization closer to fruition. Engineering design research has mainly focused on offering customers variety at costs consistent with mass production. The primary vehicle for this push has been product platforming, a product architecture strategy whereby a line of products - a product family - is developed around common components and processes [4–6]. The non-common components and processes are what differentiate the products from one another, and provide a unique value proposition to identified niches in the market [7]. Constituents of product platforming such as commonality, variety, and cost have been investigated extensively in the literature, and many methods to decrease cost, increase component commonality, and increase variety, have been proposed [8], [9].

Marketing, on the other hand, has traditionally been responsible for soliciting and interpreting customer preference data, i.e. determining “exactly what they want" [9]. The One method of quantifying customer preferences involves the use of conjoint surveys [10]. When used in conjunction with certain discrete choice models, such as hierarchical Bayes mixed logit, one can numerically represent estimations of respondent preferences for product attributes for each respondent [11]. This information can then be used to compare a respondent’s perceived value of one product to another.

In theory, incremental variety should increase a customer’s chances of finding a product that best meets their needs. Practice suggests, however, that too much variety can dampen a company’s success by flooding the market with too many options. This notion is reinforced by Iyengar (2010), who notes that too many choices can delay or discourage consumer purchase decisions due to the increased cognitive load [13]. This brings forth the challenge of offering the right amount of variety to the right market. Although engineering and marketing have traditionally been segregated fields, Michalek et al. (2005) notes the importance of incorporating more marketing information into product family design [14]. Recent work in the design community has begun to challenge this segregation, incorporating market considerations such as customer preferences and competition into product design problems [15] [16].

Although there has been increased interest in mass customization, the concept is not yet fully realized. That is, there is a gap between what the consumer can purchase in the market and what they truly desire. This discrepancy is referred to as *sacrifice gap*. Pine and Gilmore (2000) define customer sacrifice gap as *“what the customer wants exactly”* less

"what the customer settles for"[2]. Every time a customer selects a product from the shelf they make a decision based on weighing tradeoffs associated with the available options. Standard products may exhibit feature excess at a price premium, feature deficiency at a price discount, or some combination of both. By purchasing a product that does not exactly meet their needs and/or preferences, a customer experiences some magnitude of sacrifice gap. This magnitude is different for each customer and is dependent upon their preferences as well as the offerings of all firms in the market. The concept of sacrifice gap has been acknowledged in both the engineering and marketing communities, but current literature has yet to provide a means of quantifying it for or applying it to product design [2].

Both the marketing and engineering domain have established bodies of work that present tools and strategies to aide firms in their pursuit of mass customization. The body of work that utilizes tools from both disciplines in tandem to develop mass customized product lines is relatively small and under investigated, however. Recent work by the engineering design community has begun to tie these disciplines together by incorporating respondent preference information into product design optimization problems. Much of this research incorporates the respondent information indirectly, and the resulting product lines maximize firm-centric metrics such as profit and market share. Although these metrics use aspects of customer demand modeling in their calculation, the resulting products are based on the firm's interest, not the consumer's [12–14]. To more directly incorporate customer preferences into the design phase, this work proposes to quantify the concept of sacrifice gap. In addition, this thesis will investigate how a quantified sacrifice metric can be used to guide product architecture design for mass customization. This will incorporate research methods from both

engineering and marketing domains to push the resulting product lines closer to the mass customization pole from Figure 1.1. This objective is illustrated in Figure 1.2 below.

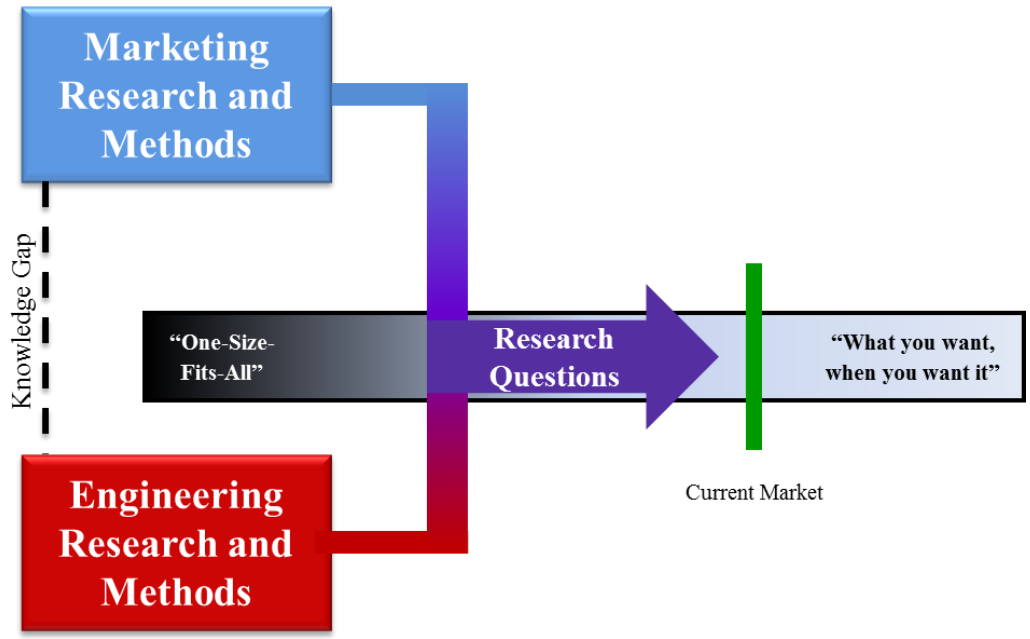

Figure 1.2: Merging Marketing and Engineering Knowledge in Pursuit of MC

1.2. RESEARCH QUESTIONS

If one of the tenets of mass customization is giving the customer "exactly what they want", then sacrifice gap indicates how close a firm is to providing that ideal. This concept has been defined in commentary, and the value of minimizing it has been expressed in multiple works. Although the concept is notably important in both engineering and marketing literature, a methodology to quantify it is absent. This void leads to the first research question (RQ1):

How can sacrifice gap be empirically defined using quantified respondent choice data?

The goal of Research Question 1 is to provide a means to measure how far alternatives in a particular market are from providing the consumer "what they want exactly". The principle challenge associated with calculating sacrifice gap is developing empirical relationships for the terms in Pine and Gilmore's equation: "what the customer wants exactly" (referred to as the "ideal product") less "what the customer settles for" (referred to as the "best available product"). A numerical representation of respondent preferences on an individual level is necessary for quantifying sacrifice gap. Furthermore, an explicit method for using these preferences to define the "ideal product" and the "best available product" that is not case-study specific is required.

Once sacrifice gap is quantified, its use in assessing and designing mass customized products can be explored. Engineering product design has approached the mass customization challenge of providing the customer "exactly what they want" by creating variety at low cost. As previously stated, this challenge has been confronted primarily through product platforming, where maximization of component commonality and variety are historically common metrics [9]. These approaches look to offer variety at low cost; this addresses the second tenet of mass customization, but not necessarily the first. To ensure that the first tenet of mass customization is also fulfilled, "what the customer wants exactly" needs to be incorporated into product design. Recent works in engineering design have begun using respondent preference information, traditionally a marketing concern, in the design

phase. Respondent preference information is commonly integrated by optimizing product line configurations for firm-centric metrics such as share of preference and aggregate contribution. Although these metrics involve embedded consumer preference information, none explicitly maximize value for the consumer. The second research question (RQ2) follows then:

How can sacrifice gap be leveraged as a customer-centric metric to guide product line design decisions towards mass customization?

Research Question 2 looks to build on previous work that indirectly incorporates respondent preference information into product design by using a consumer-centric metric as an optimization objective rather than just a firm-centric one. The goal of Research Question 2 is to explore how direct incorporation of respondent preferences can help fulfill the first tenet of mass customization from an engineering design standpoint.

The numerical representation of sacrifice gap proposed in Research Question 1 allows firms to examine the state of an existing market and assess where value can be added by better meeting customer needs. Reducing sacrifice gap in a market can then become a guiding factor in product line design, which is investigated in Research Question 2. The incorporation of sacrifice gap into product line design looks to fulfill the first tenet of mass customization by placing customer value at the center of the design process, and to draw

from marketing *and* engineering disciplines to provide an interdisciplinary approach to practical execution of mass customization strategies.

1.3. CHAPTER SUMMARY

This chapter outlines the current methods and strategies for practical implementation of mass customization principles within the realms of marketing and engineering. The research questions highlight areas where discourse and investigation is needed for further development in this area. Chapter 2 provides the context and background necessary to make clear the relevance and validity of the method formulation in Chapter 3 where Research Question 1 is addressed. Chapters 4 and 5 apply this formulation to an engineering design problem. Chapter 4 conducts a single-objective optimization where only a consumer-centric metric is considered; Chapter 5 builds on the findings in Chapter 4 and extends the optimization to include both firm and consumer-centric metrics. Both of these two chapters address Research Question 2. The work concludes with summary and future work sections in Chapter 6.

CHAPTER 2: BACKGROUND

This chapter presents the necessary background research to justify the significance of the research questions presented in Chapter 1 and to facilitate a clear understanding of the approach developed in Chapter 3. An overview and discussion of the following areas are presented: 1) definitions and commentary relating to the concept of mass customization, 2) methods of customer preference information acquisition to determine “what the customer wants”, and 3) engineering design methods and strategies to achieve “what the customer wants” at “prices consistent with mass production”.

2.1. MASS CUSTOMIZATION

The concept of mass customization (MC) was put forth by Davis over 25 years ago in his work *Future Perfect*. There, his commentary defined the term as "the same large number of customers can be reached as in mass markets of the industrial economy, and simultaneously they can be treated individually as in the customized markets of pre-industrial economies," [1]. Although Davis was the first to coin the term, his definition is now one of many; later definitions would become more specific and include a higher degree of pragmatism. Pine describes mass customization as “providing tremendous variety and individual customization, at prices comparable to standard goods and services” to fill the market “with enough variety and customization that nearly everyone finds exactly what they want” [15] . Tseng and Jiao take a manufacturing-centric viewpoint, and describe MC as “the technologies and systems to deliver goods and services that meet individual customers’ needs with near mass production efficiency,” [16]. Differences in specificity and pragmatism aside,

all definitions of mass customization share two basic constructs: 1) they aim to maximize customer value by offering customized products to the masses and 2) they aim to leverage innovation in design, manufacturing, and distribution to provide customized goods at prices comparable to mass production. These constructs are concisely described as the two tenets of mass customization in Chapter 1.

The remainder of this section discusses the benefits to the firm and consumer that mass customization provides, as well as highlights the challenges to its practical execution.

2.1.1. BENEFITS OF MASS CUSTOMIZATION

The appeal of mass customization is its ability to simultaneously increase value to the consumer and the firm when compared to mass production. In this context, customer value refers to the net benefits garnered from product purchase. Firm value refers to metrics that correlate with profitability such as brand awareness, customer loyalty, and profit.

The expected consumer value increase from mass customization is straightforward; they obtain a greater net benefit from products designed to meet their unique wants and needs than from standard, mass produced products. The benefit magnitude is greater for some consumers than others, however. Hart attributes the magnitude range to two main factors: uniqueness of customers' needs and customer sacrifice [17]. Uniqueness of needs refers to the variety of wants and needs in a particular market, later referred to as preference heterogeneity; customer sacrifice gap is the difference between "what the customer wants" and "what they settle for" in the market [2]. The more unique a customer's wants and needs are, and the larger their initial sacrifice gap, the more they stand to benefit from mass customization.

Increased customer value, then, leads to increased firm value. Minimizing sacrifice gap not only provides customers with higher value products, but Peppers and Rogers (1995) argue that a large sacrifice gap leads to less loyal customers and results in lower customer retention rates [18] . Several sources have reinforced the importance of customer retention in the market, especially as competition for customers becomes more intense [18], [19]. Developing new customer relationships is five times more expensive than retaining a current customer, and satisfied customers are more likely to purchase the same brand again [20]. In addition, satisfied customers are likely to tell three others about their positive experience, while dissatisfied customers may tell up to nine others of their discord [21]. Finally, a 5 percent reduction in customer defection can increase profits by as much as 25-85 percent depending on the circumstances and industry [20].

Not only does mass customization facilitate an improved customer-firm relationship, but it also allows firms to charge a higher price. Customers, especially those invested in the product, are often willing to pay a premium for customized. Positive motivators for this behavior include the ability of customized products to better meet the customer's unique needs, and negative motivators include avoidance of negative attributes present in standard products [22]. Increased market heterogeneity, increased customer expectations, and increased competition between firms for market share characterize today's marketplace. These conditions make progress toward mass customization highly lucrative.

Commentary on the subject makes clear the importance of recognizing and minimizing sacrifice gap in the competitive marketplace, yet a methodology to obtain quantitative measure is absent from the body of work. Engineering and manufacturing

innovations have provided product variety at a decreased price premium; this helps mitigate sacrifice gap by some degree. Excess variety can become detrimental, however, when it leads to overinflated costs without providing sufficient value in return. A mass customized product, then, would allow the customer to balance the value of additional features with monetary cost; in effect minimizing their perceived sacrifice gap. This conclusion highlights the need for investigation outlined in Research Question 1.

2.1.2. CHALLENGES TO REALIZATION

Although an increase in demand for individualized products and the prospect of lucrative benefits detailed in literature support the execution of mass customization in industry, the concept has, in the words of Ferguson et al. (2010), "largely not lived up to its promise"[23]. In a review of marketing, engineering, and distribution research related to mass customization, Ferguson et al. (2010) identify gaps in current research knowledge that may help to explain why MC is not broadly applied [23]. Their findings relevant to the research questions addressed in this work are summarized below; numbers 1-3 refer to gaps discerned from marketing literature and 4-6 from engineering literature:

1. Need for further development of tools and methods that allow quantification of customer preferences on an individual level;
2. Need for research and methods that aide in the transfer of information between the engineering and marketing domain;
3. Need for a quantitative measure of consumer readiness for MC;

4. Need for investigation of simultaneous market segmentation and product variant creation to optimize customer value;
5. Need for customer preferences elicitation methods that provide valuable engineering guidelines without overwhelming the respondent;
6. Need for engineering design metrics that quantify how well a product concept meets the need of the consumer [23].

The research questions in this work primarily address gaps 2, 4, and 6; relevant background from both engineering and marketing domains is presented in the following sections. Section 2.2 focuses on tools developed in the marketing domain that can be used to quantify customer preferences for investigation of Research Question 1. Section 2.3 focuses on the body of work in engineering that has strived to fulfill the tenets of mass customization. This thesis looks to expand upon these works in order to answer Research Question 2.

2.2. MARKETING TOOLS

To empirically define customer sacrifice gap, the two phrases, “what the customer wants exactly” and “what the customer settles for”, must be quantified. Conjoint analysis is an established method in the marketing domain that can be used for this purpose, and is the method of choice for this thesis. The conjoint analysis process, described in the sections below, is broken down into two portions: consumer preference data acquisition and consumer preference data modeling.

2.2.1. CONSUMER PREFERENCE DATA AQUISITION

One of the most popular methods to obtain quantifiable customer preference data is through conjoint analysis [10], [24], [25]. Conjoint analysis is rooted in 1960s behavioral psychology, and was not applied to marketing problems until almost 1970. Using this method, respondents are asked to complete a number of questions or tasks; each task asks them to evaluate product profiles that are defined by multiple attributes or features. An example of a conjoint analysis task is depicted in Table 2.1 below. Each column represents the product profile for a vehicle and each row represents a feature of that vehicle.

Table 2.1: Conjoint Analysis Task Example

	Vehicle 1	**Vehicle 2**	**Vehicle 3**
Engine Size	2.5L	3.0L	3.5L
Interior Color	Black	Beige	Grey
Gas Mileage	32 MPG Hwy.	25 MPG Hwy.	40 MPG Hwy.

Developments in research and application have since yielded two main approaches: traditional conjoint analysis and choice-based conjoint analysis (CBC) [11]. Traditional conjoint analysis asks respondents to rank a selection of product profiles either against one another or on a scale of, for example, 1-10. Choice-based conjoint analysis, on the other hand, simply asks the respondent to choose the one “best” product from the set of alternatives.

If Table 2.1 is used for traditional conjoint analysis, the respondent would be asked to rank order the columns or rate them on a specified scale. If Table 2.1 is used for CBC, the respondent is asked to indicate which column represents their “first choice”. Questions of this structure are repeated, and conjoint analysis yields a numerical representation (part-worth) of how important the surveyed attributes are relative to one another.

Researchers determine the part-worths by working backwards from the choice data taken from the conjoint survey. Put another way, conjoint analysis decomposes product preferences to deduce feature preferences; this stands in contrast to a compositional approach which asks respondents to rate each feature explicitly. These part-worths may be derived using a variety of mathematical tools; the particular method is dependent upon the conjoint approach used and the end use of the data.

The resulting part-worths are used to quantify the value of any product in terms of the attributes and levels featured in the conjoint tasks; this product value is referred to as its utility. This process can be used to evaluate the value of products against one another, and predict how the market will react to a particular product profile or configuration [11], [26], [27].

Comparing the two approaches, CBC is more complex than traditional conjoint analysis and requires more mathematical rigor to discern respondents’ choice preferences. While the traditional conjoint approach has always been able to estimate preferences on an individual-level, CBC has not. In the past, CBC data could only be used to derive aggregate preferences across a group of respondents. This aggregate approach created problems such as independence from irrelevant alternatives (IIA or the Red Bus Blue Bus Problem) and

ignorance of preferences of latent subgroups in a market. Advancements in mathematical modeling techniques and the technologies to execute them have alleviated this challenge. These advancements allow for a more granular representation of consumer preferences, and commercial software packages that use mathematical modeling techniques that allow for individual-level preference assessment are readily available for use. These techniques will be discussed in detail in the next section.

CBC is also a less efficient means to collect the required volume of customer preference choice data when compared to traditional conjoint; respondents must spend more time on each question and a larger number of questions must be asked. The development of commercial software packages has helped mitigate this challenge as well. Survey design has become more efficient so respondents can complete as few tasks as possible. The ability of these software packages to web-host surveys has made disseminating the tasks and collecting the choice data much easier. In addition, CBC is more reflective of a "real world" purchase decision and is "theoretically and statistically more defensible than traditional conjoint" [11]. Given its strengths and the use of technology to mitigate its weaknesses, CBC will be the conjoint analysis survey method used throughout the remainder of this work.

2.2.2. MATHEMATICAL MODELING

Since the decision maker chooses from a finite set of mutually exclusive options in CBC tasks, the process of modeling their decision making process is referred to as discrete choice analysis (DCA) [28]. For the purposes of this work, each respondent is considered an optimizer, therefore the principle of utility maximization is used. That is, a respondent is

modeled as selecting the alternative that gives them the highest utility when choosing among a set of alternatives [28].

Results from discrete choice surveys can be mathematically modeled using a variety of random utility models (RUMs). These models are derived under the utility maximization assumption and consider a decision maker, *i*, who obtains a certain amount of value (utility) from alternative *k* in a choice set. The utility for a particular alternative is known to the decision maker but not the researcher. Therefore the researcher must estimate the decision maker's utility based on selections made in the choice tasks. RUMs therefore assume two parts to the decision maker's utility; one part captures the observations garnered from the choice tasks and the other represents factors that affect utility but are not observed through the choice tasks. The utility model of Equation 2.1 illustrates this conceptual model form definition; where U_{ik} is the ith respondent's overall utility for the kth product, X_{ijk} is the ith consumer rating of the jth attribute for the kth product, β_{ij} is the scaling coefficient of the jth attribute, and ε_{ik} is an error term accounting for differences in the observed consumer response and that modeled by $\sum_j X_{ijk}\beta_{ij}$. Differences in the observed response and those predicted by the model, ε_{ik}, may be due to factors such as error in model fit, respondent selection error, or attribute levels not included in the survey [29].

$$U_{ik} = \sum_j X_{ijk}\beta_{ij} + \varepsilon_{ik} \qquad \textbf{(2.1)}$$

For the scope of this work, the most relevant RUMs are hierarchical Bayes mixed logit (HB), latent class multinomial logit (LC-MNL), and Individual Choice Analysis (ICE) models. These models can estimate heterogeneous attribute part-worth utilities, and they are available within widely-used commercial software packages. That is, they do not assume the entire market has the same preferences. Specifically, HB estimates individual-level part-worths, LC clusters individuals into homogeneous (to a certain tolerance) segments and estimates the part-worth of a segment, and ICE estimates individual-level part-worths from LC segments [30].

Comparing the three interpretations, Huber (1998) found that HB and ICE far outperformed LC in predicting individual choices [30]. In addition, although HB and ICE both work well in practice, HB is much more theoretically elegant, well established, and estimates individual-level preferences more effectively than ICE [30]. The goal of mass customization is to achieve a "market of one," ergo accurate and reliable estimation of customer preferences to that granularity is vital. For these reasons, HB modeling is used to quantify discrete choice conjoint data in this thesis.

Hierarchical Bayes uses market-and individual-level discrete choice data (hence the name "hierarchical") to derive part-worths for each respondent. A part-worth refers to the "value" of a particular level of a particular attribute; it is the β_{ij} term in Equation 2.1 above. The $X_{ijk\,j}$ term is like an "on/off" switch that determines whether a particular feature level (and its corresponding β_{ij}) is present on the product. Since the $X_{ijk\,j}$ refers only to the presence or absence of a particular β_{ij}, β_{ij}, becomes the part-worth. Summing the part-worths that

correspond to the feature levels that define a product gives the utility of that product profile, U_{ik}. Table 2.2 expands upon Table 2.1 to illustrate this concept.

Table 2.2: Part-Worth Sum Example

	Vehicle 1		Vehicle 2		Vehicle 3	
	Level	**Part-Worth**	**Level**	**Part-Worth**	**Level**	**Part-Worth**
Engine Size	2.5L	1	3.0L	6	3.5L	-5
Interior Color	Black	4	Beige	-4	Grey	3
Gas Mileage	32 MPG Hwy.	-2	25 MPG Hwy.	2	40 MPG Hwy.	1
Utility		3		4		-1

The dual-level approach to deriving part-worths is HB's key differentiating factor mathematically. On a market-level, HB modeling assumes that the collection of individuals' part-worths is distributed multivariate normal and is characterized by a vector of means and a matrix of covariances. This distribution is given as Equation 2.2, where β_{ij} is a vector of part-worths for the ith individual, α is a vector of means of the distribution of the market's part-worths, and D is a matrix of variances and covariances of the distribution of part-worths across individuals [31].

$$\beta_{ij} \sim Normal(\alpha, D) \tag{2.2}$$

On an individual-level, each respondent's part-worths are governed by a multinomial logit model. A general form of this model is given as Equation 2.3 where p_k is the probability of an individual choosing the kth concept (referred to as a product profile above) in a particular choice task and x_j is a vector of values describing the j_{th} alternative in that choice task.

$$p_k = \frac{e^{(x_k \beta_i)}}{\sum_j e^{(x_j \beta_i)}} \tag{2.3}$$

The goal of HB model fitting is to maximize the probability (also called the "likelihood") that the varied parameters reflect the selections a respondent made in the conjoint choice tasks. These varied parameters include β_i, α, and D [31].

This work uses Sawtooth's Software's CBC/HB software to fit an HB model to the choice data. The approach used in this software adopts a mixed logit model to determine the parameters. Mixed logits are a mixture of the logit function evaluated at different β's, and their error functions have an extreme value distribution (iid). An extreme value distribution is very similar to a normal distribution, but with fatter tails; this makes the model more robust because it can account for slightly more aberrant model behavior than if normal were used [29].

To determine the values of the varying parameters (β_i, α, and D), a procedure called "Gibbs sampling" or "Monte Carlo Markov Chain" is used whereby one parameter is re-estimated conditionally given current values of the other two. The process is repeated for

several thousand iterations or more, until convergence is reached. An in-depth description of how hierarchical Bayes calculates individual level part-worths is provided in [31]. Additional resources that detail all model forms discussed in this section can be found in [28], [29].

The properties of the part-worths derived by the HB model have great implications for data usage and analysis. The part-worths are interval data that have been scaled to an arbitrary additive constant within each attribute. This scaling gives all discrete choice models (including HB) two consistent characteristics 1) only differences in part-worths are relevant and 2) the scale of part-worths is arbitrary [29]. The implications of these characteristics are illustrated using Table 2.3, which is adapted from [11].

Table 2.3: Part-worth Characteristic Example

Color	*Part-worth*	*Brand*	*Part-worth*
Blue	30	A	-20
Red	-20	B	30
Green	-10	C	-10

Sawtooth Software scales the sum of an attribute's part-worths to zero, referred to as zero-centered. Because Sawtooth Software is used to fit the HB model in this work, this assumption is made throughout the remainder of this explanation. Since this table presents

utilities that are zero-centered, some utilities within an attribute must be negative. Because only differences in utility matter, the fact that Red and Green have negative utilities does not mean that they are "disliked" by the market; rather, it just means they are favored less than Blue. In addition, adding a constant to all part-worths for a particular respondent (effectively changing the scale of all utilities within each attribute) or multiplying all part-worths for a particular decision maker by the same constant has no consequence on the meaning of the data.

Although attribute part-worths can be compared for a single respondent, they cannot be compared across multiple respondents. Table 2.4 helps illustrate this concept.

Table 2.4: Comparing Part-worths Across Respondents

Respondent 1	*Part-worth*	*Respondent 2*	*Part-worth*
Blue	30	Blue	5
Red	-20	Red	5
Green	-10	Green	-10

In the table, Green has the same part-worth for Respondent 1 as it does for Respondent 2. However, this does not mean that Respondent 1 prefers green as much as Respondent 2 because the part-worths cannot be compared across respondents. The implications of these characteristics are particularly evident during the data analysis process.

The individual-level part-worths derived from CBC choice tasks and subsequent HB modeling are used to numerically define sacrifice gap (Research Question 1) which is, in turn, applied to a product line optimization (Research Question 2). The next section presents relevant work in the engineering domain that looks to fulfill the two tenets of mass customization.

2.3. ENGINEERING TOOLS

Engineering design research has looked to fulfill the two tenets of mass customization primarily through offering variety at prices consistent with mass production. The primary vehicle used to meet these challenges is the concept of product platfoming; a strategy used to create product families [6] By definition, a product platform is a "set of parameters (common parameters), features, and/or components that remain constant from product to product, within a product family," [32]. The product family, consequently, is a group of products that are created from these common parameters. Product platforming is a well-recognized method for increasing variety while reducing lead times and maintaining costs comparable to mass production [4–6], [33].

The implementation of product platforming has been a crucial tool in the push toward a practical execution of mass customization. Research has shown that initial increases in product variety increase sales because more options increase the likelihood that a customer will find the product that meets their wants and needs, but that this benefit is only seen up to a threshold [34]. This observation indicates that offering variety without regard to its characteristics or magnitude may only be able to push a market so far toward the mass customization pole.

A large body of work exists that focuses on minimizing the cost of variety (fulfilling aims associated with the second tenet of mass customization) by decreasing complexity, increasing commonality, and decreasing cost. The body of work that looks to determine the extent and characteristics of variety that best meet the wants and needs of the individual is much less developed; this is the body of work this thesis looks to build upon. This section summarizes the engineering design research that has contributed to the push toward mass customization; strategies and tools that address the first and second tenets of mass customization are noted.

2.3.1. MINIMIZING THE COST OF VARIETY

Product platforms are meant to reduce aggregate product development time, reduce incremental system complexity, and make product upgrades more accessible; factors that decrease both development and production costs through careful design of the platform architecture [6]. Platform structure or architecture refers to the means by which designers implement commonality among product family members to create efficiencies associated with mass production. There are three main product family architecture strategies: scalable, configurational or modular, and generational. Scalable platforms involve dynamic (customizable) variables that can “stretch” or “shrink” to accommodate different market segments [32]. Modular platforms involve development of a base architecture from which attributes are added, subtracted, or swapped to create variety [16], [35]. Generational platforms leverage product commonality to increase the speed of product lifecycles to keep pace with competition in the market [9].

The actual design of the product family often incorporates these architectures and involves considering numerous complex, somewhat abstract, integrated variables to create an optimal portfolio of products. Optimal in this case does not refer to a singular solution or architecture, however, because these problems are inherently multi-objective[9]. Simpson et al. (2004) conducted a review specifically targeting optimization methods used in product family design [6]. Those commonly used in previous literature included SLP, SQP, NLP, GRG, genetic algorithms (GA's), simulated annealing, pattern search, and branch and bound techniques. Since product platforming problems are typically combinatorial and complex, genetic algorithms were advocated as the most effective in general [6].

To assess how well a product platform design minimizes the cost of variety there is a need for metrics that quantify its effects on the cost of design and manufacturing. These metrics are often used as the objective functions, and have traditionally focused on minimizing complexity, increasing commonality, and decreasing cost. Works associated with developing and improving metrics used to optimize product families for maximal variety and minimal cost are discussed in the following sections.

2.3.1.1. COMPLEXITY

Intuitively, per unit cost of a product increases with system complexity and product variety. This per unit cost increase is related to direct costs such as capital expenditures, manufacturing space, engineering work hours, supplier relationships, and material costs; these costs are typically quantifiable for the firm and can be estimated with sufficient accuracy. The other component to overall cost increase, indirect costs, are heavily dependent

upon variety and much more difficult to estimate. Examples of indirect costs include logistics, quality, capacity change due to non-uniform product production, raw material inventory, work-in-progress inventory, finished goods inventory, and post sales inventory; all of which are a function of complexity [36]. Bruns and Kaplan (1987) note that overhead costing in particular is heavily situational and dependent upon the complexity of the product line; consideration must be given for component complexity, number of manufacturing operations, and number of individual components [37].

Out of the three platform architectures, modular platform architectures help reduce complexity in a product line as they greatly simplify the design and manufacture process. The body of research in this area includes methods to identify features that can be made modular, and the design of modular features to maintain performance.

One approach to modularization is from a functionality standpoint. Yu et al. (2003) used a design structure matrix (DSM) as a means to identify highly interactive product elements that could be grouped into a module, they then compared this method to MFD and heuristics to find it was the most repeatable [38]. Other works that explore methods to group product elements into modules include Malmström and Malmquist (1998) who employed MFD and DSM to quantify both technical and economic factors in early product development and Stone et al. (2000) who investigated a more elaborate heuristic formulation [39], [40].

Regardless of the module identification process, one of the keys to successful modular product platforms is the physical interchangeability of components within a family. Meyer and Lehnerd (1997), Sanderson and Uzumeri (1995), Sanchez (1994), and others

reinforce this notion by stating the importance of standard interfaces within a product family and identifying the consequences that stem from lack of standardization [41–43].

2.3.1.2. COMMONALITY

Similar to decreases in complexity, increases in commonality among product variants is a fundamental goal of product platforming meant to reduce costs in development and production. Researchers have investigated how to best measure, identify, and use commonality as a constraint or optimization objective in engineering design. Concerns regarding excess commonality, and therefore decreases in perceived variety, have also been addressed. A small sample of work in this area is discussed below.

Maupin and Stauffer (2000) utilize simplicity, direct costs, and delayed differentiation as proposed commonality metrics [44]. Examination of the related body of work yields a long list of proposed commonality indices. Thevenot and Simpson (2006) compared the following six metrics in a review: Degree of Commonality Index, Total Constant Commonality Index, Product Line Commonality Index, Percent Commonality Index, Commonality Index, and Component Part Commonality [45]. This review yielded a proposed methodology for using commonality indices in product redesign and recommendations for increasing repeatability and decreasing sensitivity. While many commonality metrics have been developed, their accuracy and their impact of product quality has not been carefully evaluated [45]. Alizon et al. take a step in filling this void by proposing the commonality vs. diversity index (CDI) in [46].

Hölttä et al. (2003) developed a five-step algorithm to find common modules across products and Dahmus et al. (2001) proposed a product family architecture created by interchangeable modules using a modularity matrix to identify commonality [47], [48]. Fellini et al. (2005) formulated the design problem to maximize shared product components without exceeding a user-defined performance loss tolerance [49]. Fellini et al. also worked on developing a modular platform design process around a commonality of components constraint [50]. Nayak, Chen, and Simpson (2002) expanded upon this work by including both commonality and performance criteria as competing objectives in optimizing the product family as a whole [51].

Increasing commonality across a product family does decrease cost, but it may also decrease revenue due to product cannibalization if products become too similar [7]. Therefore, firms must find a balance between commonality of components and variety of the end product. Simpson and D'Souza (2003) introduced a genetic algorithm that used commonality and individual product performance (likened to distinctiveness) as competing objectives [52]. A Product Variety Tradeoff Evaluation Method was proposed for assessing product platforms with varying levels of commonality by Simpson et al. (2001) [53] while Dobrescu and Reich (2003) looked to maximize commonality by incorporating shared modules among variants in a product family while maintaining key components in each different product [54].

2.3.1.1. COST

Both complexity and commonality are product line characteristics often used as a proxy measurement of cost. Estimation of actual product line cost and its use in product line design is not uncommon, however. Fujita and Yoshida (2004) developed a monotonic cost model to assess the benefits of commonality while Gonzalez-Zugasti et al. (2000) proposed a methodology for product platform design that took cost and performance requirements into account [55], [56]. Siddique and Repphun (2001) and Roemer and Fixson (2002) developed methods to link cost to product architecture decisions [57], [58]. Park and Simpson (2007) also map costs to product family components and incorporate the effect of design decisions on activity costs to give a more complete view of product family design expenses [59]. Helo et al. (2009) created a model for analysis of variety from a cost perspective and Wang et al. (2007) developed a procedure for product platform configuration to minimize cost [60], [61]. De Weck et al. (2003) optimized product platform design by maximizing profitability and minimizing cost and development time [62].

2.3.1.2. MINIMIZING THE COST OF VARIETY SUMMARY

This section has provided a small sample of all work done in the realm of product platforming as a means to offer variety at low cost. In reality, the volume of work in this area is robust. Further development in this area that increases efficiency and decreases cost can help continue to drive down the cost of variety. This work will, in turn, better fulfill the second tenet of mass customization. The following section examines the body of engineering

design work that addresses the first tenet of mass customization: determining "what the customer wants exactly".

2.3.2. INCORPORATING CUSTOMER PREFERENCES INTO DESIGN

Michalek et al. (2005) notes the importance of incorporating more marketing decisions into product family design [63]. Although the customer preference component of product design has been traditionally left to marketing research, recent work in the design field has integrated this metric into product family design. The body of work that looks to incorporate customer preferences into engineering design can be divided into two groups; market segmentation and demand modeling. Market segmentation involves dividing the market into groups of consumers that have similar preferences; products are then designed to meet the wants and needs of consumers in that segment. Demand modeling incorporates consumer choice data, typically from conjoint analysis, into the product line design process by using it to calculate and optimize metrics such as profit or market share. Relevant works in each of these areas are discussed below.

2.3.2.1. MARKET SEGMENTATION: CUSTOMER INCORPORATION PRIOR TO DESIGN

Segmentation of consumers is traditionally a marketing art rather than an engineering science, resulting in a knowledge gap between the two disciplines. Meyer and Lehnerd (1997) took a step towards bridging this gap by proposing a market segmentation grid for use in product family optimization [41]. This market segmentation grid has since become the *de facto* method to determine product differentiation in platform design problems [64]. The

purpose of this grid is to aide in product design for effective product positioning, i.e. balancing the tradeoff between customer diversity and cost of additional variation [65]. For example, Farrell and Simpson (2001) applied this strategy to identify platform leveraging strategies in a flow control valve product line [66].

In general, the market is broken up into market segments that define a particular user-group. Price/performance tiers are also divided into segments such as low cost and performance, mid-range, and high cost and performance. Market segments are plotted horizontally on a grid and price/performance tiers are plotted vertically. The intersection of a vertical market segment line and a horizontal price/performance tier line denotes a specific market niche for which a product is designed.

Although the market segmentation grid incorporates customer preferences to define the segments, it is used for product, not consumer, differentiation. Figure 2.1 provides a visual representation of three market segmentation grids with common platform strategy approaches.

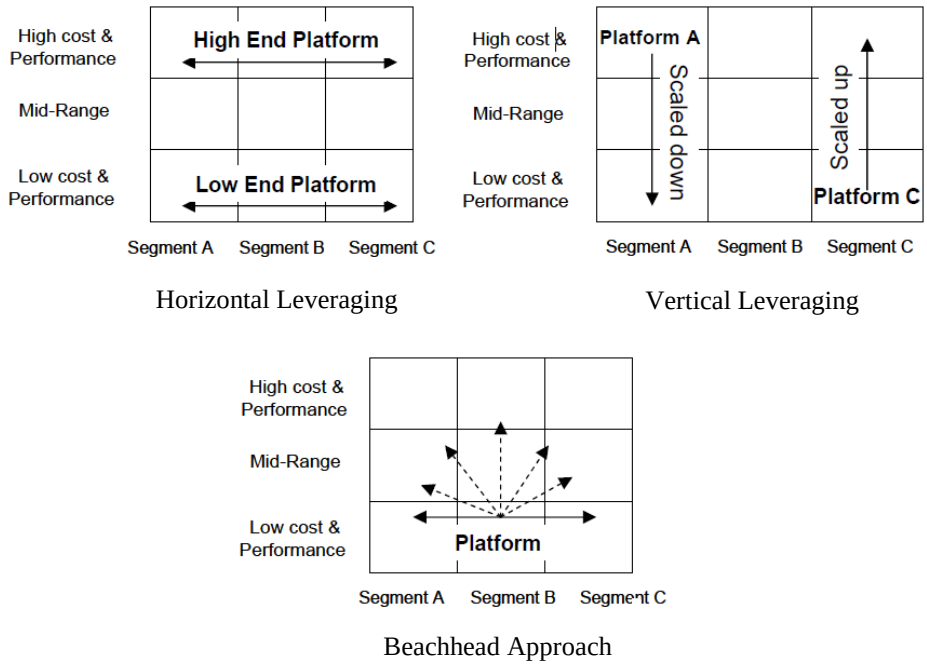

Figure 2.1: Market Segmentation Grid Diagram (adapted from Meyer and Lehnerd 1997)

More recently, work has begun to incorporate market segmentation directly into product line design optimization problems. Zhang et al. (2007) used engineering characteristics derived from customer preferences and purchasing behaviors in conjunction with fuzzy clustering as a means of market segmentation [67]. Kazemzadeh et al. (2009) also used conjoint data and clustering to segment a market and compare design of a standard product with design of custom products for each segment [68]. They found that customizing products for each segment led to increased customer satisfaction and increased cost savings due to commonality.

Although the market segmentation grid provided a key step in better linking the engineering and marketing domains, its *de facto* means of application is not sufficient to address the first tenet of mass customization. The market segmentation grid is a very high-level means of customer preference incorporation because it focuses on differentiating products based on general customer preference information. As such, it is often viewed as a corporate strategy tool rather than a primary concern in the more granular stages of product design.

Extending the market segmentation grid to better addresses the tenets of mass customization only exists as a theoretical guideline; this concept is referred to as segment-based mass customization (SBMC). Although past work on this subject is purely theoretical, it provides a basis from which practical methods may be proposed. The basic premise of this concept is implementation of mass customization to an optimal segment size rather than to a "market of one" proposed by Pine (1993) [15]. The optimal segment size is based on the market situation and company resources [69]. Jiang (2000) argues that creating unique products for each individual is, in most circumstances, sub-optimal because it becomes extremely difficult and becomes less profitable than a less granular customization strategy [69]. Lancaster (1990) listed four reasons for a company to pursue product variety within a group, three of which are used by Jiang (2000) to develop the theoretical construction of a segmentation-based mass customization strategy [69], [70]. The SBMC construct is based on the factors that affect optimal segment size from three perspectives: the individual consumer, the individual firm, and macro-marketing. Figure 2.2 below illustrates the resulting model.

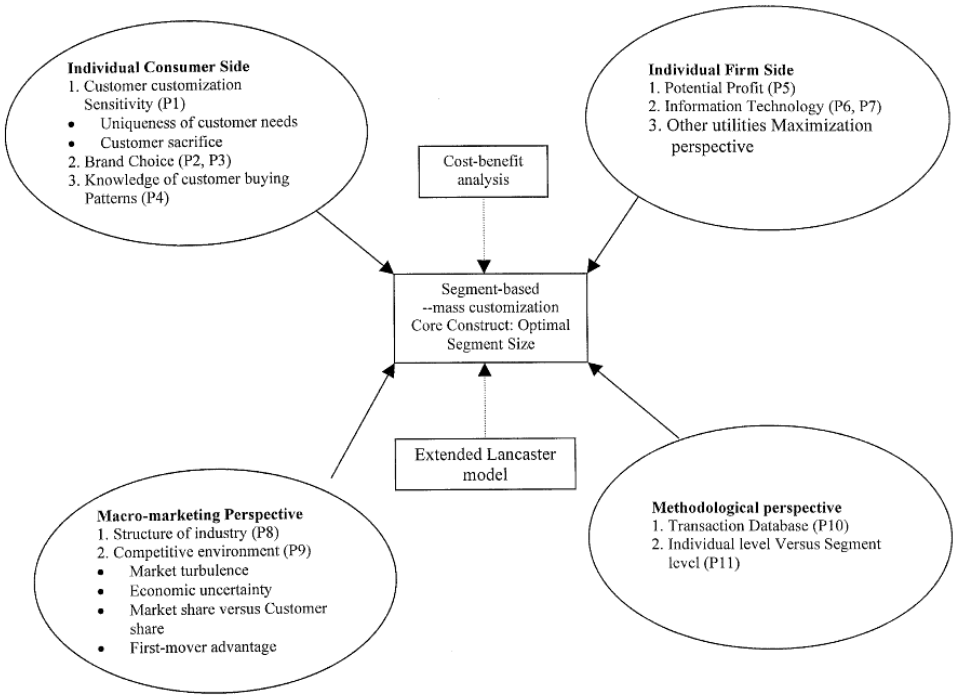

Figure 2.2: Segmentation-Based Mass Customization (SBMC) Model

The SBMC construct highlights the need to consider the firm, the individual, and the market context when making decisions regarding level of customization. Although the architecture of this paradigm is theoretical, there is opportunity to explore how its multi-perspective tenets can be used to better the engineering design process. Rather than simply offering variety at low cost, it provides motivation for designers to seek the "right amount" of variety in order to maximize overall value. The idea of SBMC provides conceptual motivation for the work conducted in this thesis.

2.3.2.2. DEMAND MODELING: CUSTOMER INCORPORATION DURING DESIGN

While the market segmentation grid itself does help determine design parameters using perceived customer wants and needs, its *de facto* method of use does not incorporate customer preference information into the product line optimization. Market-based engineering design research and method development is beginning to use customer demand modeling techniques taken from the marketing domain in conjunction with market segmentation and other consumer preference-based metrics in an effort to more directly incorporate customer preferences into engineering design optimization.

The most commonly used demand modeling method is discrete choice analysis, discussed in Section 2.2 above. Discrete choice analysis has been applied in work conducted by Wassenaar and Chen (2003), Wassenaar et al. (2005), Michalek et al. (2005), and Kumar et al. [2007] to name a few [63], [71–73]. Demand modeling allows for quantitative assessment of revenue, life-cycle cost, and profit because these metrics are, in fact, a function of customer demand. Kumar et al. 2009 used demand modeling techniques within the market segmentation grid construct to maximize profit in the design of a family of universal motors [12]. Previously, Kumar et al. (2007) also used a demand modeling approach that facilitated engineering design decisions for complex systems with profit and market share as optimization objectives [73]. In addition to revenue, share of preference and aggregate contribution measure how well products in a family meet customer preferences. Share of preference provides a percentage estimation of how much a customer prefers one product compared to all others in the market (including the ‘None’ option). Aggregate contribution

estimates the net gain to a company in the market if only direct product costs and revenues are considered.

Kumar et al. (2008) identified demand modeling not only as a tool for incorporating customer preference information into engineering design, but also as a critical link between the marketing and engineering disciplines in product development [74]. Michalek et al. (2005) commented that "marketing and engineering design goals are driven by consumer preferences and engineering capabilities, two issues that conveniently are addressed in isolation from one another" [63]. In an effort to bridge that gap, these authors proposed a method that combines analytical target cascading (ATC), a method to solve large-scale optimization problems, with established marketing tools such as conjoint analysis, discrete choice modeling, and demand forecasting. This method calls for development of an engineering design sub-problem and a marketing planning sub-problem (incorporating demand modeling) whose objectives are used in a multi-objective optimization problem [63]. Michalek et al. (2007) also used ATC as a tool in their investigation of how design changes affect both cost and revenue as well as product desirability in the marketplace [75]. The authors examine how trade-offs between cost savings and market desirability affect a firm's bottom line. Kumar et al. (2008) pursued this integration using a different approach, they combined market considerations (customer preferences and competition) and engineering considerations (modular design, shared parts and processes, etc.) to optimize a product platform for a vehicle case study [74]. Work of this nature demonstrates the recent push to facilitate better information transfer between engineering and marketing domains.

The works cited above pursue consumer demand modeling either homogeneously (everyone has the same preferences) or represent heterogeneity but dividing the market into homogeneous segments. More work has investigated the effects of granularity in demand modeling (how and to what magnitude heterogeneity is represented in the model) on the outcome of the optimization. Ferguson and Donndelinger (2010) used share of preference as a metric to assess how the choice of a Latent class multinomial logit or hierarchical Bayes mixed logit model of consumer preferences affected the configuration and performance of an optimal product family design [14] Michalek et al. (2011) performed a firm-level product line optimization (where profit was the objective) that investigated the effect of modeling consumer demand on three levels of granularity; homogeneous preferences, segmented heterogeneous preferences, and continuous (individual-level) heterogeneous preferences [13]. In general, the study found that modeling customer demand more heterogeneously provided higher value to the firm in the form of profit and market share. The use of highly granular demand models is, at this time, an underdeveloped area of consumer preference incorporation in engineering design.

Although incorporation of customer preferences through consumer demand models is a relatively recent push in engineering design, it holds great promise as an extension into execution of mass customization. For, to give consumers “what they want exactly”, a designer must first discern what characterizes these wants and needs in terms of engineering constraints, and then be able to create products that satisfy these wants and needs for the masses. Quantification of preferences is an essential tool in this process, as is the ability to do so on an individual level. Discrete choice analysis models are an established means to create

these models in the marketing community, and their prevalence in engineering optimization problems is steadily growing. Derivatives of discrete choice models that extract preferences on an individual level, and their incorporation into product line optimization, provide a potential pathway that can move design closer and closer to true mass customization.

2.4. CHAPTER SUMMARY

This chapter presents the concept of mass customization as the embodiment of two seemingly contradictory tenets: 1) *goods and services that maximize customer value by giving them "exactly what they want", and 2) providing these goods and services at "prices consistent with mass production."*

Sacrifice gap, the measure of "what the customer wants exactly" less "what the customer settles for", is a widely discussed concept that this work likens to a measure of how close a market is to mass customization. Minimizing sacrifice gap is said to benefit both the customer, by providing greater value, and the firm, by increasing customer loyalty. Despite the perceived benefits of minimizing sacrifice gap, no methodology has been proposed to quantify it.

Determining what provides customers with maximum value (referred to as utility within the context of RUMs) has largely been the work of the marketing discipline, and discrete choice analysis using choice based conjoint surveys has emerged as the most appropriate choice for the goals of this work. The data provided by discrete choice analysis can numerically describe the terms in the sacrifice gap definition discussed in Chapter 3, thereby addressing Research Question 1.

Providing variety at prices consistent with mass production has been the work of engineering and manufacturing research. Product platforming is the most common design strategy that allows firms to leverage commonality across product lines to maintain mass production efficiency and costs. Much of the research in this area has focused on decreasing costs and increasing commonality across a product line, while the incorporation of customer preference information is becoming more prevalent.

The body of engineering design work that incorporates consumer demand models that leverage discrete choice analysis, DCA, is steadily growing. Much of the existing research focuses on optimizing product lines for firm-centric metrics such as profit and market share. Although these works incorporate consumer preferences into the design process, they are done indirectly since the objective remains a firm-centric metric. In addition, the level of consumer demand model granularity has been at the aggregate or market segment level. Use of individual-level (representing continuous market heterogeneity) models has been executed in several works, and there stands significant potential for research that expands on their findings.

Collectively, commentary on the concept of mass customization highlights its potential to add value to both the firm and the consumer. Incentives that stem from current market forces should, in theory, push firms toward practical application of this strategy; yet the execution of mass customization has not been largely adopted in industry. The question is then posed, “why not?” Ferguson et al. (2010) identify several research and knowledge gaps that help to explain the mass customization application in theory and in practice [23]. The three that are addressed by this work are repeated below:

2. Need for research and methods that aide in the transfer of information between the engineering and marketing domain

4. Need for investigation of simultaneous market segmentation and product variant creation to optimize customer value

6. Need for engineering design metrics that quantify how well a product concept meets the need of the consumer [23]

The research questions work to address the knowledge gaps identified in this chapter by quantifying sacrifice gap (Research Question 1) and using the quantified customer preference metric as an objective in engineering product design (Research Question 2). Research Question 1 looks to better facilitate information transfer between marketing and engineering disciplines, while Research Question 2 aims to use this metric (which quantifies how well products meet customer needs) to optimize customer value in product design.

The remainder of this thesis is in the context of a hypothetical market scenario featuring an MP3 player company and a sample market. Chapter 3 presents a methodology for obtaining and using conjoint analysis data and formulates an empirical definition of sacrifice gap. Then, Chapters 4 and 5 investigate how sacrifice gap can be used to guide engineering design of product architectures with the aim of moving products in the marketplace from the mass production pole towards the mass customization pole (in Figure 1.1). Chapter 4 uses only the consumer-centric metric as an optimization objective in the product line design problem. Chapter 5 builds on this problem by introducing a firm-centric metric as a second objective, thereby making the problem multi-objective.

CHAPTER 3: METHOD AND METRIC FORMULATION

The first two sections of this chapter present the motivation for and assumptions used to investigate the research questions given in Chapter 1. The research questions are investigated in the context of a hypothetical market scenario which is introduced in Section 3.3. Sections 3.4 to 3.7 describe how the research questions are investigated in the context of this hypothetical market scenario. Section 3.4 provides a guideline to obtain and model the data Section 3.5 uses to formulate the sacrifice gap metric. Section 3.6 presents the process to model the alternatives in the hypothetical market. Methods to explore sacrifice gap's use in product line design are proposed in Section 3.7. These investigations take the form of a consumer-centric, single objective approach to product design and a consumer and firm-centric, multi-objective approach to product design. This chapter concludes with a summary of the key concepts in Section 3.8.

3.1. ASSUMPTIONS

The proposed approach aims to formulate and use a sacrifice gap to design product lines that better accomplish the two tenets of mass customization. To accomplish these goals, the following assumptions are used:

1. *Respondents exhibit compensatory decision making processes*

   Assuming a compensatory decision making means that the consumer is willing to make trade-offs between attributes to maximize their overall utility. For example, a customer may be willing to give up a higher positive part-worth of a feature (such as leather seats versus cloth) to avoid an even greater negative part-worth associated with

the price increase of the preferred feature. This is in contrast to non-compensatory decision models where a positive evaluation of one attribute does not compensate for a negative evaluation of another attribute [76]. A different respondent may not be willing to purchase a car without automatic transmission regardless of price. Further investigation of compensatory versus non-compensatory models is a research challenge that requires further exploration; the effect of decision process modeling becomes more and more important in design as marketing methods become increasingly incorporated in engineering design.

2. Customers who choose to customize a product are optimizers, not satisficers

This work assumes that a customer seeking mass customized products is an optimizer rather than a satisficer. An optimizer is an individual who attempts to maximize their overall utility by considering both features and price in their decision. Essentially, they believe that a "best" option exists and seek to find it. A satisficer, on the other hand, seeks to purchase the cheapest product that meets a certain user-defined threshold. Note that this may not be the optimal product in terms of overall utility. Satisficers believe that multiple products are sufficient, and are less willing to seek a "best" option.

We study the product design problem of a revenue-maximizing firm that serves a market where customers are heterogeneous with respect to their valuations and desire for a quality attribute, and are characterized by a perhaps novel model of customer choice behavior. Specifically, instead of optimizing the net utility that results from an appropriate combination of prices and quality levels, customers are "satisficers" in that they seek to buy the cheapest product with quality above a certain customer-specific

threshold [74]. Mass customization refers to the existence of a custom product which is unique to the individual, meets their needs in a way that maximizes perceived value, and is proactively specified by said customer. Since a satisficer would not be interested in maximizing value or contributing additional resources to creating such a product, one can assume that individuals interested in mass customized products are optimizers. This assumption is consistent with the utility maximization principle which provides the basis for derivation of Random Utility Models used to quantify consumer preference data in this thesis.

3. *The firm is able to produce and distribute mass customized products using the price structure defined defined price structure*
4. *The market is static at the time the product line is designed*
5. *The company has defined a subset of attributes that they can feasibly customize, and these attributes are included in the conjoint survey*
6. *The part-worths of attribute levels are linear additive and their sum yields the overall product utility*

Conjoint analysis often assumes a linear additive part-worth utility model [11]. Although it is possible to add non-linear interaction terms, this work does not explore the effect of non-linearities and therefore neglects adding them to the model.

7. *Interpolating between part-worth values for continuous attribute levels is done in a linear manner*

Several attributes featured in conjoint surveys, such as price, exhibit a near-continuous array of values in real world application. In the method described below, the prices featured in the survey range from $49 to $699. Clearly, it is infeasible for the survey to feature each price value between $49 and $699, therefore 8 different price points are chosen. Interpolating between part-worths of the 8 levels is done using a linear

function. Further, the price part-worths are constrained to be decreasing (that is a lower price is always preferred to a higher price).

The following section provides the motivation for the approach used to investigate the two research questions from Chapter 1.

3.2. MOTIVATION FOR APPROACH

The information presented in Chapter 2 highlights the generic need for better integration of customer preferences into engineering design so product line design can be pushed toward goods that better provide the customer "exactly what they want" at "prices consistent with mass production." The conclusions of a literature review conducted by Ferguson et al. (2010) support this notion, and hypothesize that the need for better mapping of information from marketing to engineering will lead to a multi-objective problem composed of competing consumer and firm value propositions; minimization of sacrifice gap being the former and minimization of production cost being the latter [23]. Ferguson et al. (2011) begin to address this hypothesis by examining challenges associated with developing the customer value metric of sacrifice gap [77]. Specifically, they investigate the complexities associated with applying marketing methods of consumer preference modeling to mass customization engineering design problems for mass customization.

Their methodology involved constructing and implementing a discrete choice survey, and then analyzing respondent data using hierarchical Bayes (HB) and Latent Class modeling techniques. Using an MP3 player as the mass customizable product, the authors discuss several challenges associated with survey creation and implementation. These challenges include: determining how many choice tasks (questions) each respondent is asked, interaction

of product attributes included in the survey (e.g. no display screen and ability to play video), and viability of text-only surveys when attributes are spatial in nature (e.g. diagonal screen size).

Using utility part-worths calculated in fitting the HB model, Ferguson et al. (2011) examine preference tendencies to determine each respondent's "ideal product." An ideal product is defined as the combination of non-price attribute levels that yields the highest cumulative utility. The cumulative price-excluded utility is referred to as the *Price Excluded Product Utility* in this work. Once each respondent's ideal product and corresponding utility are determined, this work calculates the maximum price each respondent would pay for this product [77].

To determine the maximum price a firm can charge for the respondent's ideal product, competing products and the customer's option to 'walk away' are considered. The first choice decision assumption is used in this calculation; that is, a customer will choose the product that maximizes their value. As such, the overall utility (price included) of several Apple iPods are considered to be the competing products, and the 'None' utility is the walk away option. For a customer to choose the firm's custom product, the overall utility (price included) of the custom product must be marginally higher than the next highest utility of the competing products and walk away option. The allowable price utility is taken as the difference between the Price Excluded Product Utility and the best overall utility in the outside market. This allowable price utility is then mapped back to a price value by interpolating between utility values for price values included in the survey. The work itself provides a more in depth description as well as an example. The authors suggest that each

respondent's maximum allowable price can be used as a constraint in the multi-objective optimization problem described above [77].

Upon performing this calculation, Ferguson et al. (2011) derived the histogram found in Figure 3.1 below.

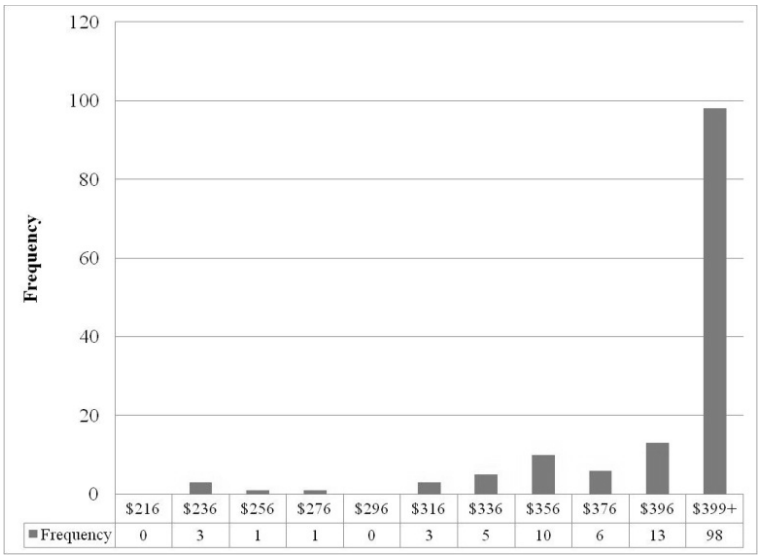

Figure 3.1: Histogram of Maximum Allowable Product Price [77]

The histogram above depicts the maximum allowable price for all respondents. Almost 100 of the 140 respondents exhibit maximum allowable prices that are above the bound covered in the discrete choice survey ($399). The respondents in this bin have remaining utility available for the firm to increase the price of the product, but the magnitude of that increase is indeterminate because it would require extrapolating beyond the data points aquired in the survey. Extrapolating beyond the bounds of the survey can provide

grossly inaccurate results because the decision maker's choice behavior is unknown and can differ drastically from trends in the known region (where the model is defined by price points included in the survey).

The conclusion of this work identifies several areas of improvement for future work to address. These issues include:

- Improvements in survey creation and execution
- Deeper understanding of how utility curves are related to consumer psychology
- How compensatory decision making is captured in conjoint surveys and the potential use of adaptive conjoint or partial profile conjoint methods
- Whether use of linear additive attribute part-worths provide accuracy sufficient for mass customization applications
- Uncertainty in respondent preference modeling
- Behavior of unique ideal product count with respect to increasing number of respondents [77]

The work described above provides a starting point for the investigation conducted in this thesis. Consumer preferences are solicited in a similar manner, taking into account concerns raised by Ferguson et al. (2011), and an HB model is fit to derive individual level attribute part-worths [77]. This work then uses attribute part-worths to quantify sacrifice gap. The hypothetical market scenario that provides the context for these case studies is described below.

3.3. MARKET SCENARIO INTRODUCTION

The hypothetical market scenario begins with a firm, Company X, mass producing a single MP3 player configuration; this configuration is referred to as the base product. Their competitors collectively produce three products; a low-price, mid-price, and high-price option. In addition to outside product competition, Company X's internal product also competes against a consumer's 'walk away' option (the 'None' part-worth utility from conjoint analysis). The internal product(s) are those produced and sold by Company X; when only the base product is produced there is only 1 internal product. The base product, three competing products, and 'None' option define the alternatives in the "mass production market".

This scenario places Company X at the beginning of the design phase for a subsequent generation of products; this generation of product will be part of the "customization market". The new generation will give consumers two options: purchase the base product at the same price as before or customize an mp3 player at a price premium. The competing products are assumed static in this market scenario. This means that in the customization market the customer will have the option of pursing a customized product in addition to all of the alternatives present in the mass production market; the prices and, as a result, utilities of these mass production market alternatives are unchanged in the customization market.

The customization options serve to push the market towards mass customization. The introduction of customization options will expand the internal product portion of available

market alternatives. In the customization scenario the internal products are all possible custom MP3 player configurations in addition to the base product.

If a customer chooses to purchase a customized MP3 player, they will choose the group of available feature levels that provide them the greatest net utility; this optimization includes consideration of both feature and price utilities. This product is called their optimal product (given a particular choice set of level options). Note that some feature adjustments increase the price of the product, while others create a net price reduction in accordance with which levels are chosen. The price of this optimal product will include the incremental price of all features present on the product as well as a customization tax penalty. This customization tax serves to account for the added financial burden to the firm of offering customization options. Details pertaining to the magnitude and application of this customization tax are included in subsequent sections.

According to literature, the inclusion of customization options should increase Company X's differentiation with respect to competing firms and increase customer loyalty [18], [19]. Sacrifice gap is used to help determine and assess the configuration of potential next generation MP3 player product lines (which feature levels are available as customization options).

The following sections detail how the research questions are investigated in the context of this hypothetical market scenario. This investigation process is depicted as Figure 3.2.

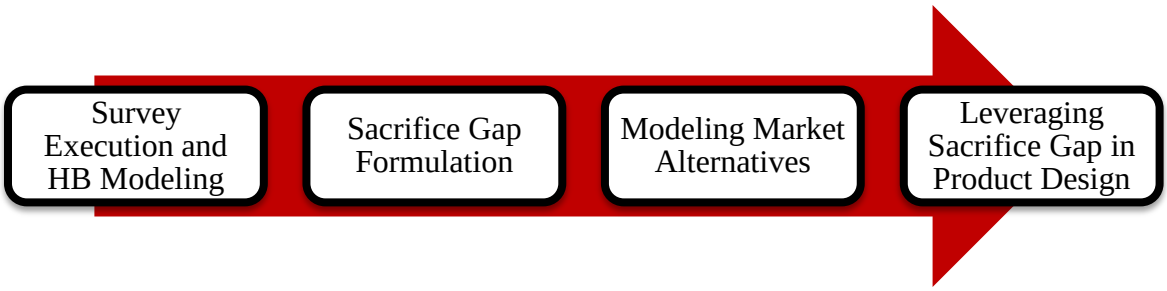

Figure 3.2: Research Question Investigation Flow Chart

Section 3.4 describes how the discrete choice survey is developed and executed using Sawtooth SSI Web, and how the resultant consumer choice data is modeled using a hierarchical Baysian approach conducted using Sawtooth Software CBC/HB. General procedures as well as a detailed account of its application to the hypothetical market scenario are given. Once the consumer preference data is acquired and modeled, Section 3.5 describes how it is used to quantify sacrifice gap on an individual and market-level. Then, Section 3.6 describes the general process used to model alternatives in the market in terms of the HB part-worths; this is also applied to the hypothetical market scenario. Finally, Section 3.7 puts forth the general procedure used in this work to incorporate sacrifice gap into product design as an objective function.

3.4. SURVEY EXECUTION AND HB MODELING

The first step in the proposed approach is the development and execution of a discrete choice survey to determine customer attribute preferences for the product in question. This section summarizes general guidelines for creating discrete choice surveys and demonstrates

how these are applied to the hypothetical market scenario. This section is highlighted on the flow chart given as Figure 3.3 below.

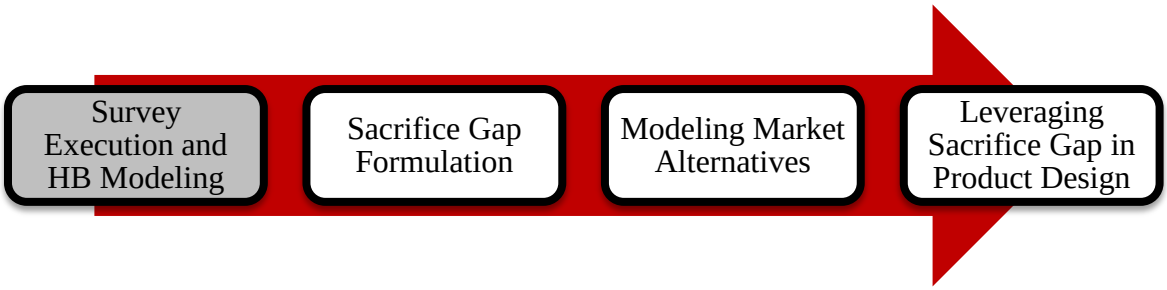

Figure 3.3: Section 3.4 Investigation Process Flow Chart

3.4.1. GENERAL GUIDELINES

The following section describes a general procedure for developing and executing a discrete choice survey in Sawtooth SSI Web and mathematically modeling the consumer choice data with HB using Sawtooth Software CBC/HB.

3.4.1.1. SURVEY DEVELOPMENT AND EXECUTION

Discrete choice survey questions give respondents several product profiles to choose from rather than asking for a direct ranking. Repetition of these questions, or choice tasks, provides the data necessary to measure the perceived values of specific product attributes [78]. For ease of construction and administration, this approach uses an academic license of Sawtooth SSI Web software to create and administer the survey [79]. For optimal survey

effectiveness, the following questions were investigated to determine general guidelines and strategies

Q: How many attributes and how many attribute levels are appropriate?

A: Although the Sawtooth License permits up to 10 attributes and up to 15 levels per attribute, Johnson and Orme (2003) suggest keeping the survey as simple as possible [80].

Q: How should survey creation be configured in Sawtooth (balanced overlap, random, complete enumeration)

A: The SSI Web Manual suggests using the 'balanced overlap' approach as it is a middle ground between random designs and complete enumeration [81].

Q: How many questions should each respondent be asked?

A: In general, Johnson and Orme (1996) found that respondents can be asked up to 20 questions without degradation of response quality because, within that range, there is no evidence of increasing random error in the model [82].

Q: How many respondents are needed to create an accurate model?

A: Johnson, the author of Sawtooth Software's CBC System, recommends the following rule of thumb for determining requisite number of respondents (Equation 3.1):

$$\frac{nta}{c} \geq 500 \tag{3.1}$$

Where n is the number of respondents, t is the number of tasks, a is the number of alternatives per task (not including 'None'), and c is the largest number of levels for any one attribute [11].

Q: Should a 'None' option be included?

If a respondent does not like any of the products displayed they may pick the 'None' option, this choice simulates the 'walk away' situation in a real world purchase case. Johnson and Orme (2003) suggest including the 'None' option because it makes choice tasks more realistic, and improves the quality of data [80].

With these considerations in mind, the survey can be designed and implemented for the product in question. The following steps provide the process used to create and administer the survey.

1. **Determine which components best describe the product to the consumer *and* provide engineering guidelines sufficient for product design. Translate these components to attributes featured in the conjoint survey**

Step 1 embodies one of the key challenges associated with integrating consumer preferences into engineering design. Discrete choice analysis data can only provide preference data for attributes featured on the survey. These attributes, therefore, must describe the product in a manner that is understood and digested by the consumer *and* provide design and performance guidelines to the engineer. The difficulty in identifying and mapping functional components to consumer identifiable attributes differs from product to product.

2. **Determine appropriate number of levels for each attribute**

Binary attributes such as Wifi/No Wifi on an e-reader or navigation/no navigation on a vehicle are either present or absent in the product configuration. However, other attributes such as storage capacity on the e-reader or exterior color on the vehicle present a greater challenge. For storage space, one must consider the range of sizes to present on the survey and how to distribute the discrete levels within this range. For exterior color, one may consider the number of hues to list as options, the finish (matte, metallic, etc.), and whether to present a custom color or custom graphic options.

Another consideration is respondent bias from the "Number-of-Levels Effect". That is, respondents tend to give attributes defined by a larger number of levels more importance. It is therefore advisable to keep the number of levels as consistent as possible across attributes [83].Also note that binary attributes may be combined to create a greater number of levels and a fewer number of attributes. Considering an MP3 player, one could present the

following levels for an attribute titled “Photo/Video Playback”: 1. Photo Playback Only, 2. Video Playback Only, 3. Photo and Video Playback, 4. No Photo or Video Playback. This is in contrast to presenting two different attributes “Photo Playback” and “Video Playback” each with “on” or “off” levels.

At the end of step 2, the requisite attributes and levels used to describe customizable features of the product have been established. Table 3.1 shows a generic representation of the resulting attribute-level matrix. This product is described in terms of 5 attributes that have varying numbers of levels. Note that attributes 1 and 4 are binary, and could be merged into one attribute with 4 levels as discussed above.

Table 3.1: Generic Attribute and Level Matrix

	Attributes				
Levels	**Attribute 1**	**Attribute 2**	**Attribute 3**	**Attribute 4**	**Attribute 5**
1	1.1	2.1	3.1	4.1	5.1
2	1.2	2.2	3.2	4.2	5.2
3		2.3	3.3		5.3
4			3.4		5.4
5			3.5		

3. Design survey in Sawtooth Software

Once the attributes and levels are established, Sawtooth SSI Web Software is used to create the conjoint survey. Sawtooth allows the user a multitude of configuration options

including aesthetics (colors, fonts, etc.), question structure, survey length, and experimental design settings.

Survey aesthetics, although not a mathematical consideration, are nonetheless important. Aspects such as color selection, size of text, and size of entire survey template on different web browsers should be considered.

Although discrete choice questions are the source of respondent preference data used directly in the following optimization procedure, the user can gain additional insights into respondent's preferences with supplementary questions. These questions may ask the respondent to describe the features of their current product, their demographic, or what the use the current product for most often, to give a few examples.

Optimal survey length is situation-dependent, but the user should keep in mind the guidelines provided in the Sawtooth Technical Papers and summarized above. The user can also consider adding holdout questions to the survey. These are discrete choice questions common to all survey versions that are not included in mathematical modeling. The purpose of holdout questions is to allow the user to check the accuracy of the model; the part-worths derived from modeling should be able to predict the respondent's answer to these questions. Johnson and Orme (2010) suggest including these questions [84].

Experimental design settings include task generation method and number of unique questionnaires. The Sawtooth SSI Web Manual suggests using the balanced overlap approach in the experimental design. Regarding the requisite number of unique questionnaire versions, the manual suggests "enough versions of the questionnaire so that the number of random

choice tasks times the number of questionnaire versions is greater than or equal to 80," but more versions is deemed advantageous [81].

Once the survey is configured to the specifications laid out above, the files are prepared for web upload by the program. The files are then uploaded to web space and respondent input can be solicited. Once a sufficient number of responses are obtained, the user can begin the mathematical modeling portion of the process.

3.4.1.2. HB MODELING

Sawtooth Software CBC/HB is used to conduct a hierarchical Baysian analysis of the consumer preference data gathered in the conjoint survey [85]. Sawtooth CBC/HB was chosen to fit the data because of its compatibility with Sawtooth SSI Web, and its ease of use. HB models may also be coded by the user to provide greater flexibility.

Unlike survey design and implementation, model fitting requires little user input to derive the part-worths used in later analysis. Conjoint data files are simply retrieved using the administration function in the Sawtooth SSI Web software and prepared for analysis. These .CHO files are then imported into Sawtooth CBC/HB. The standard settings for the Sawtooth CBC/HB software are summarized in Table 3.2.

Table 3.2: Sawtooth CBC/HB Standard Model Fit Settings

Iterations	Number of iterations before using results	10,000
	Number of draws to be used for each	10,000
	Skip factor for saving ransom draws	5
	Skip factor for displaying in graph	1
	Skip factor for printing in log file	100
Data Encoding	Total task weight	5
	Include 'none parameter	Yes
	Code variables using effects coding	Yes
Miscellaneous	Target acceptance	0.3
	Starting seed	Random
Covariance Matrix	Prior Degrees of freedom	5
	Prior variance	2
Alpha Matrix	Use Default prior alpha	Yes

Also note the standard settings yield part-worth values on a zero-centered difference scale within an attribute (the implications of this were detailed in Chapter 2.2). That is, the part-worths of all levels that describe a particular attribute sum to zero. For example, the part-worths for attribute X level 1, attribute X level 2, and attribute X level 3 sum to zero for each of the two respondents depicted in Table 3.3.

Table 3.3: Sample of Respondent Part-Worth Utilities

Part-worths for Attribute X			
Respondent Number	**Level 1**	**Level 2**	**Level 3**
1	-0.36	0.50	-0.14
2	0.75	-1.12	0.37

The survey guidelines and HB settings discussed above are applied to the hypothetical market scenario presented in Section 3.3. Details of this application are discussed below.

3.4.2. MARKET SCENARIO APPLICATION

Similar to the previous section, the following is grouped into two parts: survey development and execution and mathematical modeling.

3.4.2.1. SURVEY DEVELOPMENT AND EXECUTION

The attributes used to define MP3 players in this case study are based on iPod models currently in the market, assuming that a competing MP3 player company would have similar capabilities. Several additional features and levels are added (such as additional color options or the addition of a background graphic), all of which are based on technologies that are reasonable and accessible for an MP3 player company. Since the data from the survey is meant to collect consumer preference information for use in engineering design applications, selection of features to include in the survey is pivotal. The feature levels must be feasible to design and manufacture, provide information that can be quantified by designers, and be presented in a manner that describes the product fully to consumers.

Using information provided by apple.com, the following technical features were selected [86]:

- Color
- Capacity (hard or flash drive storage)

- Size and Weight
- Wireless Capability
- Display (screen size)
- Camera, Photo, and Video Capability
- External Buttons and Controls
- Sensors (gyroscope, accelerometer, light sensor)

Using the above list as a base, the attribute and level configuration was iterated upon to produce the most effective survey possible. The final list of attributes is described in Table 3.4 and the configuration is given in Table 3.5.

Table 3.4: Final Attribute Description

Attribute	Description
Photo/Video/Camera	photo playback capability, video playback capability, and still camera.
Web/App/Pedometer	WIFI for web access, app capability, presence of pedometer
Input	method of user input, e.g. touchscreen
Screen Size	diagonal length of screen
Storage	hard drive of flash drive storage capacity
Background Color	color of back side and trim around screen on front
Background Overlay	graphic or pattern overlay on colored portion of the MP3 player

Table 3.5: Final Attribute and Level Configuration

	Attributes							
Lvl.	**Photo/ Video/ Camera**	**Web/ App/ Ped**	**Input**	**Screen Size**	**Storage**	**Back-ground Color**	**Background Overlay**	**Price**
1	None	None	Dial	1.5 in diag	2 GB	Black	No pattern / graphic overlay	$49
2	Photo only	Web only	Touch-pad	2.5 in diag	16 GB	White	Custom pattern overlay	$99
3	Video only	App only	Touch-screen	3.5 in diag	32 BG	Silver	Custom graphic overlay	$199
4	Photo and Video Only	Ped only	Buttons	4.5 in diag	64 GB	Red	Custom pattern and graphic overlay	$299
5	Photo and lo-res camera	Web and App only		5.5 in diag	160 GB	Orange		$399
6	Photo and hi-res camera	App and Ped only		6.5 in diag	240 GB	Green		$499
7	Photo, video and lo-res camera	Web and Ped only			500 GB	Blue		$599
8	Photo, video and hi-res camera	Web, App, and Ped			750 GB	Custom		$699

Attribute and level configuration was established using the guidelines presented in the above section. Notable changes and considerations encountered during iteration include the following:

1. Reducing number of attributes
    - Combined multiple features into one attribute. e.g combining the binary attributes of web, app, and ped into one 8-level attribute.

2. Keeping number of levels per attribute as consistent as possible to mitigate "Number-of-Levels Effect"
    - Reduced overall number of price levels and combined binary features into a single attribute.
3. Providing upper bounds on numerical attributes (such as price and storage) per suggestions from Ferguson et al. (2011) [77].
    - Introduced price and storage levels that well-exceed characteristics of current products.

Once the attribute and level configuration was established, the survey was designed in Sawtooth SSI Web software. Each respondent was asked 12 choice tasks, 10 random choice tasks and 2 fixed choice tasks. Figure 3.4 depicts an example of a choice task.

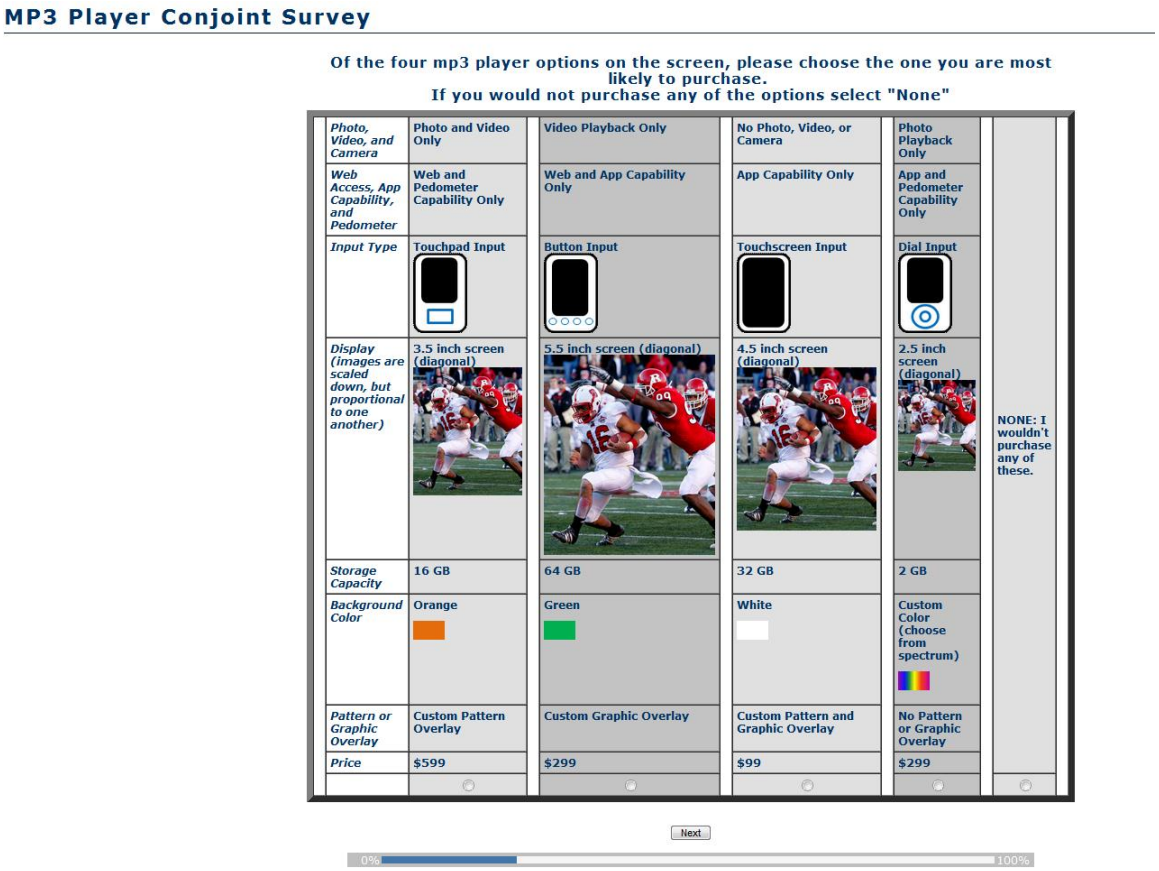

Figure 3.4: Choice Task Example

Outside of structural guidelines discussed in Chapter 3, the following survey aesthetic aspects were considered to make the choice tasks as effective as possible.

1. Visualization of Attribute Level Characteristics

   - Attributes such as color are ambiguous (e.g which shade of blue?) and others are difficult for the user to visualize (e.g. how big is a 3.5 inch diagonal screen?). To increase consistency of attribute and level perception across all respondents, images were included for ‘Input Type’, ‘Display’, and ‘Color’ attributes.

2. Survey Orientation in Varying Browser Windows

   - The size of the survey in the internet browser window is dependent upon both the size and volume of text and images. Since volume is unique to a particular product configuration, some choice tasks did not fit in the window and required the user to scroll. To ensure that entire survey was visible in the window (without requiring the user to scroll down or to the side) in various internet browsers and screen resolutions the text size was reduced and the images were scaled down.

At the conclusion of the choice task portion, each respondent was prompted, but not required, to enter demographic and functional use information. Figure 3.5 depicts the demographic questions, and Figure 3.6 depicts the functional use questions. The information collected from this portion of the survey is not utilized in this thesis, but may prove useful in future work.

Figure 3.5: Demographic Questions

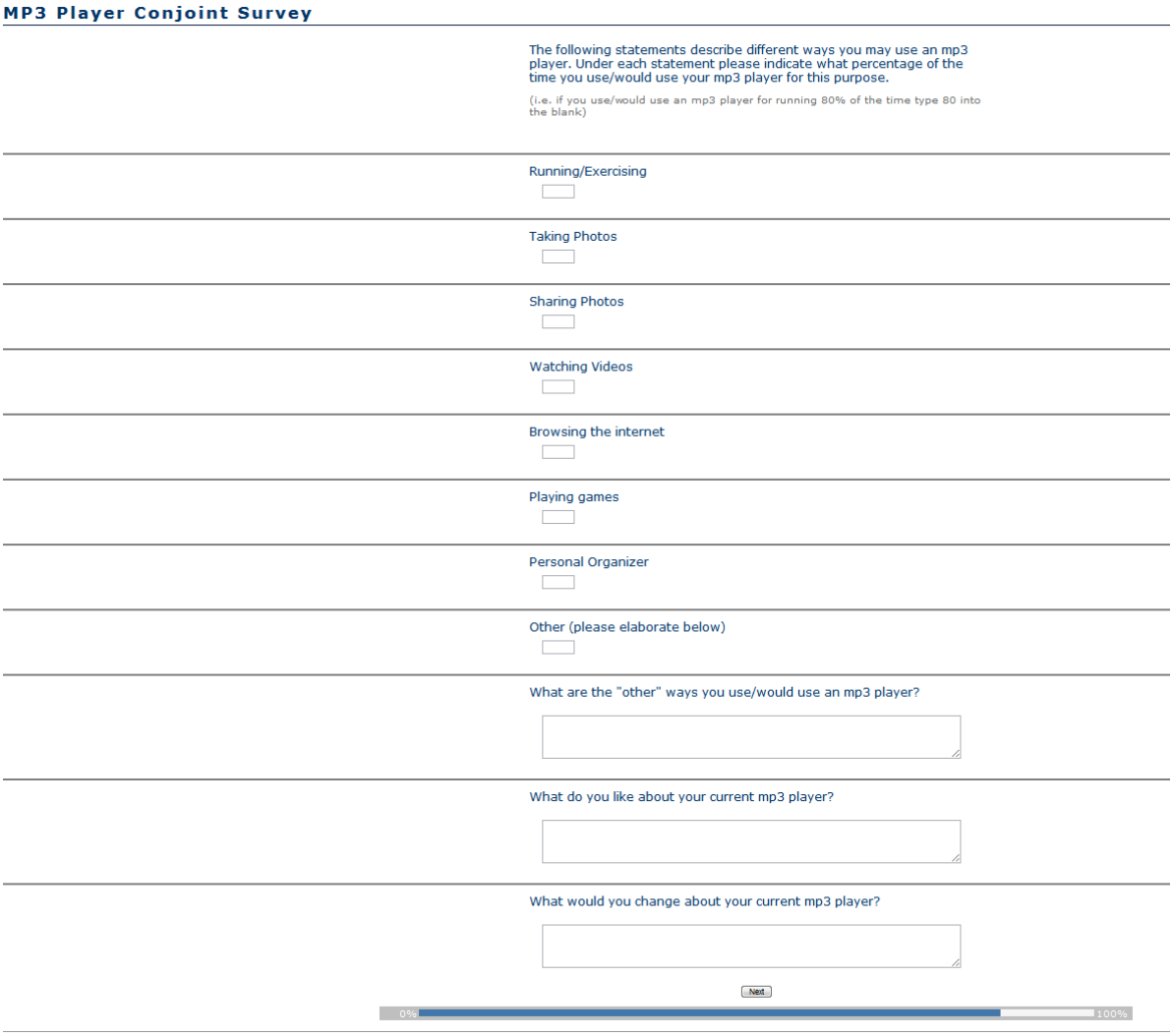

Figure 3.6: Functional Use Questions

The conjoint survey was prepared in Sawtooth SSI Web, and uploaded to previously purchased web space. Respondents could then access the survey via a URL that was disseminated through email, social media, and word of mouth. Using web-based rather than paper-based administration allowed for greater volume and diversity of participants, while

reducing data collection and preparation time expenditure. After a sufficient volume of responses was reached the data was retrieved using the Sawtooth SSI Web admin function and imported into the program. The data was then prepared for use in Sawtooth CBC/HB.

Administration of the survey garnered 205 complete responses; that is, all 12 choice tasks were completed. These 205 respondents make up the theoretical market used in the case study. The survey was dispersed primarily through graduate students and faculty of North Carolina State University, so it is expected that the majority of respondents are in the 18-25 demographic and have obtained or are in the pursuit of higher education. The respondent pool used in this survey does not accurately represent the "real world" MP3 player market since the number and diversity of respondents is relatively small.

Since this work is academic in nature, the number and diversity of respondents is sufficient. For "Investigative" studies, research suggests that "30-60 respondents may do" although identifying an appropriate sample size is generally considered a complex issue [11]. 205 responses is deemed sufficient because Equation 3.1 holds true when all variables are substituted for the appropriate constants. The nature of this work also means that the validity of respondent-level consumer information (i.e. each respondent's answers accurately reflect their purchase behavior) is far more important than the demographic makeup of the theoretical market. In a "real world" product development problem it is expected that a company would expand their respondent base to include a greater number and variety of consumers.

3.4.2.2. HB MODELING

After customer preference data is sequestered, Sawtooth CBC/HB is used to derive individual-level part-worths for each level of each attribute. In general, the standard Sawtooth CBC/HB settings are maintained in this approach, and only the constraint parameter is modified. Constraints refer to limitations and rules placed on the part-worths within a single attribute. In Sawtooth CBC/HB there are 3 options: constrain best-to-worst, constrain worst-to-best, and Prefer Level _ to Level _ (can be used with any combination of 2 attribute levels). Constraining best-to-worst means that attribute level 1 is preferred to level 2, level 2 preferred to level 3, etc.; mathematically the part-worths are monotonically decreasing. Constraining worst-to-best means that level 2 is preferred to level 1, level 3 is preferred to level 2, etc.; mathematically the part-worths are monotonically increasing. Individual level preference constraints are self-explanatory, and the part-worth of the selected preferred attribute should always be higher than the selected un-preferred attribute.

Use of this function is at the discretion of the analyst, but can be advantageous to enforce intuitive customer-attribute relationships. For example, most people prefer high quality to low quality, long life to short life, and low price to high price [87]. It is possible for HB utilities to produce results inconsistent with these relationships due to random error or respondent fallacy [88]. Since price interpolation is a key aspect to the latter steps of the approach, this attribute is constrained to be monotonically decreasing, i.e. a customer should always prefer a lower price to a higher price in terms of part-worth value.

Once the user specifies any desired non-standard parameters the program performs the analysis to yield part-worth values for each attribute level and the ‘None’ option for each

respondent. The market scenario uses this generalized procedure to fit part-worth utilities to 55 attribute levels: 46 referring to features, 8 referring to price and 1 referring to the 'None' option. These part-worths are used to assign utility values to internal products, competing products, and the 'None' option in the static market, as well as to calculate sacrifice gap.

The following section details the formulation of sacrifice gap from the quantified customer choice data obtained in discrete choice analysis.

3.5. QUANTIFYING SACRIFICE GAP

This section details the process and rational behind the empirical definition of sacrifice gap developed in this thesis. This section is highlighted on the flow chart given as Figure 3.7 below

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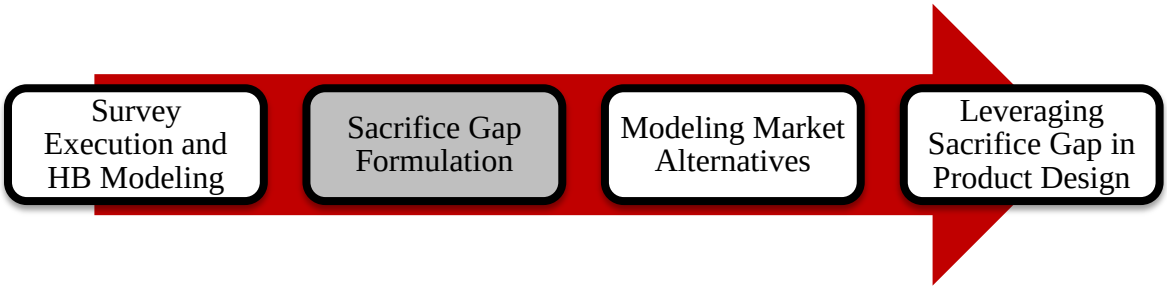

Figure 3.7: Section 3.5 Investigation Process Flow Chart

The conceptual definition of sacrifice gap is "What the customer wants exactly" less "what the customer settles for" [2]. To formulate a numerical definition for this quantity, each term is interpreted in the context of engineering design and assigned an empirical definition that utilizes the quantified consumer preference data discussed above.

In the context of demand modeling for engineering design, “what the customer wants exactly” is defined as the combination of features that gives a customer the greatest benefit. In a real world purchase decision the consumer would face tradeoffs due to price constraints, and the challenge of incorporating this limitation is discussed in the following subsection. “What the customer settles for”, can be viewed as a consumer’s product optimization problem. This optimization would result in selection of the product that gives the customer the highest net utility, assuming a first-choice decision scenario. Implied in this definition is the trade-off between feature and price utility.

Using these considerations, quantifying “what the customer settles for” is straightforward; it is the numerical value of the alternative in the market that maximizes the respondent’s overall utility (the sum of price and feature utilities). To address the concerns associated with establishing a numerical definition of “what the customer wants exactly” two approaches are proposed and analyzed to determine which is more appropriate given the following considerations: 1) the ability of the metric to provide a static datum for a customer, *i*, in a given market, and 2) incorporation of the trade-off between desire for additional features and the price one must pay for those features. Once an approach is chosen, sacrifice gap can be quantified for all respondents in the market on an individual level. To make this metric usable for product platform design, a method to incorporate individual sacrifice gap into a market-wide measure is also proposed.

3.5.1. CHOOSING A "WHAT THE CUSTOMER WANTS EXACTLY" DATUM

In defining the "What the Customer Wants Exactly" datum, two formulations are proposed:

Formulation 1: the "Ideal Product"

The first formulation of a sacrifice gap baseline datum is referred to as the ideal product (IP). In the context of this paper, the configuration of customer *i's* ideal product is dependent upon the values of *feature* utilities, only; i.e. utilities that correspond to product characteristics, not price. This fits the contextual representation presented above; the notion that "what the customer wants exactly" is driven by the benefits garnered from features. The utility of the ideal product is determined by, first, summing the maximum level part-worths for each feature attribute. Then, the price corresponding to that configuration of attribute levels is calculated using a price-structure based on mass production efficiencies; this work assumes that a company would have access to this information. This IP price is linked to a part-worth utility, using interpolation and the assumption that price part-worths are monotonically decreasing. It is imperative that the price utility correspond to the combination of ideal features because it mirrors the feature/price trade-off consumers face in the marketplace.

Adding the feature and price part-worths gives the overall ideal product utility. Equation 3.2 illustrates this definition where U_{IP} is the ideal product utility, $n_{att.}$ is the number of attributes, $U_{x_j max}$ is the maximum part-worth (corresponding to the level with the highest positive part-worth) of attribute *j*, and $U_{P_{IP}}$ is the utility that corresponds to the price charged for the configuration of features that define the ideal product.

$$U_{IP} = \sum_{1}^{n\ att.} U_{\mathrm{j,max}} + U_{P_{IP}} \tag{3.2}$$

The price a company would charge for the configuration of features that define the ideal product is dynamic because it changes with respect to external stimuli such as product in question, market conditions, and production conditions. It follows that the utility associated with the ideal product price will change if it were *manufactured* and *purchased* by this consumer. However, the IP and its corresponding utility refer to a *conceptual product* and are used as a static datum in this approach. This work argues that while the price of features may change, the customer's ideal configuration of levels does not; i.e. customer *i* will always prefer an automatic transmission vehicle to a manual transmission vehicle in terms of raw HB part-worths. Defining the configuration of "exactly what the customer wants" by considering only feature part-worths and keeping prices consistent with mass production provides a stationary datum from which to measure other goods in the market.

Formulation 2: The "Optimal Product"

The second potential formulation of a sacrifice gap baseline is referred to as the customer's optimal product (OP). It is so named because its calculation requires the user to find the utility that optimizes the trade-off between feature and price utility values associated with a product. That is, the optimal product is dependent upon both the *feature* and *price* utilities. The optimal product utility is found through use of an optimization algorithm. The algorithm of choice iteratively calculates the overall utility that results from different combinations of feature levels and their corresponding price. This process is illustrated in

Equation 3.3 where U_{OP} is the utility of the optimal product, $n_{att.}$ is the number of attributes, U_{j_h} is the utility of the hth level of the jth attribute and U_P is the utility that corresponds to the price of the product defined by $\sum_1^{n_{att.}} U_{j_h}$.

$$U_{OP} = \max(\sum_1^{n_{att.}} U_{j_h} + U_P) \tag{3.3}$$

Since the OP configuration is dependent on both feature and product utilities it is described as a moving datum that experiences some magnitude of price sensitivity. If this formulation is used in quantifying sacrifice gap, the configuration of "exactly what the customer wants" will change with price structure and would require optimization each time a price change occurs to re-determine the optimal products. Furthermore, it would conflict with Davis' "prices consistent with mass production" clause of mass customization cited above. The benefit of a moving datum is that the actual purchase decision of a customer, given its price sensitivity, is captured in this formulation.

In juxtaposing these two formulations, it is apparent that they describe two unique consumer behaviors. The ideal product captures the desires of the customer while the optimal product captures the trade-off between price and functionality. Since the goal of mass customization is to provide "what a customer wants exactly" at prices "consistent with mass production", the ideal product formulation will be used as the baseline in the sacrifice gap calculation. This is due to the expectation that manufacturing and supply chain management improvements will help push prices lower, but that the customer's desire for one feature level over another will remain relatively constant (given a particular array of feature options).

Since the idea of sacrifice gap is taken from the paradigm of a customer, and the ideal product provides a datum that is derived from the consumer's preferences it is proposed as baseline for sacrifice gap measurement.

3.5.2. SACRIFICE GAP METRIC DEFINITION

After choosing a baseline from which sacrifice is measured, the calculation on an individual level becomes straightforward. Table 3.6 below likens the subjective definition given by Pine to the objective definition derived from HB model utilities. "What the customer wants exactly" is the ideal product equation taken from above, and "What the customer settles for" is the maximum of the utilities of the competing products (other firms), the utilities of the internal market (one's firm's products), and the utility of not purchasing a product ('walk away' or 'None' option).

Table 3.6: Qualitative and Quantitative Definitions

WHAT THE CUSTOMER WANTS EXACTLY ***(Ideal Product)***	$U_{IP} = \sum_{1}^{n_{att.}} U_{\mathrm{j,max}} + U_{P_{IP}}$
WHAT THE CUSTOMER SETTLES FOR ***(Best Available Product)***	$U_{BA} = \max(U_{cmp.prod}, U_{int.mkt}, U_{none})$

Customer *i*'s sacrifice gap is then the difference in these two values, given as Equation 3.4.

$$SG_i = U_{IP} - U_{BA} \tag{3.4}$$

Inherent in the definition of mass customization is the implication that customization is available to the masses. Ideally, firms could design product lines that minimize sacrifice to the individual by designing products for an entire market. This means that although the definition of sacrifice gap pertains to individual-level product characteristics, an aggregate or market-level definition is also necessary. The characteristics of discrete choice models discussed in Chapter 2.2.2 provide a challenge in this regard.

Since utilities cannot be compared across respondents because each is based on its own scale, and because individual sacrifice gap is simply the difference between two utilities, a market-level measure of sacrifice cannot be derived from the values given by Equation 3.4. To combat this challenge, sacrifice gap is converted from a difference of two values to a normalized, dimensionless number by dividing the difference between the ideal product and the best available option by the difference between an individual's maximum possibly utility and their minimum possible utility. This creates a normalized quantity.

This is very similar to how attribute importances are calculated from conjoint analysis data. The importance of an attribute refers to how much difference said attribute makes in a customer's purchase decision. The importance is calculated by dividing the range of a

particular attributes part-worth values by total range of utilities. The example given as Figure 3.8 below illustrates how importances are calculated.

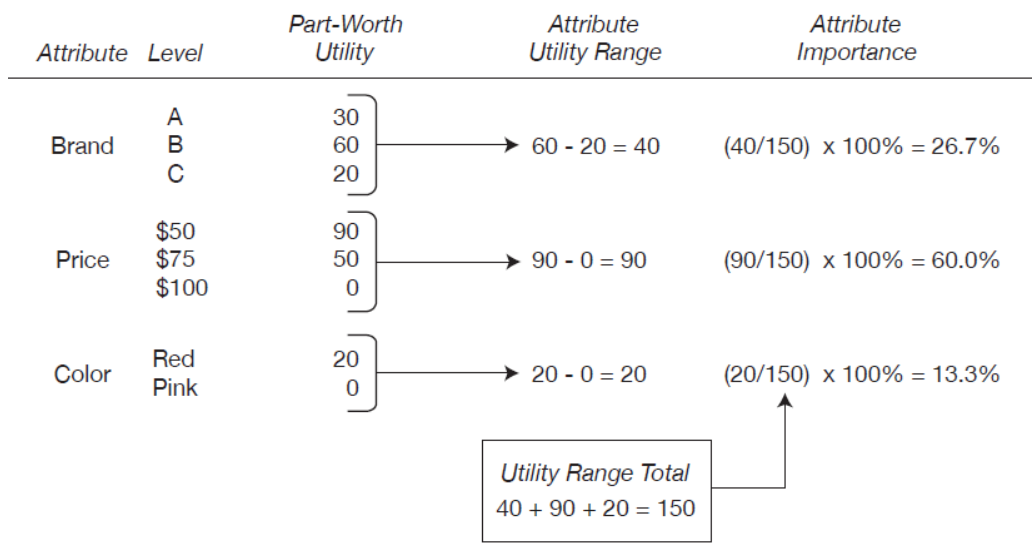

Figure 3.8: Attribute Importance Calculation Example

The "utility range total" is the denominator in the normalized sacrifice gap equation presented below as Equation 3.5. U_{IP} is the utility of the ideal product and U_{BA} is the utility of the best current alternative (the product in the market that gives the customer the highest overall utility). $U_{max,i}$ is the sum of the highest part-worths for each attribute and $U_{min,i}$ is the sum of the lowest part-worths for each attribute; both include price as an attribute.

$$SG_{Nnorm,i} = \frac{U_{IP} - U_{BA}}{U_{max,i} - U_{min,i}} \tag{3.5}$$

Formatting normalized sacrifice gap in this manner gives a fraction characterized by the distance between "what the customer wants exactly" and "what the customer settles" for over the distance between their highest possible utility and their lowest possible utility. This is illustrated as Figure 3.9.

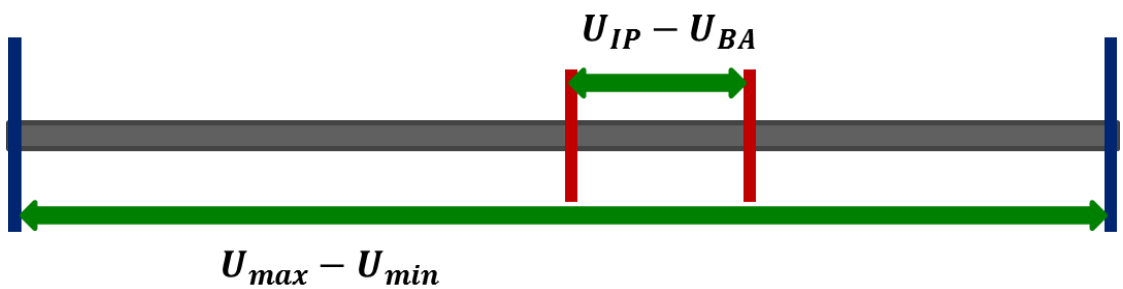

Figure 3.9: Normalized Sacrifice Gap Illustration

Sacrifice gap is now a dimensionless quantity that provides a static, individualized datum, and "individual sacrifice gap" will now refer to the dimensionless form. A market-average sacrifice gap can now be calculated from each individual's dimensionless sacrifice gap value. The term "sacrifice gap" will refer to the market average quantity in the case studies presented below. This market average sacrifice gap is given as Equation 3.6 where n is the number of customers in the market and $SG_{norm,i}$ is the normalized sacrifice gap for customer i. It is an objective function in the case studies presented in Chapters 4 and 5.

$$SG_{MKT\ AVG} = \frac{\sum_1^n SG_{norm,i}}{n} \tag{3.6}$$

Obtaining a single value for sacrifice gap across all respondents in the market provides a usable metric of consumer preference for applications such as product line optimization. It is used in the hypothetical market scenario product line optimization problems in Chapters 4 and 5 as an objective function.

3.6. MODELING MARKET ALTERNATIVES

Once individual part-worths are calculated, they are used to define the utility value of all alternatives in the market. These utility values are a key component to the sacrifice gap metric formulated above, and are necessary for its quantification and subsequent use in product design problems. This section is highlighted on the flow chart given as Figure 3.8 below.

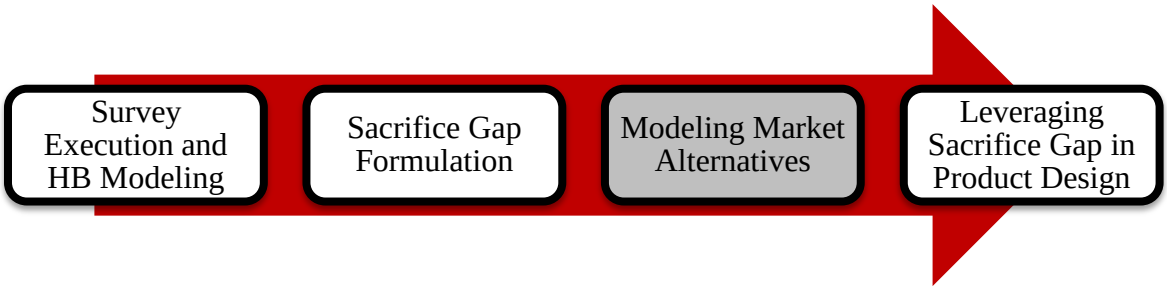

Figure 3.10: Section 3.6 Investigation Process Flow Chart

In a first-choice product selection scenario, a consumer chooses the available alternative that maximizes their utility. Available alternatives are broken down into three

categories: competing products, internal products, and the ‘None’ option. This section describes the general procedure for obtaining these part-worths. It also provides a description of the market environment in the hypothetical scenario and demonstrates how the general procedure was applied to assign value to all alternatives in the market.

3.6.1. GENERAL PROCEDURE

Assuming a static market, competing product utilities are defined by summing the part-worths of their respective attribute levels, and using interpolation of numerical values (such as price) when necessary. The ‘None’ utility is taken directly from the HB model and is only a concern if a ‘None’ option is included in the discrete choice survey. Competing products and the ‘None’ option are collectively referred to as the external market. Reiterated from above, internal products include any product that the firm has the ability to create (the base product or a custom product). In terms of modeling for a customization scenario, custom products include any product that can be defined by the combination of 1 level from each attribute that is represented in the conjoint survey.

The utility calculation process for an internal or competing product is discussed in Chapter 2.2. Table 3.7 provides an example that uses the features in the discrete choice survey to demonstrate how feature and price utilities are summed to obtain an overall product profile utility. The overall utility is highlighted in grey.

Table 3.7: Product Utility Sum Example

Attribute	Description	Part-Worth
Photo/Video/Camera	None	-0.051
Web/App/Ped	Web and App	3.378
Input	Touchscreen	4.728
Screen Size	2.5 in diag	4.013
Storage	16 GB	2.825
Background Color	Blue	-1.903
Background Overlay	No pattern / graphic overlay	1.283
Price	$299	-1.268
		13.005

To obtain the price utility shown in Table 3.7, a pricing structure was developed that is based on the MSRP's of current iPod models. iPods accounted for roughly 70% of "real world" MP3 player market share as of October 2011 [89]. This study assumes that the companies in the hypothetical market scenario would have similar manufacturing capabilities, and therefore prices, to this industry leader.

The pricing structure is based upon a subjective allocation of total MSRP to different components. This was done by examining the difference in price and feature configuration among 18 iPod products, and attributing the price difference between products to specific features. For example, there is a significant price difference between similar iPod models with different storage sizes. The pricing structure should, then, exhibit an incremental price difference of similar magnitude for increasing or decreasing storage size. The component prices in the pricing structure were iterated upon until the price of a component additive MP3 player was similar to the MSRP for that same configuration. For example, the price of a blue

8GB iPod Nano calculated using the mass production price structure below was slightly above the current MSRP. The pricing structure is summarized in Table 3.9 below.

Table 3.8: Mass Production Attribute Pricing Structure

	Attribute						
Lvl.	**Photo / Video / Camera**	**Web / App / Ped**	**Input**	**Screen Size**	**Storage**	**Back-ground Color**	**Back-ground Overlay**
1	$0	$0	$0	$0	$0	$0	$0
2	$5	$20	$5	$25	$45	$10	$5
3	$10	$20	$40	$45	$120	$10	$10
4	$15	$10	$20	$60	$200	$10	$15
5	$17	$40		$70	$250	$10	
6	$30	$30		$80	$300	$10	
7	$32	$30			$350	$10	
8	$42	$50			$400	$20	

The prices in Table 3.9 refer to an incremental price of that level, over and above a base price of $65. This base price refers to the selling price of a product whose attributes are all configured to level 1 (note that all level 1 prices are $0). The mass production selling price of a product in the hypothetical market is, then, the linear additive sum of the prices of its attribute levels, plus a base price of $65. Table 3.10 provides an example of how product prices are calculated. Note that in this example level 1 of screen size and background overlay refer to the base level and therefore have no incremental price.

Table 3.9: Example of Product Mass Production Price Calculation

	Level on Product	Incremental Price
Photo/Video/Camera	2	$5
Web/App/Ped	4	$ 10
Input	3	$ 40
Screen Size	1	$ 0
Storage	2	$ 45
Background Color	3	$ 10
Background Overlay	1	$ 0
Base Price		$ 65
Price		**$ 175**

Using this price structure, the mass production purchase price of any hypothetical market product configuration can be calculated. The customization tax, discussed in the subsequent section, is added to this mass production price to give the overall purchase price of a custom product. The price utility associated with the price is calculated using linear interpolation between price points included in the discrete choice survey.

The following sections discuss how the competing products and base product were designed in this study and how the customization tax was developed and applied to custom products.

3.6.2. COMPETING PRODUCTS

There are three competing products in the hypothetical market scenario. These three products were designed to maximize market share of preference of the competition against the ‘None’ option only. That is, the market shares of preference for each competing product

is summed and maximized; this is to make the competitive products as desirable as possible with respect to the customers' "buy nothing" option. Market share of preference for one of the competing products is given by Equation 3.7 where the competing product is represented by *n*, *i* is an individual in the market of *I* customers and *k* represents one of *K* alternatives in the competitive space.

$$MSP = \frac{\sum_{i=1}^{I} e^{U_{ni}}}{\sum_{i=1}^{I}\sum_{k=1}^{K} e^{U_{ki}}} \tag{3.7}$$

The three competing products were also constrained so that multiple price levels were represented. The price constraints, market share of preference, feature level configuration and selling price of the three competing products are summarized as Table 3.10.

Table 3.10: Hypothetical Market Scenario Competing Products

	Competing Product 1	Competing Product 2	Competing Product 3
Market Share	34%	33%	15%
Price Constraints	$49-$300	$300-$500	$500-$699
Configurations			
Photo/Video/Camera	Photo,video and hi-res camera	Photo,video and hi-res camera	Photo,video and hi-res camera
Web/App/Ped	App only	Web and App only	Web and App only
Input	Dial	Touchscreen	Touchscreen
Screen Size	1.5 in diag	4.5 in diag	4.5 in diag
Storage	16 GB	32 BG	160 GB
Background Color	Black	Black	Silver
Background Overlay	Custom graphic overlay	Custom pattern and graphic overlay	Custom graphic overlay
Price	$182	$382	$517

The competing products are always priced according to the mass production pricing structure given as Table 3.9 and remain static when Company X introduces customization options. The overall utility for each competing product for each respondent is calculated using the procedure given in Section 3.6.1.

3.6.3. BASE AND CUSTOM PRODUCTS

Products in the internal market are broken down into two categories, the base product and custom products. The base product is a single configuration of attribute levels offered at mass production prices. Custom products are combinations of feature levels a customer chooses to maximize their overall utility. This is dependent on the amount of customization options Company X decides to offer and their price includes a customization tax.

The base product in this hypothetical market scenario is designed using the same process as the competitive products. Market share of preference for company X's base product is maximized using Equation 3.7. The 'None' option and the competing products are included in the alternatives set (K) so that Company X's market share of preference is maximized against the entire competitive space. Because the base product is meant to be Company X's first MP3 player in this market, it is kept "basic" by setting the Photo/Video/Camera and Web/App/Pedometer features to the "None" levels. The market share of preference and configuration for the base product is given in Table 3.11. The utility of the base product for each respondent is calculated using the procedure in Section 3.6.1.

Table 3.11: Hypothetical Market Scenario Base Product

Base Product	
Market Share	12%
Configuration	
Photo/Video/Camera	None
Web/App/Ped	None
Input	Touchscreen
Screen Size	3.5 in diag.
Storage	16 GB
Background Color	Black
Background Overlay	Custom pattern and graphic overlay
Price	$210

The price calculation for custom products is what differentiates them from the base and competing products. A customization tax is added to the mass production price of these

products that accounts for financial burdens to the firm associated with supply chain complexity, purchase of new machinery, increased workforce, design expenses, etc. The financial burden of customization is passed directly to the customer; that is, it is assumed equivalent to the financial impact of customization on the firm. Therefore the customization tax increases the purchase price of a product without affecting the overall profitability of the firm.

The following customization tax structures are hypothetical and are not based on industry data. Table 3.12 presents two different customization tax structures. One is for "simple" customization attributes and the other is for "complex" customization attributes. Simple customization attributes include storage space, background color, and background overlay while complex customization attributes include (photo, video, camera (PVC), web, app, and pedometer (WAP), input type, and screen size. The customization tax for complex attributes is due to a relatively greater increase in design and manufacturing costs passed on to the consumer. The tax is roughly twice as high for complex attributes as compared to simple attributes because complex attributes greatly impact design and manufacturing while simple attributes primarily affect manufacturing.

Table 3.12: Customization Tax Structure

Levels	Customization Tax (Simple Attributes)	Customization Tax (Complex Attributes)
1	$10.00	$20.00
2	$14.00	$27.00
3	$16.00	$31.00
4	$18.00	$36.00
5	$20.00	$39.00
6	$21.00	$42.00
7	$22.00	$44.00

The above customization tax structures are applied to each attribute in turn, and then summed to yield a single customization tax value. For example, if 2 additional PVC levels, 1 additional storage level, and 3 additional background color levels are the customization options offered, the customization tax would be given as:

$PVC(2) + $STOR(1)+$COL(3) = $ 17.00+ $ 5.00+ $ 10.50= $32.50

The process is identical for any combination of custom levels and is added to the purchase price of all custom products in the subsequent generation regardless of their attribute level configuration; this can be likened to an increase in overhead expenses for customization.

The following section describes how the customer choice data collected and modeled in Section 3.4, the sacrifice gap metric developed in Section 3.5, and the market alternative

quantification process outlined in this section are used in the optimizations conducted in Chapters 4 and 5.

3.7. LEVERAGING SACRIFICE GAP IN PRODUCT DESIGN

Building on the recent, and increasing, volume of engineering design literature that incorporates customer preference data into product design, this work proposes to use market average sacrifice gap minimization as an objective in product line design for mass customization. This section is highlighted on the flow chart given as Figure 3.9 below.

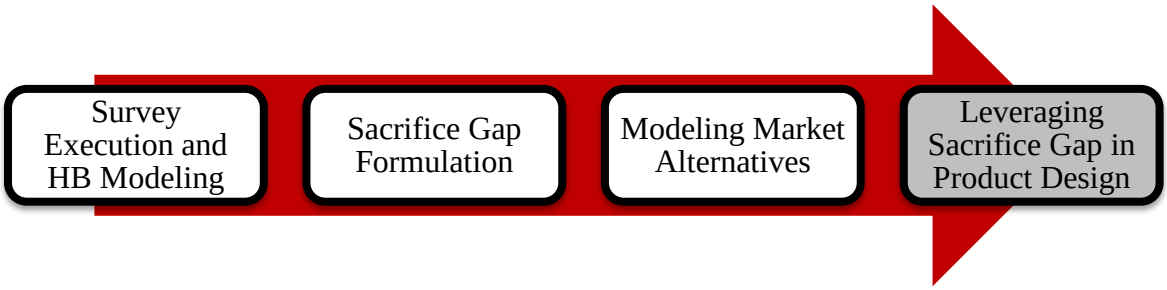

Figure 3.11: Section 3.7 Investigation Process Flow Chart

Chapters 4 and 5 will investigate the use of sacrifice gap in product line design, both as a tool to assess proximity to mass customization and as a guideline during the design process. Chapter 4 focuses on maximizing value to the customer by designing a product line that seeks to minimize the market's sacrifice gap. This problem will take the form of a single-objective optimization where market average sacrifice gap is the objective function.

The purpose of this chapter is to demonstrate how the metric can be used in practice and to investigate overall effects on the consumer and firm when used as an objective function.

Chapter 5 will take a more pragmatic approach in that it will incorporate firm interests. Sacrifice gap will be used in tandem with a firm-value metric to design product lines that optimize value to both parties. This problem will take the form of a multi-objective optimization problem where market average sacrifice gap and aggregate contribution (an established profit measure that represents firm value) are the two objectives. This chapter will place a heavier emphasis on analysis of what sacrifice gap means on a market and individual-level and what changes in this metric mean within the context of engineering design. Both chapters include a case study-specific procedure for execution and an analysis of the results. General procedures for the two case studies conducted in these chapters as well as the common parameters are described below.

3.7.1. GENERAL CASE STUDY PROCEDURE

The optimal product line(s) for each of the two cases described above were found using a Genetic Algorithm in the MATLAB Optimization Toolbox. The optimization seeks to minimize the objective(s) by turning "on" or "off" availability of custom options (the design variables), pricing the custom products accordingly, and calculating a market average sacrifice gap and/or aggregate contribution (an established surrogate profit measure) based on all of the available alternatives in the markets.

The algorithm determines the optimal configuration through an iterative process. The objective function value(s) is calculated for a user-specified number of design variable strings (Population Size); this iteration of objective function calculations is called a

generation. At the end of each generation, the Population strings are altered according to the parameters specified by the user. Additional information regarding the Genetic Algorithm settings and parameters can be found in the MATLAB help menu within the program or online [90]. Some Population strings are carried through directly into the subsequent generation while others undergo crossover or mutation [90].

The process of calculating objective function value(s) is repeated until the algorithm converges to an optimal solution(s). The design variable values that yield the lowest market average sacrifice gap define the optimal single-objective customization configuration. The multi-objective optimization looks to maximize firm and consumer value simultaneously. This means that, assuming the two objectives compete, a number of "optimal" solutions are possible. This process is illustrated in Figure 3.10.

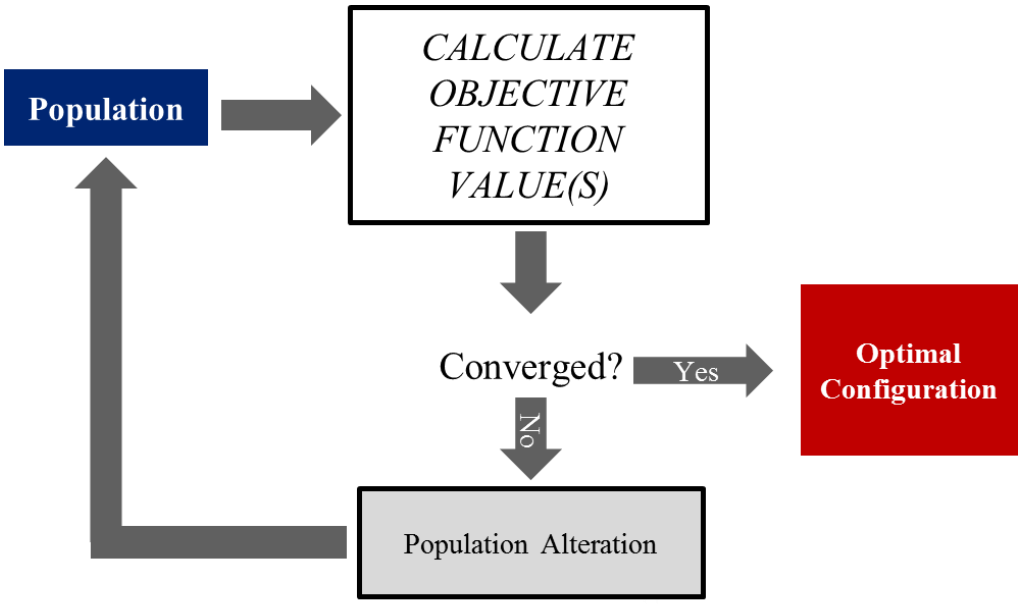

Figure 3.12: Genetic Algorithm Process

This general process is used in both Chapters 4 and 5. Specific parameters formulations necessary for execution are detailed for each case separately.

3.7.2. VARIABLE REPRESENTATION

The design variables, each representing a non-base attribute level, are constrained to values of either 0 or 1; this is called binary encoding. 1 indicates the level is available ("on"), 0 indicates it is not ("off"). Since there are 39 design variables, a vector of 39 0's and 1's are passed to the Genetic Algorithm and the objective function value(s) associated with that particular design string is calculated. The base levels for each attribute are not represented by

design variables because they are always available as customization options. A summary of each feature level and its corresponding design variable representation is given in Table 3.14.

Table 3.13: Summary of Multi-Objective Optimization Attribute Level Representation

Attribute Level Number	Level Description	Design Variable Representation	Attribute Level Number	Level Description	Design Variable Representation
1	No PVC	Base level	4	4.5 in diag.	x_{20}
2	Photo only	x_1	5	5.5 in diag.	x_{21}
3	Video only	x_2	6	6.5 in diag.	x_{22}
4	Photo and Video Only	x_3	1	2 GB	x_{23}
5	Photo and lo-res camera	x_4	2	16 GB	Base level
6	Photo and hi-res camera	x_5	3	32 BG	x_{24}
7	Photo, video and lo-res camera	x_6	4	64 GB	x_{25}
8	Photo,video and hi-res camera	x_7	5	160 GB	x_{26}
1	No WAP	Base level	6	240 GB	x_{27}
2	Web only	x_8	7	500 GB	x_{28}
3	App only	x_9	8	750 GB	x_{29}
4	Ped. only	x_{10}	1	Black	Base level
5	Web and app only	x_{11}	2	White	x_{30}
6	App and ped. only	x_{12}	3	Silver	x_{31}
7	Web and ped. only	x_{13}	4	Red	x_{32}
8	Web, app, and ped.	x_{14}	5	Orange	x_{33}
1	Dial	x_{15}	6	Green	x_{34}
2	Touchpad	x_{16}	7	Blue	x_{35}
3	Touchscreen	Base level	8	Custom	x_{36}
4	Buttons	x_{17}	1	No pattern / graphic overlay	x_{37}
1	1.5 in diag.	x_{18}	2	Custom pattern overlay	x_{38}
2	2.5 in diag.	x_{19}	3	Custom graphic overlay	x_{39}
3	3.5 in diag.	Base level	4	Custom pattern and graphic overlay	Base level

3.7.3. FIRM VALUE METRIC: AGGREGATE CONTRIBUTION

Aggregate contribution is a surrogate profit measure metric likened to firm value; it is used as a comparative tool in both cases and an objective in the multi-objective case study.

Its calculation is described in Equation 3.8. If the firm produces more than one product they sum the aggregate contributions for each of their products to obtain an overall aggregate contribution margin.

$$AC = market\ share\ of\ preference \times size\ of\ market\ \times (revenue - cost) \tag{3.8}$$

Market share is given above as Equation 3.7, and revenue comes from the price at which each of the products is "sold". Competing products and the base product are "sold" at the value calculated from a user-defined price structure detailed above. The revenue from custom products is also only dependent upon the mass production price structure. This is because the customization tax is equivalent to the financial burden of customization to the firm; therefore it does not provide them any amount of profit. The cost of the product is assumed to be 2/3 of its selling price (not including customization tax); this provides a 1/3 markup passed on to the consumer.

In the case of a customized product, the contribution is calculated for each respondent separately. The market share is the individual customer's preference share, the market size is 1, revenue is the selling price of the custom product (less customization tax), and cost is 2/3 the revenue. The aggregate contribution, then, is the sum of individual contribution from

each respondent in the market. Customization AC is given as Equation 3.9 where *i* is the number of consumers in the market and *i* refers to an individual consumer.

$$AC_{CUST} = \sum_{i=1}^{I} preference\ share_i \times 1 \times (revenue - cost)\ from\ product_i \qquad (3.9)$$

For the purpose of this case study, the size of the market is equal to the number of respondents who completed the survey and whose data was used to derive HB part-worths. Note that a firm would have access to this information and the estimation for research purposes is not based on company data.

3.8. CHAPTER SUMMARY

This chapter discusses the assumptions, provides motivation, introduces a hypothetical market scenario, develops a methodology and presents the process used to quantify customer sacrifice gap and apply it to product line design problems for mass customization. The method and process include a general procedure for acquiring customer preference data, and fitting a hierarchical Baysian model to the consumer choice data. Details of how this procedure is applied to the hypothetical market scenario are also included. The part-worths are then used to formulate an empirical definition of sacrifice gap. The process used to quantify alternatives in the market using the HB part-worths is also discussed in general and as it is specific to the hypothetical market scenario. Using the information gathered from the previous sections, a general process for investigating its use in product line optimizations is presented. Chapters 4 and 5 apply the process to the hypothetical case study

to optimize product lines for consumer value (single objective), and then for a balance between consumer and firm value (multi-objective).

CHAPTER 4: CUSTOMER-CENTRIC PRODUCT DESIGN

Before the sacrifice gap metric formulated in Chapter 3 is applied to either of the case studies outlined above, an example sacrifice gap calculation is presented. This example details the process by which sacrifice gap is calculated for each customer in the market to yield $SG_{norm,i}$ from Equation 3.5 and $SG_{MKT\ AVG}$ from Equation 3.6. Once the sacrifice gap calculation process is detailed, the procedure for using the metric in the single-objective optimization case study is given. A single-objective case is considered first to gauge how the metric behaves as an objective function in a less complex problem and to reinforce the need for design in the multi-objective space.

The first case study investigates how sacrifice gap can be used to assess and design product lines that maximize value to the consumer by minimizing market average sacrifice gap, calculated using Equation 3.6. Per the outline in Chapter 3, the optimal product line configuration is found using a Genetic Algorithm in the MATLAB Optimization Toolbox [90]. Details of this optimization procedure are followed by an analysis of the resulting product line configuration. The analysis will focus on examining metric behavior in the context of engineering design by examining the effect of customer-centric product line optimization on the individual customers and on market-level metrics that measure value to the firm and consumer.

4.1. SACRIFICE GAP CALCULATION EXAMPLE

To illustrate better how to calculate individual and market average sacrifice gap from Equations 3.5 and 3.6, an example is provided below. Customer *i's* sacrifice is calculated using the HB part-worths from the hypothetical market scenario and Equation 3.5. Assuming that this process is carried out for all customers in a market ($i = 1 \ldots n$), the market average sacrifice gap is calculated using Equation 3.6.The process is detailed below.

1. To calculate the utility of customer *i's* Ideal Product, start by summing the highest feature part-worths for each attribute to get the feature utility. Table 4.1 demonstrates this step for the Photo/Video/Camera attribute; the level with the highest part-worth is highlighted in grey. This is the level that is present on the Ideal Product. This same process is repeated for all attributes.

Table 4.1: PVC Part-worths for customer *i*

	No Photo, Video, or Camera	Photo Playback Only	Video Playback Only	Photo and Video Only	Photo and Lo-Res Camera	Photo and Hi-Res Camera	Photo, Video, and Lo-Res Camera	Photo, Video, and Hi-Res Camera
Part-Worth	3.051	-2.126	-2.745	-0.550	-0.758	1.723	0.389	1.016

Once the configuration of ideal feature levels is determined using this process, the price that corresponds to that configuration is calculated using the procedure provided in Chapter 3.6 for determining the price of internal products. Because this product is "Ideal" only the price structure corresponding to mass customization is considered; there is no customization tax on the ideal product. Table 4.2 gives customer *i's* Ideal Product configuration and the mass customization prices associated with those levels. The total price of customer *i's* Ideal Product is also given.

Table 4.2: Customer *i's* Ideal Product Configuration and Price

Attribute	Description	Price
BASE PRICE		$65
Photo/Video/Camera	None	$0
Web/App/Ped	Web, app, and ped	$50
Input	Touchscreen	$40
Screen Size	4.5 in diag	$60
Storage	240 GB	$300
Background Color	Silver	$10
Background Overlay	No pattern / graphic overlay	$0
Price		**$525**

The utility associated with the price of the Ideal Product is found using interpolation between price points included in the discrete choice survey. Customer *i's* price part-worths are given as Table 4.3.

Table 4.3: Customer *i's* Price Part Worths

	$49	$99	$199	$299	$399	$499	$599	$699
Part-Worth	6.167	5.897	5.772	3.988	-1.645	-2.653	-8.539	-8.987

Since the price of the ideal product is $525, linear interpolation between the $499 and $599 price points is used to find the price utility associated with $525 for customer *i*. The price utility for customer *i's* Ideal Product is then -4.184.

Now that the feature part-worths and the price utility have been calculated, they are all summed to obtain the Ideal Product Utility for customer *i*. Table 4.4 summarizes all of the relevant part-worths and provides the overall utility (highlighted in black).

Table 4.4: Customer *i's* Ideal Product Utility

Attribute	Description	Part-Worth
Photo/Video/Camera	None	3.051
Web/App/Ped	Web, app, and ped	3.378
Input	Touchscreen	4.728
Screen Size	4.5 in diag	4.013
Storage	240 GB	4.825
Background Color	Silver	2.903
Background Overlay	No pattern / graphic overlay	1.283
Price	$525	-4.184
Ideal Product Utility	U_{IP} **=19.997**	

2. The utility of customer *i's* Best Available Product is now calculated. This involves determining the utility for each alternative in the market (internal products, competing products, and the 'None' option).

    a. **Custom Product**: For each respondent, there is only one relevant custom product. This product is the one created by Company X that gives customer *i* the greatest overall utility; this overall utility accounts for feature utility and price utility. The configuration, price, and corresponding utility of this internal product may change when Company X changes which levels are turned "on" and "off" in the customization case studies. If, for example, company X only offered touchscreen or touchpad as input customization options, customer *i's* optimal custom product may only contain one of those two levels. The process used to calculate the optimal custom product utility is detailed in Chapter 3.6.

    b. **Base Product:** Since the base product is the same in the mass production and customization markets, its utility for customer *i* is always the same. The overall utility is the sum of part-worths for each feature level as well as the corresponding, interpolated price utility. The configuration and utility calculation process are detailed in Chapter 3.6.

    c. **Competing Products:** Like the base product, the outside market is assumed static in this market scenario; therefore the utilities of the competing products for customer *i* are static as well. The process to calculate the competing product utilities is the same as the base product; it is detailed in Chapter 3.6.

d. **<u>'None' Option:</u>** The 'None' option is assigned a utility in the HB modeling process. This utility is also static and requires no additional calculation.

Once the utilities of each alternative are calculated, the highest is selected as the Best Available Product Utility. Customer *i's* utilities for all market alternatives are given as Table 4.5. The utility of the Best Available Product is highlighted in dark grey at the bottom.

Table 4.5: Customer *i's* Best Available Alternative Utilities

Alternative	**Utility**
Custom Product	18.631
Base Product	15.896
Competing Product 1	18.268
Competing Product 2	12.887
Competing Product 3	17.361
None' Option	15.281
$\boldsymbol{U_{BA}}$ **=18.631**	

3. The final pieces of the normalized sacrifice gap equation are the bounds for the total utility range. These are calculated by taking the minimum and maximum part-worths from each attribute and summing them. Table 4.6 provides an example.

Table 4.6: Total Utility Range Calculation Example

Attribute	Max Part-Worth	Min Part-Worth
Photo/Video/Camera	3.05072	-2.7449
Web/App/Ped	3.37806	-5.5577
Input	4.72788	-2.9803
Screen Size	4.01348	-2.6983
Storage	4.82467	-8.8491
Background Color	2.90299	-2.3177
Background Overlay	1.28305	-0.7687
Price	6.16715	-8.9869
Total	$U_{max,i}$ =**30.348**	$U_{min,i}$ =**-34.904**

4. The difference between the Ideal Product and Best Available Product is taken as customer *i's* individual sacrifice gap. Because the mean of each individual's sacrifice gap is used to find a market average, the normalized form of individual sacrifice gap is used (Equation 3.5); an explanation for why individual sacrifice gap must be normalized is provided in Chapter 3.5. The calculation is shown below as Equation 4.1.

$$SG_{norm,i} = \frac{U_{IP}-U_{BA}}{U_{max,i}-U_{min,i}} = \frac{19.997-18.631}{30.348+34.904} = 0.021 \tag{4.1}$$

Note that, although it is not the case in this example, individual and/or market average sacrifice gap has the potential to be negative. This would occur it the utility of the Best

Available alternative (U_{BA}) in the market is larger (either for the individual or on average) than the Ideal Product (U_{IP}). The Best Available alternative will always have a lower or equivalent feature utility than the Ideal Product. The price utility, then, is what would cause the Best Available alternative to have a larger net utility than the Ideal product. Put another way, a sufficiently low price structure for alternatives in the market (individuals pay less than they expect for a particular product) can lead to a negative sacrifice gap.

5. This process is repeated for all customers in the market *(i= 1…n)* to yield *n* normalized, individual sacrifice gaps. The market average sacrifice gap is the mean of all normalized individual sacrifice gap values and is calculated using Equation 3.6, re-depicted below.

$$SG_{MKT\ AVG} = \frac{\sum_1^n SG_{norm,i}}{n} \tag{3.6}$$

Market average sacrifice gap is an objective function for both case studies presented in Chapters 4 and 5 that represents customer value. The means by which this metric is incorporated into the single-objective (minimize sacrifice gap) optimization problem is provided below. Its application to the multi-objective (minimizing sacrifice gap and maximizing aggregate contribution) is discussed in Chapter 5.

4.2. SINGLE OBJECTIVE OPTIMIZATION PROCEDURE

This optimization seeks to minimize market average sacrifice gap by turning "on" or "off" availability of custom levels (the design variables), finding the optimal product for each respondent (price and utility) given the available feature levels, and calculating market average sacrifice gap based on the available product configurations (in the internal and external markets). The standard form of the optimization problem is as follows:

Objective:

MIN: $f_1 = SG_{mkt\ avg}$ (4.2)

Bounds:

ST: $x_i \epsilon 0, 1 \quad i = 1 \ldots 39$

These design variables define the attribute levels from which a customer would customize their optimal MP3 player. An example is provided below to illustrate how the design variables are used to calculate the objective functions.

If the attribute levels highlighted in white in Table 4.7 below are the available custom levels (black are unavailable), the design variable representation would be that given in Table 4.8. Note that the base product levels are also highlighted in white to depict all available customization levels.

Table 4.7: Example Available Attribute Configuration

Attributes							
Levels	**Photo/Video / Camera**	**Web/App/ Ped**	**Input**	**Screen Size**	**Storage**	**Background Color**	**Background Overlay**
1	None	None	Dial	1.5 in diag	2 GB	Black	No pattern / graphic overlay
2	Photo only	Web only	Touchpad	2.5 in diag	16 GB	White	Custom pattern overlay
3	Video only	App only	Touchscreen	3.5 in diag	32 GB	Silver	Custom graphic overlay
4	Photo and Video Only	Ped only	Buttons	4.5 in diag	64 GB	Red	Custom pattern and graphic overlay
5	Photo and lo-res camera	Web and App only		5.5 in diag	160 GB	Orange	
6	Photo and hi-res camera	App and ped only		6.5 in diag	240 GB	Green	
7	Photo, video and lo-res camera	Web and Ped only			500 GB	Blue	
8	Photo, video and hi-res camera	Web, app, and ped			750 GB	Custom	

Table 4.8: Example Available Attribute Variable Representation

Attributes							
Levels	**Photo/Video/ Camera**	**Web/App/ Ped**	**Input**	**Screen Size**	**Storage**	**Background Color**	**Background Overlay**
1	1	1	0	0	0	1	1
2	0	0	0	0	1	1	0
3	0	0	1	1	0	1	0
4	1	0	0	1	1	0	1
5	0	0		0	0	0	
6	0	1		0	1	1	
7	1	1			0	1	
8	1	1			0	0	

The feature levels represented by a 1 provide the customization options for this particular optimization iteration. The number of build combinations for this particular design string is 960. Since one level from each feature must be chosen to define a complete product, this is calculated by multiplying the number of available levels for each feature together. Referring to Table 4.8, the number of available levels for each feature from left to right are 4, 4, 1, 2, 3, 5, and 2. The number of build combinations is then calculated by the following product:

$$Build\ Combinations = 4 \times 4 \times 1 \times 2 \times 3 \times 5 \times 2 = 960$$

Given these options, the combination of one available level from each feature and the corresponding price including customization tax calculated from Tables 3.8 and 3.12 correspond to the feature and price utilities for each potential customized product alternative.

The customization tax in this example is $124. Its calculation is illustrated using Table 4.9 below where the total customization tax is the sum of the incremental customization taxes for each attribute. Once the customization tax is determined, the price utility for any custom product that can be built using the options defined by the design variables (from Table 4.8) can be calculated.

Table 4.9: Customization Tax Calculation Example

Levels	**Photo/ Video/ Camera**	**Web/ App/ Ped**	**Input**	**Screen Size**	**Storage**	**Back-ground Color**	**Back-ground Overlay**	**Total**
# of Custom Levels	3	3	0	1	2	4	1	
Incremental Cust. Tax	$31	$31	$0	$20	$14	$18	$10	**$124**

Note that if enough attribute levels are made available (creating a high customization tax) and the product profile calls for a sufficient number of expensive feature levels, the price of a custom product profile may exceed the $699 price point ceiling in the discrete choice survey. Extrapolation of utilities beyond the bounds of the model may produce greatly inaccurate results. This study limits the price of custom products to $699 and any product profile that exceeds this price for a particular design string is eliminated from a consumer's consideration set.

Since this particular design variable string can yield 960 potential build combinations, there are 960 potential custom product utilities; each corresponds to a particular build combination. An example calculation for one of these 960 build combinations is illustrated using Table 4.10. As detailed in Chapter 3.6, the part-worths corresponding to each of the attribute levels are summed with the corresponding price utility (which includes the customization tax). The overall utility for custom product profile *j* is 13.024 in this example.

Table 4.10: Custom Product Profile Utility Calculation Example

Attribute	Description	Price	Part-Worth
Photo/Video/Camera	None	$0	-0.056
Web/App/Ped	Web, app, and ped	$50	3.378
Input	Touchscreen	$40	4.728
Screen Size	4.5 in diag	$60	4.013
Storage	16 GB	$45	4.825
Background Color	Green	$10	-0.999
Background Overlay	None	$0	-1.263
Price (Including Customization Tax)		$394	-1.602
			$U_j = 13.024$

This process is repeated for all of the potential custom product profiles for each respondent. The custom product with the highest overall utility for each respondent are the only custom product in the Best Available Alternative consideration sets due to the

assumption that the respondents are optimizers (they would not choose a sub-optimal custom product profile).

This thesis calculates the overall utility for each potential product profile for each respondent before selecting the highest utility from this set of numbers. This gives one optimal custom product utility for each respondent. This approach is effective for this work because the problem is sufficiently small. Increasing the number of respondents in the hypothetical market or the number of potential build combinations (by adding additional attributes or levels to the discrete choice survey) could make this approach inefficient or ineffective. Another approach that could help mitigate this issue for bigger problems is called Branch and Bound. Additional information regarding this technique can be found in [91–93].

Once the overall utility of the Best Available Custom Product is determined, sacrifice gap can be calculated for each individual and then for the market. This process is detailed in the above section. A step-by-step method for calculating the market average sacrifice gap objective function is provided in the following sub-section.

4.2.1. OBJECTIVE FUNCTION CALCULATION

The calculation process for the desired objective function is described below.

START MATLAB GA

I. Import necessary constants

II. Send design variables to Objective Function

OUTPUT: Design Variables (binary vector of "on"/"off" attribute level configuration 39 elements long)

START OBJECTIVE FUNCTION

IMPORT: Design Variables (binary vector of "on"/"off" attribute level configuration 39 elements long)

1. Count the number of custom levels offered for each attribute in turn. Use this in conjunction with the customization price structure to determine the customization tax (Table 3.12).
2. Apply a penalty to all respondent part-worths corresponding to unavailable custom levels. That is, if the DV corresponding to that attribute level is 0, the utility for that attribute level is set to a large, negative number to make it suboptimal.

IMPORT: *Internal Products Feature Utility Matrix (IPFUM), Internal Products Price Vector (IPPV)*

   i. IPFUM is an array of feature utilities for each potential internal product configuration for each respondent. For this case study its dimensions are [205 x 393,216].
   ii. IPPV is an array of price points ($) for each potential internal product configuration. For this case study, the vector is 393,216 elements long.

3. Add the customization tax value ($) to each element in the IPPV
4. Interpolate to find the price utility for each internal product price point in the amended IPPV. If the price of a particular product profile is greater than $699, eliminate it from consideration. This is done for each respondent to yield an internal products price matrix (IPPM) matrix.

5. Add the corresponding price and feature utility values of the IPPM and IPFUM matrices.
6. Locate each respondent's highest overall utility and note its internal product configuration number. Match the index value of the product with the highest overall utility with its price.

Once each respondent's optimal available product utility and price are known, they are used to calculate the sacrifice gap and aggregate contribution values.

IMPORT: utility values for all competing products, the base product, and the 'None' option

- The competing products and base product utilities are calculated in a manner consistent with the description in Chapter 3.6 above and the 'None' utilities are taken directly from the model fit data; both are independent of Company X's customization configuration.

At this point in the process, a utility value unique to each respondent has been assigned to each product in the market (optimal custom product, external products, and the 'None' option).

7. Calculate the dimensionless sacrifice gap for all market products for all respondents using Equation 3.5 developed in Chapter 3. Identify and record which product in the market provides each respondent the lowest sacrifice, as well as the dimensionless sacrifice gap value. This step identifies *i* products and *i* measures of individual sacrifice.

8. Calculate the market average sacrifice gap using Equation 3.6. **<u>This is the objective function value.</u>**

OUTPUT: Market Average Sacrifice Gap

<u>RETURN OUTPUT TO GA, REPEAT TO CONVERGENCE</u>

4.2.2. GENETIC ALGORITHM PARAMETERS

The parameters used in the execution of the MATLAB Optimization Toolbox Genetic Algorithm are as follows:

Population Type: bitstring
Population Size: 350
Pareto Fraction: 0.50
Generations: 43
Mutation Function: Uniform
Initial Population: random binary
Selection Function: Tournament
Crossover Function: Scattered

4.3. SINGLE OBJECTIVE OPTIMIZATION RESULTS

Optimizing Company X's next generation product line to minimize market average sacrifice gap yielded a configuration with 27 of the 39 design levels turned "on". As expected, the solution does not prescribe all attributes to be "on"; this indicates that the model reflects the price/feature utility trade-off customers face in the market. In Table 4.11 below, all of the available levels (including base product levels) are denoted by white and the unavailable levels are denoted by a black background.

Table 4.11: Single Objective Optimization Configuration

	Attributes						
Levels	**Photo/ Video/ Camera**	**Web/ App/ Ped**	**Input**	**Screen Size**	**Storage**	**Background Color**	**Background Overlay**
1	None	None	Dial	1.5 in diag	2 GB	Black	No pattern / graphic overlay
2	Photo only	Web only	Touchpad	2.5 in diag	16 GB	White	Custom pattern overlay
3	Video only	App only	Touchscreen	3.5 in diag	32 BG	Silver	Custom graphic overlay
4	Photo and Video Only	Ped only	Buttons	4.5 in diag	64 GB	Red	Custom pattern and graphic overlay
5	Photo and lo-res camera	Web and App only		5.5 in diag	160 GB	Orange	
6	Photo and hi-res camera	App and ped only		6.5 in diag	240 GB	Green	
7	Photo, video and lo-res camera	Web and Ped only			500 GB	Blue	
8	Photo, video and hi-res camera	Web, app, and ped			750 GB	Custom	

Implementing this product line decreases market average sacrifice gap from 0.0336 (σ = .0975) in the mass production market to -0.0095 (σ = .0619) in the optimally customized market. The difference in sacrifice gap between the two markets is 0.0431. Also note that the standard deviation has decreased in the custom market, indicating that there is less variation in sacrifice gap at the individual level.

Market average sacrifice gap in the customization market is negative, a phenomenon described briefly in the sacrifice gap calculation example in Section 4.1. Once again, the negative magnitude is due to the pricing structure of alternatives in the market. Although the ideal product provides the product configuration that gives a particular consumer the most feature benefit, a sufficiently low price of market alternatives makes the utility of the Best Available alternative (U_{BA}) higher than the utility of the Ideal Product (U_{IP}). When this occurs for enough individuals in the respondent pool, market average sacrifice becomes negative.

Although the reduction of market average sacrifice gap reduction is positive for respondents overall, it is unclear how sacrifice gap values of individual respondents are affected. The next section examines sacrifice gap in the mass production and customization markets at an individual level to understand better these effects. Once the effects on the individual are examined, the impact of customization on the firm is also assessed.

4.3.1. INDIVIDUAL-LEVEL SACRIFICE ANALYSIS

The individual-level sacrifice gap analysis is broken down into two sub-sections. The first section looks at general trends that correlate individual-level sacrifice gap and Best Available alternative selection in the market. The second examines the magnitude of sacrifice gap reduction on a respondent-by-respondent basis.

4.3.1.1. BEST AVAILABLE ALTERNATIVE ANALYSIS

Per the hypothetical market scenario description given in Chapter 3.3, the customization market gives each respondent the option of choosing a customized product in

addition to the original alternatives in the mass production market. Because of this construct, no individual respondent can experience an increase in sacrifice gap due to customization; they may, however, experience no change if they choose the same alternative in both markets. A summary of sacrifice gap change behavior for all respondents in the market is given as Table 4.12 below.

Table 4.12: Sacrifice Gap Change Behavior from Mass Production to Customization

Decrease	Increase	No Change
109	0	96

The ratio of respondents who benefit from the customization scenario (their sacrifice gap is decreased) and those who do not (sacrifice gap is constant) is 53% to 47% for this case study. This means that the customized product utility that incorporates the trade-off between added feature variety benefit and customization tax penalty is sufficient to outperform the mass production market alternatives for 53% of the market. The remaining 47% may have their feature wants and needs met by the alternatives in the market (and therefore have no incentive to pay for a custom product) or do not garner a sufficient amount of feature benefit from the prescribed customization offerings to overcome the customization tax penalty. These statistics are specific to this case study and would change based on the price structure used and attributes modeled.

Since the only way for a respondent to decrease their sacrifice gap is by choosing a custom product in the customization market (in a first choice decision scenario), 109 respondents' Best Available alternative switches from one available in the mass production market to a custom product. To observe which alternative these respondents switch from, the choice behavior of all respondents in the market is determined. The distribution of respondents' Best Available alternatives in the mass production and customization markets are given as the white rows in Table 4.13. The incremental change in respondents for each alternative between the mass production and customization markets is given as the third row and the percent of respondents retained by that alternative as the fourth row.

Table 4.13: Respondent Choice Behavior Summary

	Custom Product	**Base Product**	**Competing Product 1**	**Competing Product 2**	**Competing Product 3**	**'None'**
Mass Production	0	22	58	62	26	37
Customization	109	10	49	8	6	23
Change	109	-12	-9	-54	-20	-14
Retention	-	45%	84%	13%	23%	62%

Examination of Table 4.13 provides several interesting insights. First, as is common when a new product of similar functionality is introduced by a company, there is some cannibalization from the base product. In this case 12 individuals switch from selecting the base product to selecting a custom product. Although cannibalization from an existing product does not allow a company to build their customer base (in magnitude) it may have other benefits. One of the firm benefits of mass customization described in literature is its ability to build a more loyal customer base by providing superior products that better meet consumers' wants and needs [18]. Even though these individuals are cannibalized from an existing product, providing them with a higher value alternative through customization may prove beneficial in the long run since it can facilitate higher customer retention.

Also of note is that most respondents switch from the higher priced products in the mass production market (Competing Products 2 and 3) rather than the lower priced products (Competing Product 1 and the Base Product). Competing Products 2 and 3 are priced at $382 and $517, respectfully, and Competing Product 1 and the Base Product are priced at $182 and $210, respectfully. The retention between the mass production and custom markets for Competing Product 1 and the Base Product is also much higher. This suggests that respondents who choose a higher-priced product in the mass production market are more likely to benefit from customization because their feature utilities can overcome the penalty of a higher price. Respondents who choose a lower-priced product experience the opposite effect where their feature utilities cannot outweigh a higher price penalty.

To investigate whether these observations can be identified using the respondents' HB utility data, the importance of each feature is calculated for each individual. The aggregate importance of features and the importance of price are calculated for all individuals in the mass production market. This data is summarized as Table 4.14.

Table 4.14: Feature and Price Importances by Best Available Alternative in Mass Production

	Base Product	**Competing Product 1**	**Competing Product 2**	**Competing Product 3**	**'None'**
Feature Importance	72%	61%	81%	78%	67%
Price Importance	28%	39%	19%	22%	33%

As expected, individuals who chose the base product and Competing Product 1 in the mass production market place a higher importance on price relative to individuals who chose Competing Products 2 or 3. This can be applied to the 'None' option as well. The 'None' option retains a relatively high number of individuals between the mass production and customization markets and the individuals who chose the 'None' option exhibit a relatively high price importance.

4.3.1.2. INDIVIDUAL SACRIFICE DISTRIBUTION ANALYSIS

Although sacrifice gap is decreased on a market level and 53% of respondents experience some magnitude of sacrifice gap reduction, the distribution of sacrifice gap values within the market has not yet been observed. Figure 4.1 divides respondents up by their Best Available alternative and plots all individual, normalized sacrifice gaps in the mass production and customization markets. For the purposes of analysis, high sacrifice gap values are those between 0.4 and 0.1, medium sacrifice gap values are those between 0.1 and -0.1, and low sacrifice gap values are those between -0.1 and -0.2. This definition of high, medium, and low sacrifice gap is used throughout the analysis.

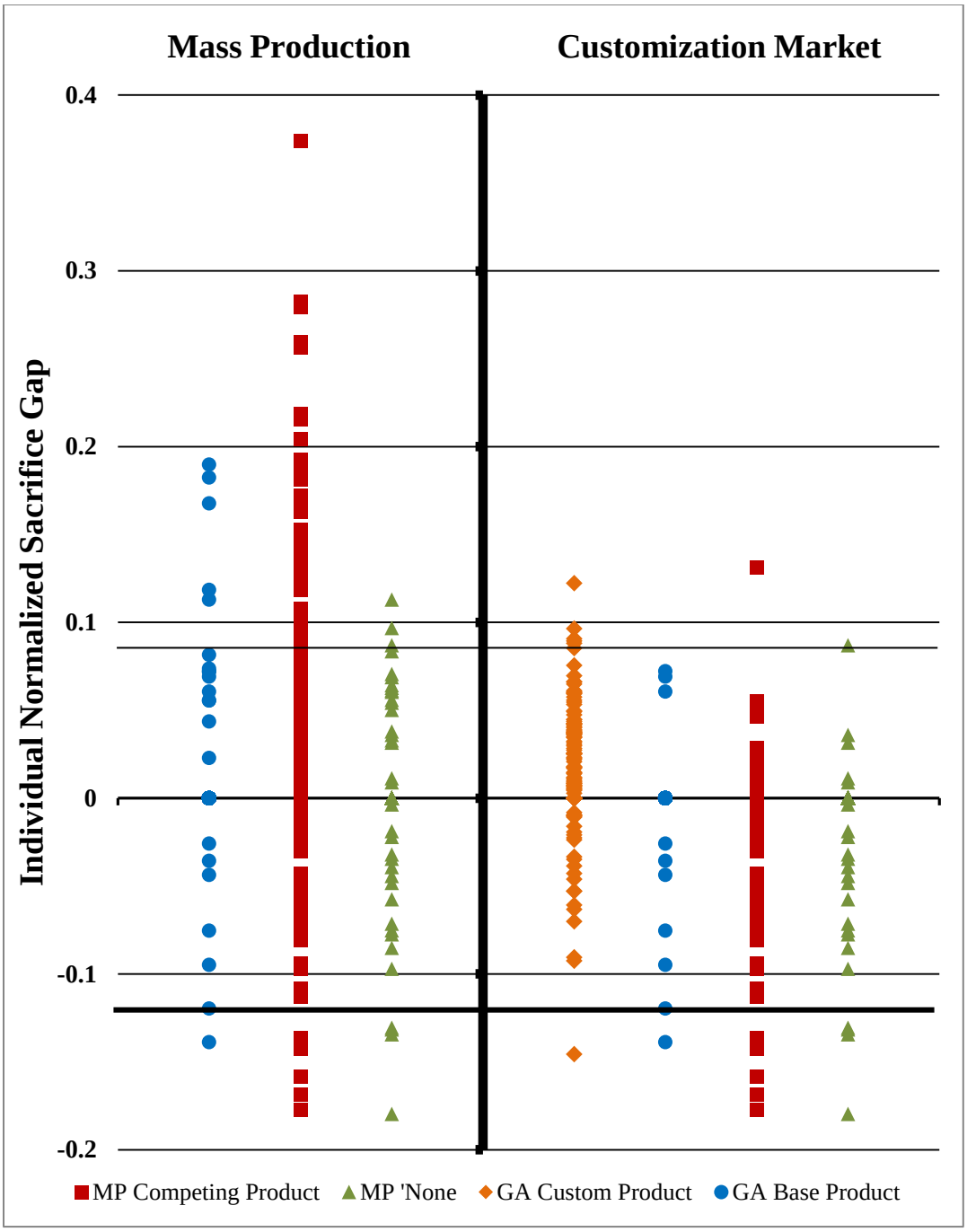

Figure 4.1: Sacrifice Gap Distribution by Best Available Alternative

Visual inspection of Figure 4.1 indicates that implementing the optimal customization configuration pushes the highest sacrifice gap values lower while the lowest sacrifice values appear unaffected. This observation is reinforced by the fact that the maximum sacrifice gap in the market has declined from 0.374 to 0.131 between the two markets, while the minimum sacrifice gap is constant at -0.18. The sacrifice gap values are also less distributed in the customization market, reinforcing the decrease in standard deviation noted at the beginning of this section.

In terms of Best Available alternative selection, respondents with the highest initial sacrifice gap tend to be the ones who switch to a custom product while those with the lowest initial sacrifice gaps tend to maintain their choice from the mass production market. Table 4.12 shows that the majority of respondents who switch to a custom product come from a competing product; an observation that is reinforced by Figure 4.1. The majority of the high-sacrificing points in the mass production market are in the competing products column and all of these points have been shifted down to sacrifice gap values below 0.131 in the customization market; ergo they have switched to a customized product.

Although visual inspection of Figure 4.1 shows that respondents with high sacrifice gaps experience reduction through customization (the points on the left-hand side of the plot do not appear on the right-hand side), the sacrifice gap behavior for medium and low sacrifice individuals is unclear. To understand better this behavior, all respondents' sacrifice gaps are plotted according to whether they do or do not experience sacrifice gap reduction between the two markets. Figure 4.2 plots the sacrifice gaps for respondents who experience

no change in sacrifice in orange, and those who experience a decrease in red (for the mass production market) and blue (for the customized market).

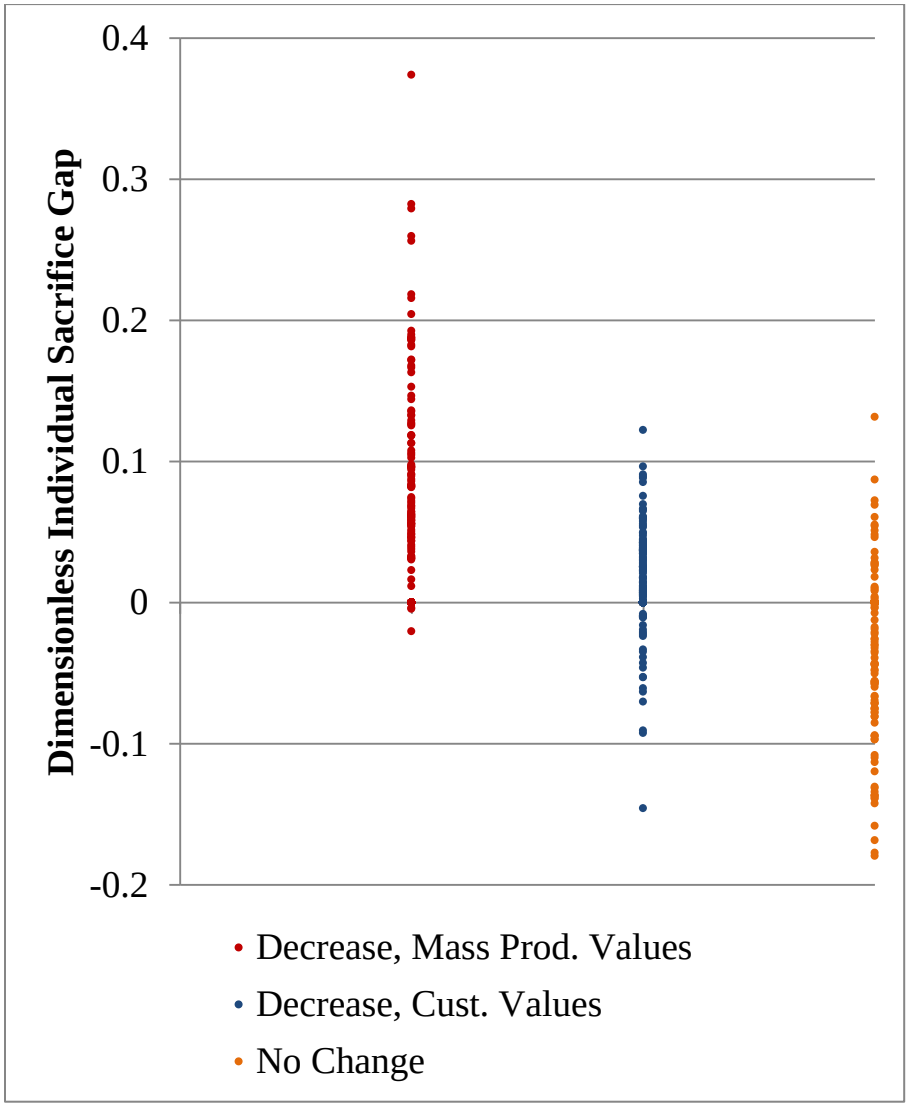

Figure 4.2: Sacrifice Gap by Change Behavior

Figure 4.2 confirms that respondents in this case study who experience the lowest sacrifice gaps in the mass production market are those that do not benefit from the variety offered in the customization market. The overall lowest individual sacrifice gap present in the mass production market is -0.18 while the lowest individual sacrifice gap in the mass production market that is reduced through customization has a magnitude -0.02. Any respondent whose mass production sacrifice gap falls in between this range (-.02 and -.18) does not benefit from customization. On the other hand, respondents who experience mass production sacrifice above 0.13 always experience sacrifice gap reduction through customization (this was discussed above). The behavior of respondents who experience mass production sacrifice between 0.13 and -.02 experience case-specific reduction; some respondents maintain their Best Available alternative selection while others switch to a customized product.

Although this figure shows general trends between mass production sacrifice gap and tendency to benefit from customization, it does not show the magnitude of sacrifice reduction on an individual level. Sacrifice gap for 8 respondents with varying mass production sacrifice gap values are examined. Their sacrifice in the mass production and customization markets are plotted to show their magnitude of reduction. This is given as Figure 4.3.The top of each vertical line segment represents each respondent's sacrifice gap in the mass production market and the bottom of each line segment represents their sacrifice gap in the customization market. The length of the line segment represents the magnitude of sacrifice gap reduction and the labels at the top of the line segment indicate the alternative the

respondent switched from. In Figure 4.3 CP refers to competing product, BP refers to base product, and None refers to the None or walk away option.

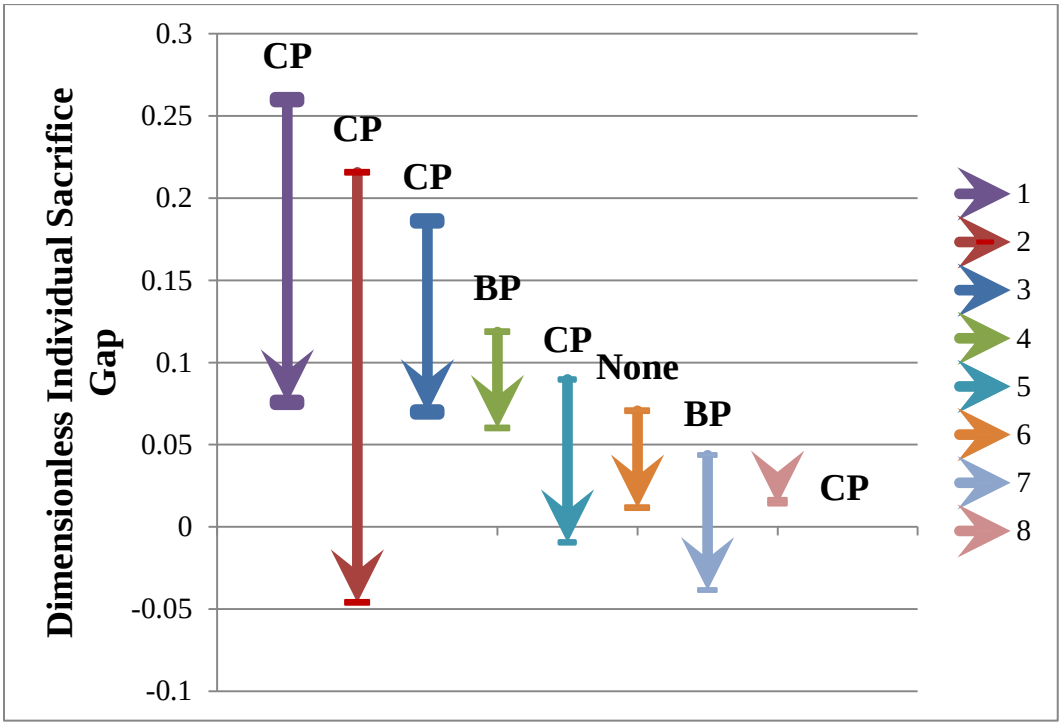

Figure 4.3: Individual Sacrifice Gaps in Mass Production and Custom Markets

All respondents depicted in Figure 4.3 switch from an alternative in the mass production market to a custom product because this switch decreases their sacrifice gap. The incremental value gained from this switch (their sacrifice gap reduction) is a measure of how much a respondent is moved along the spectrum depicted in Figure 1.1 toward choosing "what they want exactly" in the market. Respondents who experience the highest sacrifice

gap reduction, then, are those that experience the greatest jump toward mass customization. From a firm's perspective, these are the respondents who should experience the greatest increase in loyalty and customer retention potential.

Given this correlation, the red line (number 2) would have the most potential for added loyalty and retention from the optimally customized product line and the pink line segment (number 8) would have the least. Commentary in literature indicates that respondent number 2 would exhibit more loyalty and better retention than respondent 8 because their benefit from customization is greater. Although respondents who exhibit a small value increase from customization choose a custom product in a first-choice decision scenario, they would be more likely to switch to a different alternative if the parameters changed. Using respondents 8 and 2 from Figure 4.3 as an example, respondent 8 would be susceptible to switching their Best Alternative selection if the price of the competing product they switched from was lowered. In contrast, a much more drastic price decrease would be necessary for respondent 1 to switch back to their mass production Best Available alternative selection.

In the context of product line design, should a firm design a customized product for respondents (such as number 8) that would not exhibit a large increase in loyalty and are more likely to switch their purchase behavior? Or, should they focus their design effort on respondents (such as number 1) that have a higher potential to benefit from customization? Following this line of thinking, a customer-centric product line design problem like the one presented in this chapter could be used to determine which customers have the most and least

potential to benefit from customization, and which should be targeted in the final customization product line design.

The following section looks the impact of the customization configuration on the firm. Both profitability and complexity metrics are considered in the analysis.

4.3.2. FIRM IMPACT ANALYSIS

The following market-level metrics are used to assess the effects of the optimal product line configuration provided by the genetic algorithm on the firm: Sacrifice Gap, Aggregate Contribution, First Choice Market Share of Preference, and Build Combinations. Sacrifice gap and aggregate contribution are customer and firm value metrics defined in Chapter 3. First Choice Market Share of Preference (FCMSP) refers to the percentage of the 205 respondents in the hypothetical market that would choose Company X's product in a first choice decision scenario. Put another way, it counts how many times Company X's product (custom or mass produced) is the Best Available alternative in the market and divides by the size of the respondent population. Build combinations refers to the number of internal product combinations possible given the configuration of feature levels that are turned "on" and "off". Because a product is defined by one level from each feature, this is found my multiplying the number of available levels in feature 1 by the number of available levels in feature 2, continuing in this manner through feature 8.

The values of the market-level metrics are given in Table 4.15 below for the mass production and customization markets.

Table 4.15: Optimal GA Configuration Market-Level Metrics

	Market Average SG	Aggregate Contribution	FCMSP	Build Combinations
Mass Production Market	0.0336	$1,660	10.73%	1
Customization Market	-0.0095	$13,661	58.05%	35,840

As expected, offering the customization options defined by the optimal configuration benefit the firm by providing added aggregate contribution, increasing the customer base, and providing higher value products to the market.

Both aggregate contribution and FCMSP increased significantly when the custom configuration product line is offered. Aggregate contribution increases by 8.2x from $1,660 to $13,661 while FCMSP increases by 5.4x from 22 to 119. The increase in aggregate contribution is primarily caused by the drastic increase in FCMSP, but can also be attributed to the price of the internal products. In the base case customers could only purchase one MP3 player configuration for $210; $70 of this price contributes to aggregate contribution. In the customization case, on the other hand, each respondent can choose one of thousands of build combinations. A combination of costlier feature options and the customization tax have increased the average price of Company X's products to $512 ($\sigma$ = $131); $114 of this average price contributes to aggregate contribution.

Although the firm does benefit from offering the customization options defined by the customer-centric optimization, the magnitude of benefit may not be optimal. There may be

points in the design space that provide higher aggregate contribution at a higher sacrifice gap, making these two metrics competing objectives.

The sub-optimal configurations evaluated by the genetic algorithm were examined to determine whether any data points exhibited a higher sacrifice gap value *and* a higher aggregate contribution than the optimal configuration; i.e. a point that provides more firm value but less consumer value than the optimal point. The market average sacrifice gap and aggregate contribution for one such point and the optimal point are plotted in Figure 4.4 below. The point that corresponds to the optimal single-objective optimization configuration is given in red and the sub-optimal point (higher sacrifice gap) is plotted in blue.

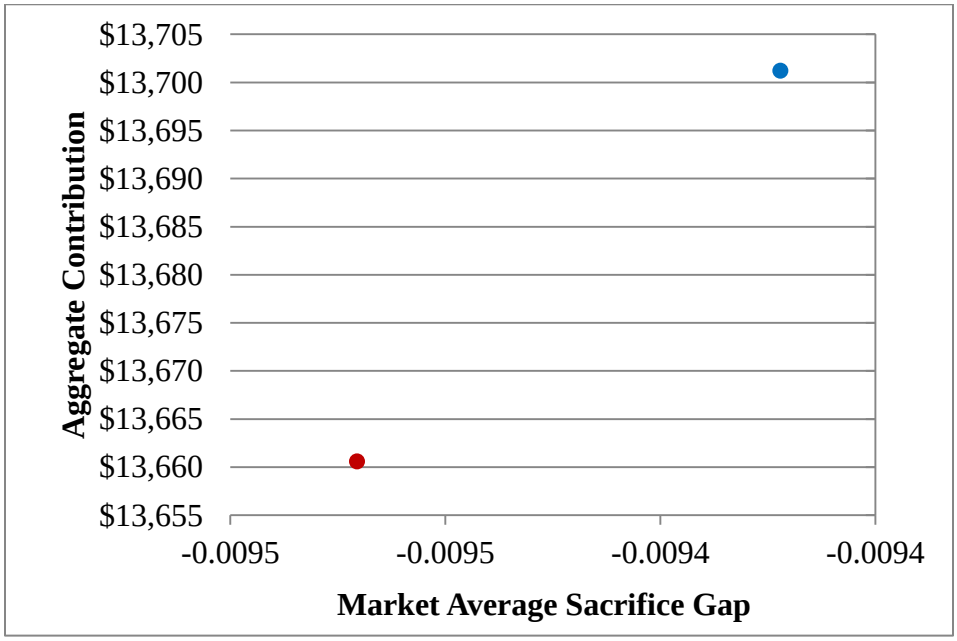

Figure 4.4: Relative Firm Value Assessment

The point given in blue above illustrates that the firm does not achieve an optimal benefit from the custom configuration prescribed by optimizing customer value. On the contrary, it poses sacrifice gap and aggregate contribution as competing objectives.

In addition to financial impact of customization, another concern for the firm is the added system complexity required to offer this level of variety. One way to measure product line complexity from a firm perspective is to calculate the number of potential product build combinations that can be created from the available feature levels. In the case of the optimal product line, the number of potential build combinations is 35,840. To put this number in perspective, engineers have to design parts that are compatible in 35,840 different combinations, manufacturing must accommodate the assembly and packaging of 35,840 different products and consumers must decide among 35,840 MP3 players.

Although this product line may maximize value to the consumer in terms of minimizing the market's sacrifice gap, it may not be optimal, or even feasible, for a firm to provide this level of variety. Although the increase in fiscal investment necessary for this jump is modeled in the case study through the customization tax, additional challenges such as strain on human resources, development of distribution networks, and the time required to make such changes are not. These and other such challenges are as important a consideration as the initial product line design; a product design cannot provide value to the firm or consumer if the company is not equipped to produce, distribute, or sell it to customers in the market.

4.4. CHAPTER SUMMARY

This chapter began by presenting an example calculated for the sacrifice gap metric formulated in Chapter 3. A detailed procedure for using a single-objective optimization to configure the availability of customization options to minimize market average sacrifice gap was then detailed. The procedure included instructions for objective function calculation as well as algorithm parameters used in this case study. The general process and context of the case study were provided in Chapter 3. After the procedure is presented, the resulting customization option configuration was analyzed with respect to its effects on the consumer and the firm.

Analysis of the resulting customization configuration confirmed several expectations regarding how market average sacrifice gap behaves as an objective function. The optimal customization configuration offered 27 of the 39 attribute levels posed as design variables. The observation that not all attributes re turned "on" indicates that the model captures the trade-off customers face between price and feature utilities of products in the market.

As expected, analysis at an individual level showed that some respondents benefit more from customization than others (experience different magnitudes of sacrifice gap reduction) while others are more satisfied with an external market or base product than a custom product. Examination of sacrifice gap reduction on an individual level indicated that customers with high sacrifice gap values in the mass production market were those that were most likely to purchase a custom product (and reduce their sacrifice gap) in the customization market. On the contrary, those with low initial sacrifice gap values tended to maintain their alternative selection from the mass production market.

The correlation between sacrifice gap reduction and magnitude of progress toward mass customization on an individual level was also drawn. Since progress toward mass customization yields greater customer loyalty and better retention, customers with greater sacrifice gap reduction exhibit these characteristics to a higher degree. This brings forth the question of whether firms should work to design custom products for individuals who do not experience a high level of sacrifice gap reduction. This observation also puts forth the possibility of using customer-centric product line design (like that used in this chapter) as a means to identify the customers that would benefit most from customization and using that information in the remainder of the design process.

Implementation of optimal customization reduced market average sacrifice gap, increased aggregate contribution, and allowed company X to capture a large number of customers relative to the mass production market. The increases in aggregate contribution were due primarily to increase in market share of preference but also to increased net sales per product. Most of the respondents that caused the increase in market share of preference came from a competing product, but some were cannibalized from those that purchased the base product. In the context of mass customization, this cannibalization indicates that customization options provided these customers with a greater value than the base product that can translate into greater loyalty and higher customer retention.

The firm impact analysis also showed that aggregate contribution (a firm value metric) and market average sacrifice gap (a consumer value metric) are competing objectives, meaning that the firm is not achieving optimal benefit from the customer-centric product line design.

The analysis conducted in Chapter 4 provided information regarding metric behavior within optimization problems and general trends that link sacrifice gap and customer purchase behavior in the optimal configuration. The analysis of Chapter 4 confirmed several expected outcomes of minimizing a custom product line for sacrifice gap, indicating that the metric behaves as expected. Chapter 5 looks to build on this process by introducing aggregate contribution as a firm-value objective function. The jump to a multi-objective design space provides a more realistic design scenario. The multi-objective design space provides information that can lead to deeper insight into how customer purchase behavior changes when a firm makes small changes (such as turning “on” or “off” a particular feature level) or when market average sacrifice gap fluctuates. It also gives firms a larger source of information from which they can use other engineering design tools to make product line decisions. The process for and analysis of the multi-objective optimization problem is given in the next chapter.

CHAPTER 5: FIRM AND CONSUMER-CENTRIC PRODUCT DESIGN

The results and analysis from the first case study indicate that market average sacrifice gap behaves as expected when applied to product line optimization problems. Chapter 5 builds on the first case study by adding a second objective function (aggregate contribution) to the design problem. This addition makes the problem more realistic (by incorporating firm value) and provides a greater information base of potential customization configuration designs (for analysis and for use in design decisions).

The multi-objective problem is solved using a multi-objective genetic algorithm (MOGA) and yields a Pareto frontier of optimal points that balance the two objectives. Each point is in itself optimal, but provides a different (relative) proportion or value to the consumer and the firm. In theory, having a number of optimal points to choose from would allow a firm to balance consumer value (minimizing sacrifice gap) with their own value (aggregate contribution and FCMSP) and level of acceptable complexity (potential build combinations). Details of the optimization procedure used to conduct the MOGA as well as an analysis of the results are included below.

5.1. MULTI-OBJECTIVE OPTIMIZATION PROCEDURE

This optimization uses a procedure very similar to that of the single objective detailed in Chapter 4, the only difference is that aggregate contribution is calculated in tandem with sacrifice gap, and the pair is output as the objective function values. All examples provided in Chapter 4 are relevant to Chapter 5 as well. The objective function values are minimized

by turning “on” or “off” availability of custom levels (the design variables), finding the optimal product for each respondent (price and utility) given the available feature levels, and calculating market average sacrifice gap based on the available product configurations (in the internal and external markets). Note that aggregate contribution is output as its negative value so that minimizing the output yields a maximization of the actual aggregate contribution value. The standard form of the optimization problem is as follows:

Objective:

MIN: $f_1 = SG_{mkt\ avg}$ (5.1)

$f_2 = -AC_{MC}$ (5.2)

Bounds:

ST: $x_i \epsilon\ 0, 1 \quad i = 1 \ldots 39$

5.1.1. OBJECTIVE FUNCTION CALCULATION

The overall process for determining the optimal objective function values is identical to the single objective case, with the exception of calculating and outputting aggregate contribution as a second objective function. For this reason steps 1 through 6 are omitted from this section; they can be found in Chapter 4.2. The calculation process for the two desired objective functions is described below.

START MATLAB MOGA

III. Import necessary constants

IV. Send design variables to Objective Function

OUTPUT: Design Variables (binary vector of "on"/"off" attribute level configuration 39 elements long)

START OBJECTIVE FUNCTION

IMPORT: Design Variables (binary vector of "on"/"off" attribute level configuration 39 elements long)

•

•

•

7. Calculate the dimensionless sacrifice gap for all market products for all respondents using Equation 3.5 developed in Chapter 3. Identify and record which product in the market provides each respondent the lowest sacrifice, as well as the dimensionless sacrifice gap value. This step identifies *i* products and *i* measures of individual sacrifice.
8. Calculate the market average sacrifice gap using Equation 3.6. **This is the first objective function value.**
9. Calculate the preference share of the optimal customized product for each respondent, and multiply it by the corresponding optimal custom product price. This yields that respondent's contribution. Sum each respondent's contribution to get aggregate contribution for a customized market in accordance with Equation 3.9. **This is the second objective function value.**

OUTPUT: Market Average Sacrifice Gap, Aggregate Contribution

RETURN OUTPUT TO MOGA, REPEAT TO CONVERGENCE

5.1.2. MULTI-OBJECTIVE GENETIC ALGORITHM PARAMETERS

The parameters used in the execution of the MATLAB Optimization Toolbox Multi-Objective Genetic Algorithm are as follows:

Population Type: bitstring
Population Size: 600
Pareto Fraction: 0.5
Generations: 112
Mutation Function: Uniform
Initial Population: Random binary
Selection Function: Tournament
Crossover Function: Scattered

5.2. MULTI-OBJECTIVE OPTIMIZATION RESULTS

The MOGA conducted per the procedure detailed in the previous section returned 37 unique points on the Pareto frontier, corresponding to 37 unique product line configurations. The Pareto frontier for these optimal points is given as Figure 5.1 below. For ease of reference, each point is given an index value that ranges from 1 to 37; 1 being the point that provides the lowest sacrifice gap and, relatively, lowest aggregate contribution. Note that, as expected, the optimal solution from the single-objective optimization in Chapter 4 appears as the left-most point on the MOGA frontier; it has an index value of 1.

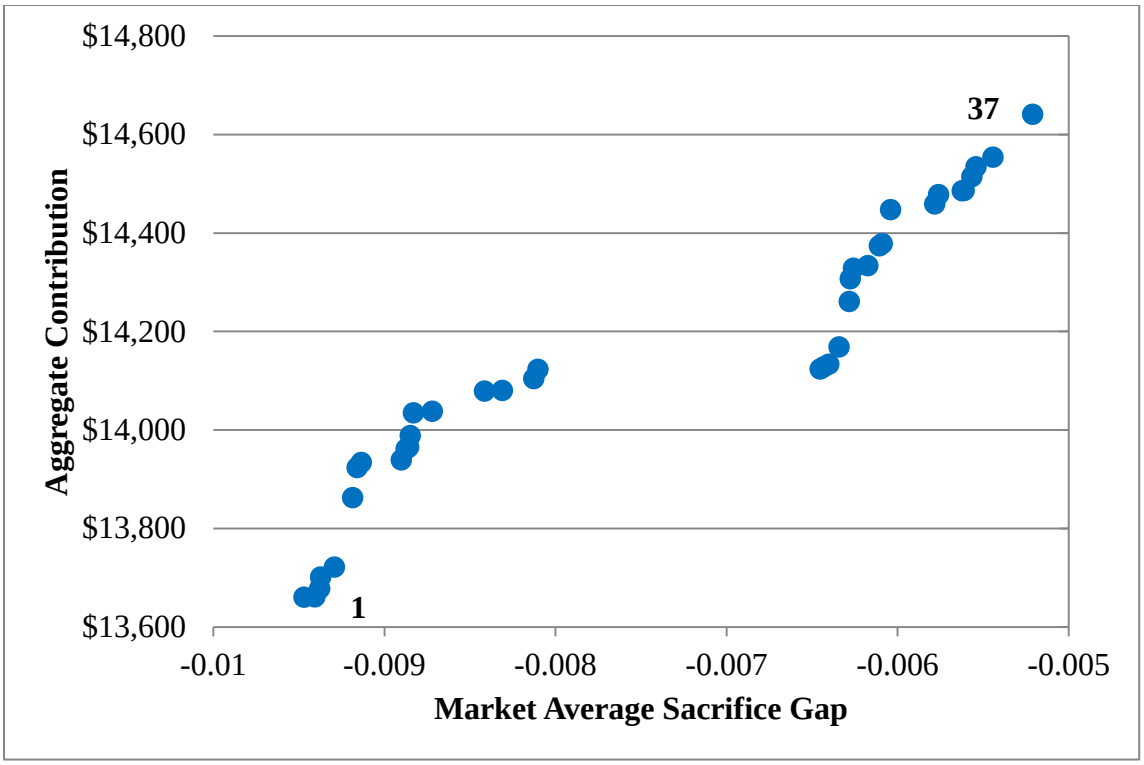

Figure 5.1: Pareto Frontier

As expected, Figure 5.1 shows that there is an apparent trade-off between sacrifice gap and aggregate contribution, therefore they are competing objectives. The sacrifice gap and aggregate contribution values for each optimal point are given as Table 5.1 below.

Table 5.1: Objective Function Values for Pareto Points

Index	Sacrifice Gap	Aggregate Contribution		Index	Sacrifice Gap	Aggregate Contribution
1	-0.0094705	$13,661		**20**	-0.0064331	$14,128
2	-0.0094066	$13,661		**21**	-0.0064008	$14,133
3	-0.0093775	$13,678		**22**	-0.0063416	$14,169
4	-0.0093721	$13,701		**23**	-0.0062819	$14,261
5	-0.0092923	$13,721		**24**	-0.0062771	$14,307
6	-0.0091852	$13,863		**25**	-0.0062585	$14,328
7	-0.0091602	$13,924		**26**	-0.0061734	$14,334
8	-0.0091343	$13,934		**27**	-0.0061065	$14,374
9	-0.0089013	$13,939		**28**	-0.0060901	$14,378
10	-0.0088725	$13,961		**29**	-0.0060408	$14,448
11	-0.0088585	$13,965		**30**	-0.0057826	$14,459
12	-0.0088497	$13,989		**31**	-0.0057592	$14,478
13	-0.0088300	$14,035		**32**	-0.0056211	$14,486
14	-0.0087207	$14,038		**33**	-0.0056107	$14,486
15	-0.0084141	$14,079		**34**	-0.0055645	$14,515
16	-0.0083107	$14,081		**35**	-0.0055411	$14,535
17	-0.0081269	$14,104		**36**	-0.0054412	$14,554
18	-0.0081021	$14,123		**37**	-0.0052098	$14,641
19	-0.0064520	$14,124				

The variation in aggregate contribution magnitude is $980 for the respondent market of 205 individuals. This magnitude may seem inconsequential, but in a real market comprised of thousands or millions of potential customers this figure can drastically increase. The variation in market average sacrifice gap is 0.00426, but the meaning of this magnitude is unclear without further analysis because sacrifice gap itself is a dimensionless number. The following analysis looks to determine how this variation in market average sacrifice affects the individual consumer and, in turn, how it can guide firm level design decisions.

A closer examination of the customization configuration for these points (which levels are turned “on” and “off”) shows that 19 levels are always turned “on”, 8 are always turned “off”, and 12 fluctuate along the frontier. This means that the variation seen in Figure 5.1 is due to 12 of the 39 attribute levels. A summary of attribute configuration behavior is given as Table 5.2 and the configuration of all “sometimes offered” levels for each Pareto point is given as Table 5.3.

Table 5.2: Level Configuration Behavior Summary

Levels Always Offered				
Photo and Video Only	Web, app, and ped.	6.5 in diag.	Silver	Custom
Photo, video and lo-res camera	Touchpad	32 GB	Red	Custom pattern overlay
Photo,video and hi-res camera	4.5 in diag.	64 GB	Orange	Custom graphic overlay
Web and app only	5.5 in diag.	160 GB	Green	
Levels Sometimes Offered			**Levels Never Offered**	
Video only	App only	240 GB	Photo only	1.5 in diag.
Photo and lo-res camera	App and ped. only	White	Ped. only	2.5 in diag.
Photo and hi-res camera	Web and ped. only	Blue	Dial	500 GB
Web only	2 GB	No pattern / graphic overlay	Buttons	750 GB

Table 5.3: Pareto Configuration for “Sometimes Offered” Levels

Index	Video only	Photo and lo-res camera	Photo and hi-res camera	Web only	App only	App and ped. only	Web and ped. only	2 GB	240 GB	White	Blue	No ptrn. / grap. ovly.
1	1	1	1	0	0	0	1	1	0	1	1	1
2	1	1	1	0	0	0	1	1	0	0	1	1
3	1	1	1	0	0	0	1	1	0	1	0	1
4	1	0	1	0	0	0	1	1	0	1	1	1
5	1	0	1	1	0	1	1	1	0	1	1	1
6	1	1	1	1	1	0	1	1	0	1	1	1
7	1	0	1	1	1	1	1	1	0	1	1	1
8	1	0	1	1	1	0	1	1	0	1	1	1
9	1	1	1	0	1	0	1	1	0	1	1	1
10	1	0	1	0	1	0	1	1	0	1	1	1
11	0	0	1	1	1	0	1	1	0	1	1	1
12	1	0	1	0	1	1	1	1	0	1	1	1
13	0	0	0	1	1	0	1	1	0	1	1	1
14	0	0	0	1	1	0	1	1	0	1	0	1
15	0	0	0	0	1	0	1	1	0	1	1	1
16	0	0	0	0	1	0	1	1	0	1	0	1
17	0	0	0	0	1	0	1	1	0	0	1	0
18	0	0	0	0	1	0	1	1	0	1	0	0
19	1	0	1	0	0	0	1	0	0	1	0	1
20	1	1	0	0	0	0	1	0	0	1	1	1
21	1	1	1	0	0	0	1	0	1	1	1	1
22	0	1	1	0	0	0	1	0	0	1	1	1
23	1	1	1	1	1	1	1	0	0	1	1	1
24	1	1	1	1	1	0	1	0	0	1	1	1
25	1	0	1	1	1	1	1	0	0	1	1	1
26	1	0	0	1	1	0	1	0	0	1	1	1
27	1	0	1	0	1	0	1	0	0	1	1	1
28	0	0	1	1	1	0	1	0	0	1	1	1
29	0	0	0	1	1	0	1	0	0	1	1	1
30	0	0	0	1	1	0	0	0	0	0	1	1
31	0	0	0	1	1	0	0	0	0	1	0	1
32	0	0	0	0	1	0	1	0	0	1	1	1
33	0	0	1	0	1	0	0	0	0	1	1	1
34	0	0	0	0	1	0	1	0	0	0	1	1
35	0	0	0	0	1	0	1	0	0	1	0	1
36	0	0	0	0	1	0	0	0	0	1	0	1
37	0	0	0	0	1	0	0	0	1	1	1	1

The configuration behavior of the attribute levels along the frontier provides several insights into general market preferences. The respondents typically favor having photo and video functions together as well as web access and app capability. In addition, touchpad and touchscreen input options are heavily favored to dial and buttons. This is consistent with the preference for larger screen sizes (the 1.5” and 2.5” diagonal screen sizes are never offered). The mid-range storage sizes are most frequently offered to this group of respondents, 2GB is rarely offered and 500 GB and 700GB are not offered in any of the configurations.

The Pareto point configurations are analyzed relative to the one another and to the base case in the following sections to determine how moving along the Pareto frontier affects respondents in the market (individual sacrifice gap and product choice behavior) as well as the firm (aggregate contribution, first choice market share of preference (FCMSP), and build combinations).

5.2.2. CUSTOMER IMPACT ANALYSIS

Using First Choice Market Share of Preference for each of the 6 alternatives (custom product, base product, 3 competing products, ‘None’), respondents choice behavior is first examined from a market level. FCMSP for each alternative in each Pareto point is given as Table 5.4.

Table 5.4: Pareto Point FCMSP for All Alternatives

Index	Custom Product	Base Product	Competing Product 1	Competing Product 2	Competing Product 3	'None'
1	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
2	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
3	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
4	52.68%	5.37%	23.90%	3.90%	2.93%	11.22%
5	53.66%	5.37%	23.41%	3.41%	2.93%	11.22%
6	54.15%	4.88%	23.90%	3.41%	2.93%	10.73%
7	54.15%	5.37%	23.41%	3.41%	2.93%	10.73%
8	53.66%	5.37%	23.90%	3.41%	2.93%	10.73%
9	53.66%	4.88%	23.90%	3.90%	2.93%	10.73%
10	53.17%	5.37%	23.90%	3.90%	2.93%	10.73%
11	53.17%	5.37%	23.90%	3.90%	2.93%	10.73%
12	53.66%	5.37%	23.41%	3.90%	2.93%	10.73%
13	52.68%	5.37%	23.90%	3.90%	2.93%	11.22%
14	52.68%	5.37%	23.90%	3.90%	2.93%	11.22%
15	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
16	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
17	52.68%	5.37%	23.41%	4.39%	2.93%	11.22%
18	52.68%	5.37%	23.41%	4.39%	2.93%	11.22%
19	52.68%	5.37%	23.90%	3.90%	2.93%	11.22%
20	52.68%	4.88%	23.90%	3.90%	2.93%	11.71%
21	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
22	53.17%	4.88%	23.90%	3.90%	2.93%	11.22%
23	54.15%	5.37%	23.41%	3.41%	2.93%	10.73%
24	54.15%	4.88%	23.90%	3.41%	2.93%	10.73%
25	54.15%	5.37%	23.41%	3.41%	2.93%	10.73%
26	53.17%	5.37%	23.90%	3.41%	2.93%	11.22%
27	53.17%	5.37%	23.90%	3.90%	2.93%	10.73%
28	53.17%	5.37%	23.90%	3.90%	2.93%	10.73%
29	53.17%	5.37%	23.90%	3.41%	2.93%	11.22%
30	53.17%	5.37%	23.41%	3.90%	2.93%	11.22%
31	53.17%	5.37%	23.41%	3.90%	2.93%	11.22%
32	52.68%	5.37%	23.90%	3.90%	2.93%	11.22%
33	53.17%	5.37%	23.90%	4.39%	2.44%	10.73%
34	53.17%	5.37%	23.41%	3.90%	2.93%	11.22%
35	53.17%	5.37%	23.41%	3.90%	2.93%	11.22%
36	54.15%	5.37%	23.41%	3.41%	2.44%	11.22%
37	53.17%	5.37%	23.41%	4.39%	2.44%	11.22%

Looking at the values, in Table 5.4, there is little difference in FCMSP for custom products. Across all Pareto points, FCMSP ranges from 53.17% to 54.15%, this corresponds to between 108 and 111 respondents for this case study. To better assess how choosing one Pareto point over another affects respondents in the market, incremental changes in individual sacrifice gap are examined.

For the purposes of the analysis, respondents in the market are segmented into 4 groups based on their purchase behavior in the first choice decision scenario. The characteristics and population size of these groups are summarized in Table 5.5.

Table 5.5: Customer Segmentation Summary

Respondent Type	Number of Respondents	Description
1	41	Respondents that always choose a custom product with the same configuration
2	89	Respondents that never choose a custom product
3	64	Respondents that always choose a custom product but with varying configurations
4	11	Respondents that sometimes choose more than one market alternative along the frontier

Each segment of respondents is examined in its own subsection to investigate how changes in Pareto configuration affect the individuals within that segment.

5.2.2.1. TYPE 1 RESPONDENTS

Type 1 respondents purchase a custom product regardless of which Pareto point is considered; 41 respondents (20% of the market) fall into this category. Closer examination of custom products chosen by these individuals showed that all products for Type 1 respondents can be created using only levels that are always available per Table 5.2. This observation is expected given that Type 1 respondents choose the same custom product in all Pareto configurations. Since the Best Available Alternative for Type 1 respondents is comprised of custom levels that are always present in optimal custom configurations, their wants and needs are similar to others in the custom market.

Although these respondents' Best Available alternative is static, their sacrifice gap among all Pareto configurations is not. Since the feature utility for these respondents remains constant, changes in their individual sacrifice gap along the frontier are due only to fluctuations in price utility. Because these fluctuations in price utility are due to customization tax only, they are a function of complexity in the custom product lines. The minimum customization tax is $166 at point 36 and the maximum customization tax is $189 at point 23; this gives a $23 range for all Pareto points. This group would garner the highest sacrifice gap reduction from the selection of point 36 because of the customization tax magnitude, but any product line on the frontier yields a reduction in sacrifice gap with respect to the mass production market.

The mean sacrifice reduction for all Type 1 respondents ranges from -0.065 (σ = 0.059) to -0.060 (σ = 0.058). Figure 5.2 depicts this reduction for a representative subset

of Type 1 respondents. Each orange data point corresponds to a sacrifice gap value for a respondent in the mass production market and each collection of blue data points represents their sacrifice gap values for all Pareto configurations.

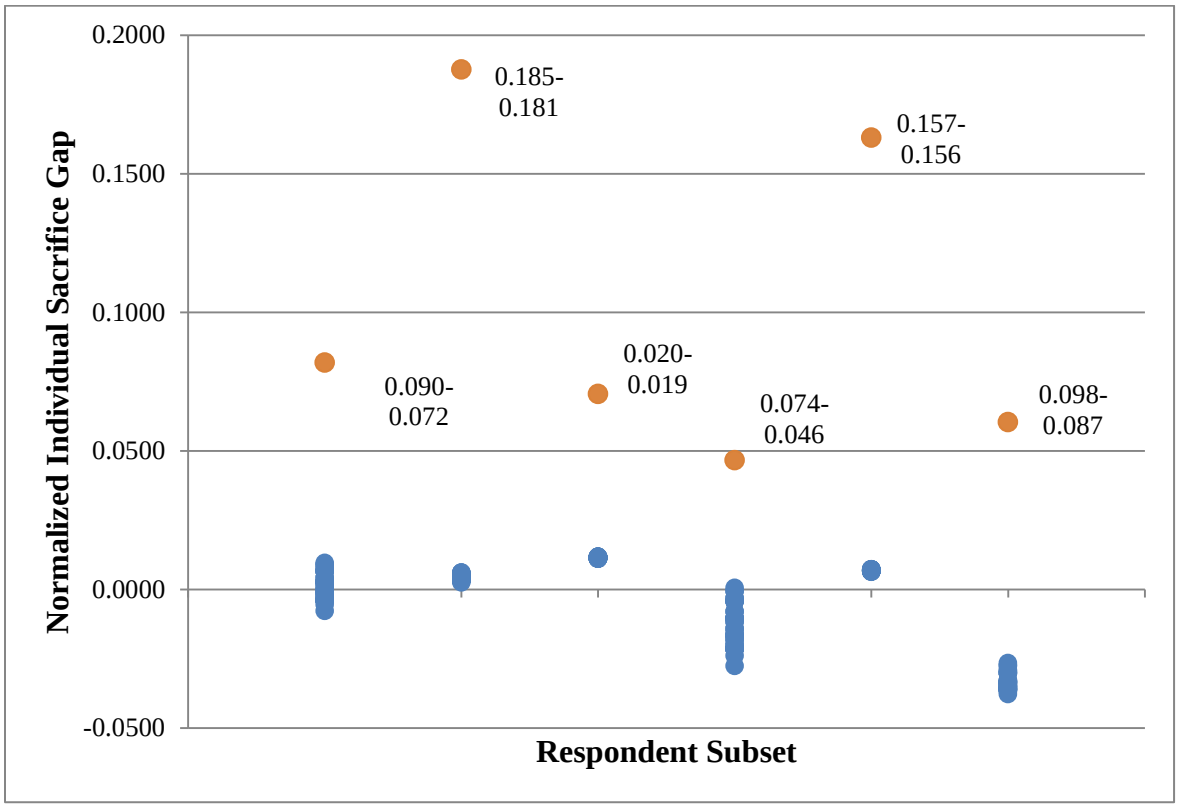

Figure 5.2: Sacrifice Gap Reduction for Type 1 Respondent Subset

Within the Type 1 population, 12 of the 41 respondents exhibit high mass production market sacrifice gap (higher than 0.1 per the definition in Chapter 4), the remainder exhibit medium mass production market sacrifice gap (between 0.1and -0.1). The subset of

respondents in the figure above reflects that ratio. Note that the individuals with higher mass production sacrifice gaps tend to experience a higher sacrifice reduction and thus benefit more from customization. Also note that the magnitudes of mass production sacrifice gap show greater variation than the custom market sacrifice gaps. This is similar to the observations in Chapter 4 where customization pushed all individual sacrifice gaps down below a certain threshold.

The 6 respondents in Figure 5.2 experience sacrifice gap reduction that is reflective of with the average for the Type 1 respondent population. The consistent reduction indicates that regardless of which Pareto configuration is chosen, the customization market is superior to the mass production market. In addition, the magnitude of reduction indicates that the majority of these individuals will benefit from any optimal custom configuration, even if minor price fluctuations occur.

5.2.2.2. TYPE 2 RESPONDENTS

Type 2 respondents exhibit choice behavior that is opposite of the Type 1's - they do not choose a custom product regardless of the Pareto configuration selected. Rather, Type 2's choose the base product, a competing product, or the 'None' option in both the mass production market and the customization market. 89 of the 205 respondents in the hypothetical market (43%) choose a non-custom alternative regardless of Pareto configuration. Compared to the Type 1's, who had an average mass production sacrifice gap of 0.321 ($\sigma = 0.167$), Type 2's generally exhibit a much lower mass production sacrifice gap. The mass production market average sacrifice gap for the Type 2 population is -0.050

($\sigma = 0.062$), this is considered the low-end of medium per the definition in Chapter 4. In fact, 77.53% of these respondents exhibit a negative sacrifice gap. As such, Type 2 respondents are the primary cause of a negative market average sacrifice gap in the customization markets.

The Type 2's tendency to always choose a non-custom product is consistent with the conclusions in Chapter 4 which indicate that individuals with lower sacrifice in the mass production market are less likely to benefit from customization. Since Type 2's who choose the base product in both markets have a different impact on the firm than Type 2's that choose an outside alternative, these subgroups of individuals are analyzed separately. Type 2's that choose an outside product are examined first.

There are 80 respondents in the hypothetical market that choose an outside alternative regardless of the optimal customization configuration selected. This analysis will first investigate how close the available custom products are to overtaking these respondents' Best Available alternatives. A representative subset of 6 respondents whose Best Available alternative is always an outside market product were selected. The sacrifice gap value associated with their Best Available alternative is plotted along with the sacrifice gap that corresponds to their most favorable custom product (the optimal custom product when considering all possible Pareto custom configurations and the corresponding customization tax). This illustrates how close Company X is to designing a custom product that reduces these respondents' sacrifice gap. Figure 5.3 plots the Best Available alternative sacrifice gaps

in orange and the sacrifice gap associated with the most favorable custom product in blue. The magnitude difference between these values is given as the data label.

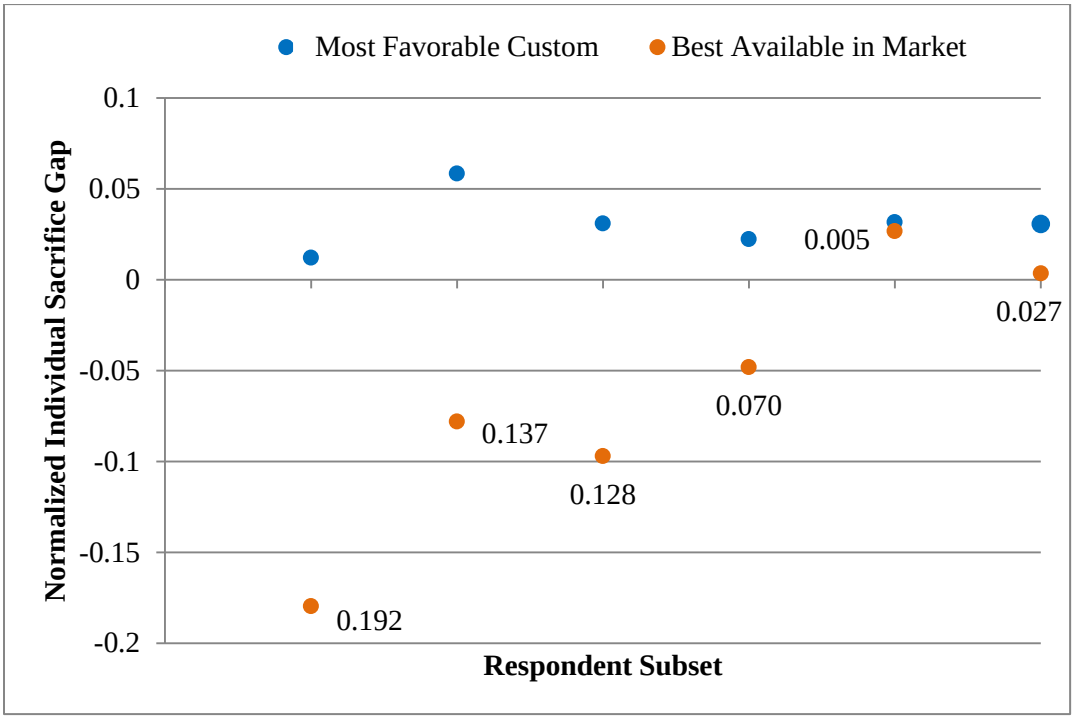

Figure 5.3: Type 2 Proximity to Sacrifice Gap Reduction

The average sacrifice gap difference between Best Available alternative sacrifice gap and most favorable custom product sacrifice gap is 0.074 (σ = 0.053). Although there are a few individuals (the fifth respondent in Figure 5.3 for example) whose most favorable custom product provides a sacrifice gap on very close to the current Best Available alternative in the market, the majority of respondents obtain substantially higher value from

an outside product compared to a custom product. In general, respondents who fall into the Type 2 category appear to be content with their Best Available alternative when the current set of attribute levels and pricing structures are considered. Convincing them to switch to a custom product would require introduction of new feature levels or a change in the pricing structure.

Those whose most favorable custom products are close in sacrifice gap magnitude to their Best Available alternative may be convinced to purchase a custom product if the price was reduced sufficiently. However, given the discussion in the previous chapter about the relationship between customer loyalty and retention and sacrifice gap reduction, this may not be a favorable long-term strategy for Company X.

The second sub-group within the Type 2 population is composed of respondents who always choose the base product. The size of this population is smaller than the other subset of Type 2's as only 9 respondents fall into this category. Similar to the other sub-group of Type 2's, these respondents exhibit mid to low mass production market sacrifice gaps. The mass production sacrifice gap values for these 9 respondents are shown in Figure 5.4.

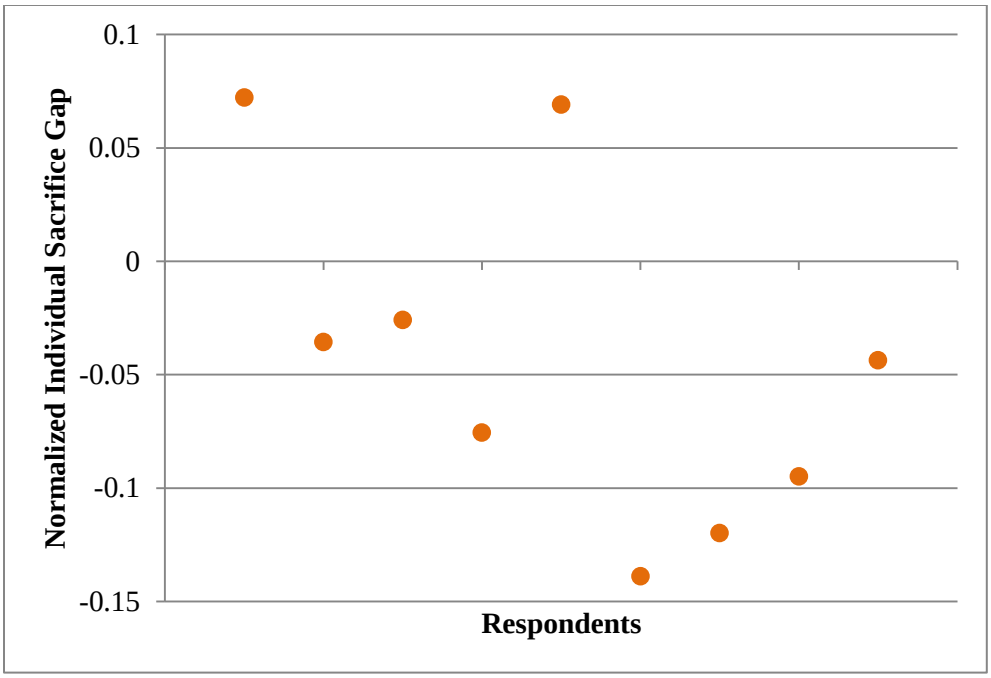

Figure 5.4: Type 2, Base Product Selecting Individual Sacrifice Gaps

Respondents who always choose the base product have wants and needs that line up well with the features present on and price of the base product that is available in both the mass production and customization scenarios. Because of their relatively low sacrifice gap values, these respondents are expected to exhibit customer loyalty and retention similar to Type 1 respondents in the customization market, without the added complexities of customization. There is no incentive for the company to persuade these respondents to switch to a custom product unless they introduce additional features or a different price structure that can provide them a sacrifice gap reduction.

5.2.2.3. TYPE 3 RESPONDENTS

Type 3 respondents choose a custom product regardless of the Pareto configuration, but the configuration of this custom product is not constant; they make up 31% of the market. Respondents in this category have between 2 and 6 different custom product variations among the 37 different Pareto configurations. The following analysis will examine why these respondents switch between custom product configurations and investigate how choosing one Pareto point over another affects these respondents at an individual level.

5.2.2.3.1. *Custom Product Configuration Switching Analysis*

To investigate why some respondents switch from one custom configuration to another, custom product configuration, sacrifice gap, level availability, and customization tax were viewed at an individual level. Upon inspection, two intuitive causes for configuration switching were identified: changes in attribute level availability and changes in customization tax.

Because this model considers all respondents optimizers, each respondent will always choose the product configuration that maximizes their net utility. In the case of Type 1 respondents this product is always available because it is comprised of levels that are always offered. This is not the case with Type 3 respondents, however, and thus becomes a cause for custom product configuration variation.

Respondent 165 switches between 5 different custom product configurations for the 37 Pareto points, resulting in a $31 price range. The configuration this respondent chooses

for a particular Pareto configuration is governed by 2 attributes: Photo, Video, and Camera and Web Access, App Capability, and Pedometer. First, upon examining the tendency to choose one PVC level over another it is noted that this individual chooses Photo and Hi-res Camera whenever it is available and Photo, Video, and Hi-res Camera when it is not. A comparison of this respondent's feature level choice and the availability of that particular feature level is given as Table 5.6. A 1 in a particular column indicates "yes" and a 0 in a particular column indicates "No". Note that the level they chose for a particular Pareto configuration is bolded

Table 5.6: Respondent 165's Level Choice Behavior (PVC)

Index Number	Photo and hi-res camera	Available?	Photo,video and hi-res camera	Available?
1	**1**	**1**	0	1
2	**1**	**1**	0	1
3	**1**	**1**	0	1
4	**1**	**1**	0	1
5	**1**	**1**	0	1
6	**1**	**1**	0	1
7	**1**	**1**	0	1
8	**1**	**1**	0	1
9	**1**	**1**	0	1
10	**1**	**1**	0	1
11	**1**	**1**	0	1
12	**1**	**1**	0	1
13	0	0	**1**	**1**
14	0	0	**1**	**1**
15	0	0	**1**	**1**
16	0	0	**1**	**1**
17	0	0	**1**	**1**
18	0	0	**1**	**1**
19	**1**	**1**	0	1
20	0	0	1	1
21	**1**	**1**	0	1
22	**1**	**1**	0	1
23	**1**	**1**	0	1
24	**1**	**1**	0	1
25	**1**	**1**	0	1
26	0	0	**1**	**1**
27	**1**	**1**	0	1
28	**1**	**1**	0	1
29	0	0	**1**	**1**
30	0	0	**1**	**1**
31	0	0	**1**	**1**
32	0	0	**1**	**1**
33	**1**	**1**	0	1
34	0	0	**1**	**1**
35	0	0	**1**	**1**
36	0	0	**1**	**1**
37	0	0	**1**	**1**

Since Photo, Video, and Hi-res Camera is always available but Photo and Hi-res Camera is not, examining this respondent's choice when both are offered provides insight into which level they prefer to the other. Since this respondents chooses Photo and Hi-res Camera even though Photo, Video, and Hi-res Camera is always offered, one can infer that the former feature level is their preference. This choice behavior can be described as a hierarchy; the top level in the hierarchy is selected until it is unavailable, then the respondent moves to the second level in the hierarchy. The other governing attribute, WAP, exhibits the same hierarchical tendencies. For this attribute 3 levels are arranged in a hierarchy where Web Only is chosen over Web and Pedometer Only and both are chosen over Web, App, and Pedometer.

The top choice attribute in a hierarchy does not necessarily correspond to which level provides that respondent with the highest part-worth. As an example, respondent 165's relevant part-worths for the WAP attribute are given as Table 5.7 below.

Table 5.7: Respondent 165's WAP Part-Worths

	Web only	**Web and ped. only**	**Web, app, and ped.**
Part-Worth	1.3834745	0.410279	2.659038
Hierarchy Rank	1	2	3

Since each individual optimizes their net utility, their feature choice is dependent upon not just the value they gain from a feature, but the monetary value they have to give up to acquire it. This is why Web, App, Pedometer is not at the top of the hierarchy although it gives the respondent the greatest feature utility of the three options. Since the hierarchy proceeds from left to right in this specific example, Web Only would give this respondent the greatest net utility at the product configuration's price point.

It is important to note that this hierarchy only reflects respondent 165's choice behavior for this particular situation and for a range of prices. The relative net utility of one level to another is dependent upon the overall price of the product in question because price utilities are not linear from the highest overall to the lowest overall price point; this work only assumes they are linear *between* price points. In practice, this means that this respondent may favor Web Only to Web and Pedometer or Web, App, and Pedometer at a $200 product price point but not at a $500 price point. Respondent 46 exemplifies this situation.

Respondent 46's custom product configurations are governed by the storage and custom overlay attributes. For 36 of the 37 Pareto points this respondent chooses Custom Graphic Overlay regardless of whether No Pattern or Overlay is offered. For these 36 Pareto points the overall price of the custom product ranges from $408 to $471. In the final Pareto configuration, the 240 GB storage size becomes available, and by selecting it the respondent's custom product price increases to $696. This shift in overall product price causes them to now choose No Pattern/Graphic Overlay even though Custom Graphic

Overlay is available. This represents a shift in the respondent's overlay attribute hierarchy due to a change in product's overall price.

In addition to attribute level availability, changes in custom product configuration selection may be due to changes in customization tax value. Respondent 6 provides an example of this relationship. Respondent 6's custom configuration is governed by storage size and PVC attributes. Both storage sizes this individual selects (16GB and 64GB) are available in all Pareto configurations and the PVC levels (Photo, and Lo-Res Camera and Photo, Video, and Hi-Res Camera) exhibit the same behavior described using Respondent 165. Looking at storage for Pareto points 4 and 5 specifically, the availability and choice behavior for this respondent are summarized in Table 5.8.

Table 5.8: Respondent 6's Storage Choice Behavior for Lines 4 and 5

Index	16 GB	Available?	64 GB	Available?
4	**1**	**1**	0	1
5	0	1	**1**	**1**

Examination of the data in Table 5.8 shows that the availability for these two levels does not change, yet the respondent switches from choosing the 16GB hard drive to the 64GB one. In addition, no other attribute levels are changed in this respondent's custom product. This switch in feature level selection is, therefore, due to changes in customization

tax. The increase in customization tax (due to increased availability of attribute levels that were not chosen by this respondent), makes the particular feature levels from Pareto point 4 less desirable from a net utility standpoint. This allows a similar, more expensive, configuration to have a higher net utility because of its added feature utility. Table 5.9 shows this numerically.

Table 5.9: Respondent 6 Custom Configuration Switching Example

	Pareto Point 4		**Pareto Point 5**	
Configuration Number	**Price**	**Utility**	**Price**	**Utility**
390,692	$479	14.76	$487	14.55
390,756			$642	14.56

The utility of the optimal custom product in Pareto point 4 (number 390,692) drops from 14.76 to 14.55. This allows configuration number 390,756 to become optimal with a net utility of 14.56. Note that the change in customization is $8, a seemingly minute amount in relation to the price of the product. In this model, the $8 customization tax increases causes this respondent to choose a product that is $155 greater. This is due to the assumptions that customers are optimizers and choose the product that gives them the highest net utility as well as the assumption that custom product purchase is modeled as a first choice decision scenario. It is unclear if this truly models what this individual would pursue in a real world

purchase scenario. This observation highlights the need for a granular, accurate representation of customers' valuation of product price points and purchase behavior.

5.2.2.3.2. *Sacrifice Gap Analysis*

Type 3 respondents exhibit an average mass production market sacrifice gap of 0.109 (σ = 0.074). This average is at the dividing line between high sacrificers and medium sacrificers as they are defined in this work. The distribution of respondents in the Type 3 population who are characterized as high sacrificers to medium sacrificers is 29:35, and the majority of the population (55 out of the 64 respondents) has a mass production sacrifice gap that lies between 0 and 0.2. Figure 5.5 depicts the distribution of sacrifice gap values for all Type 3 respondents. The blue rhombuses represent the respondent's sacrifice gap in the mass production market (and the sacrifice gap they would have if customization were not available, if they chose the next best alternative in the market), the red squares represent the lowest sacrifice gap that respondent obtained when all Pareto points were considered, and the green triangles represent the highest sacrifice gap a respondent obtained if all Pareto points were considered.

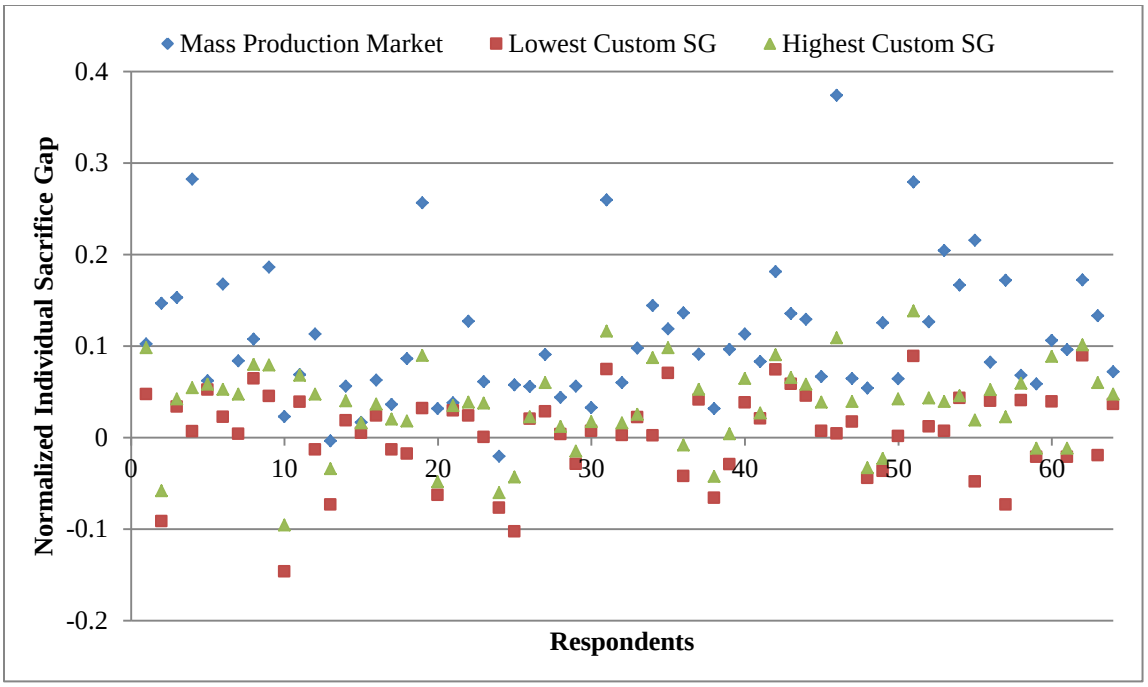

Figure 5.5: Mass Production and Custom Individual Sacrifice Gap for Type 3 Respondents

Visual inspection of Figure 5.5 provides several observations. Respondents who exhibit a mass production sacrifice gap below 0.1 tend to have a relatively lower sacrifice gap reduction magnitude than those with mass production sacrifice gap above 0.1. The average reduction for the high sacrificers is between 0.149 (σ = 0.078) and 0.110 (σ = 0.0649) and the average reduction for the medium sacrificers is between 0.065 (σ = 0.039) and 0.044 (σ = 0.033). Logically, this observation makes sense. A respondent's sacrifice gap decreases when the features on the Best Available alternative in the market become more optimal. If a product in the market is close to optimal (the respondent's sacrifice gap is already low) it is difficult to decrease it further by reconfiguring the same set

of features and levels. To decrease an already low sacrifice gap would require introduction of new features or levels or a decrease in price.

Also of note is that since these respondents choose a custom product in all optimal configurations, their contribution to Company X's market share of preference is not affected by choosing one Pareto point over another in the short run and when the assumptions used in this model hold true. In the long run, customer loyalty and retention become a factor. Also, the assumptions made in this work do not reflect a respondent's purchase behavior perfectly. A subset of 5 respondents' sacrifice gaps are given as Figure 5.6 for discussion. This figure is identical to Figure 5.5 except that it does not depict the entire Type 3 population.

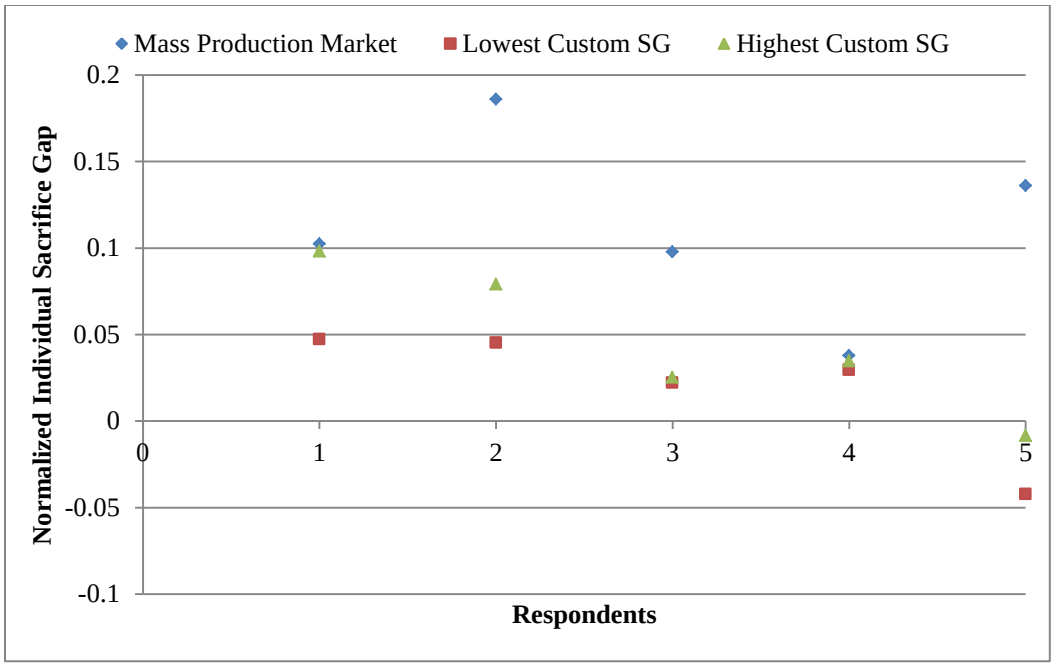

Figure 5.6: Type 3 Respondent Subset

Subset respondents 2, 3, and 5 in the figure are relatively insensitive to changes in Pareto point selection. Respondents 2 and 5 experience a reduction magnitude that outweighs the fluctuation in sacrifice gap due to Pareto point selection while respondent 3 experiences very minute sacrifice gap fluctuations along the frontier. Respondent 4 experiences little fluctuation in sacrifice gap across the frontier. However, their optimal custom product at each point does not decrease their sacrifice gap by a substantial magnitude. Not only does this affect the amount of long term benefit the firm would garner from designing a custom product for this respondent, but the purchase decision is based on assumptions used in this work. Since the model does not perfectly capture this respondent's purchase behavior, they may not choose a custom product at all in a real world purchase scenario.

Respondent 1 exhibits both a significant fluctuation in sacrifice gap and, if the "worst" Pareto point is considered, may be sensitive to the assumptions of the model. Respondents that exhibit the same characteristics as respondent 1 are those that are most sensitive to changes in Pareto point configuration. If the Pareto point that is represented by the red square is chosen they will experience a sacrifice gap reduction that can accommodate some assumptions of the model. If the point represented by the green triangle is chosen, the magnitude of reduction may be small or they may choose a different alternative depending on how well the assumptions reflect their purchase behavior.

Overall, the Type 3 respondent population benefits from customization regardless of which Pareto point is chosen. The average reduction in sacrifice with respect to the mass production market is between 0.103 (σ = 0.073) and 0.074 (σ = 0.060). In addition, the fluctuation of sacrifice gap (range of sacrifice gaps for optimal customization) is 0.029 (σ = 0.023) on average. Since the customization market is superior to (albeit almost equivalent to in some cases) the mass production market, Type 3 respondents benefit from the implementation of any Pareto configuration.

5.2.2.4. TYPE 4 RESPONDENTS

Type 4 respondents are individuals who switch between purchasing a custom product and a different alternative as the Pareto configurations change. There are 9 respondents who fall into this category, thus they make up the smallest subset of the respondent population. Although they are not the majority, this subset of respondents is the only ones who impact on market share of preference in the short run. Thus, this analysis will investigate why these

respondents switch between custom and non-custom products and, subsequently, how switching between products affects the respondent's sacrifice gap.

5.2.2.4.1. *Respondent Switching Analysis*

Upon examination, the reasons a Type 4 respondent switches from a custom to a non-custom product are similar to why a Type 3 respondent would switch from one custom configuration to another: availability of certain levels and changes in customization tax.

To illustrate the effects of attribute level availability, Respondent number 43 either chooses one specific custom product configuration or the 'None' option. In turn, this custom configuration's availability is governed by the Photo and Hi-res Camera feature level because all other levels present on this configuration are always available. When this particular level is offered, the respondent purchases a custom product (where the selling prices ranges from $667 to $684) otherwise this respondent purchases nothing; this corresponds to a $165 increase in aggregate contribution. In addition, the purchase of a custom product gives this respondent a sacrifice gap reduction between 0.021 and 0.018 over the 'None' option. Since the Photo, Video, and Hi-res Camera level is turned on in all Pareto configurations and since Photo and Hi-res Camera represents a subset of these technologies it may be in the firm's best interest to choose a Pareto configuration with the Photo and Hi-res Camera level if multiple individuals exhibit these same preferences.

To illustrate the effects of customization tax magnitude, Respondent 123 only chooses a custom product over a competing product in Pareto configuration 36; this configuration has the lowest customization tax of the 37 points. In addition, all levels present

on the chosen customized product are available in all Pareto configurations; therefore the only difference between Pareto point 36 and all others is the magnitude of customization tax. From a firm perspective, since all levels in their optimal custom product are always available this particular respondent could be convinced to buy a custom product without adding any additional complexity to the system.

It should be noted that the customization tax in product line 36 is $166 and the next lowest customization tax magnitude is $169. That is, a $3 in customization tax switches this respondent from purchasing a $382 competing product to a $633 custom product. This occurs, once again, because of the assumption that all respondents are first-choice optimizers in a customization purchase decision.

5.2.2.4.2. *Sacrifice Gap Analysis*

Type 4 respondents are characterized as medium sacrificers; the overall range of mass production sacrifice gaps for this population of respondents is between 0.105 and .00321, with most lying between 0.06 and 0.03. The fluctuation in sacrifice gap magnitude is also small for these respondents. The fluctuation in sacrifice gap values is depicted in Figure 5.7 where each Type 4 respondents' maximum and minimum sacrifice gap values are plotted. Note that the distance between the Non-custom alternative and the Custom Product is also each individual's potential sacrifice gap reduction because the non-custom alternative is the Best Available alternative in the mass production market.

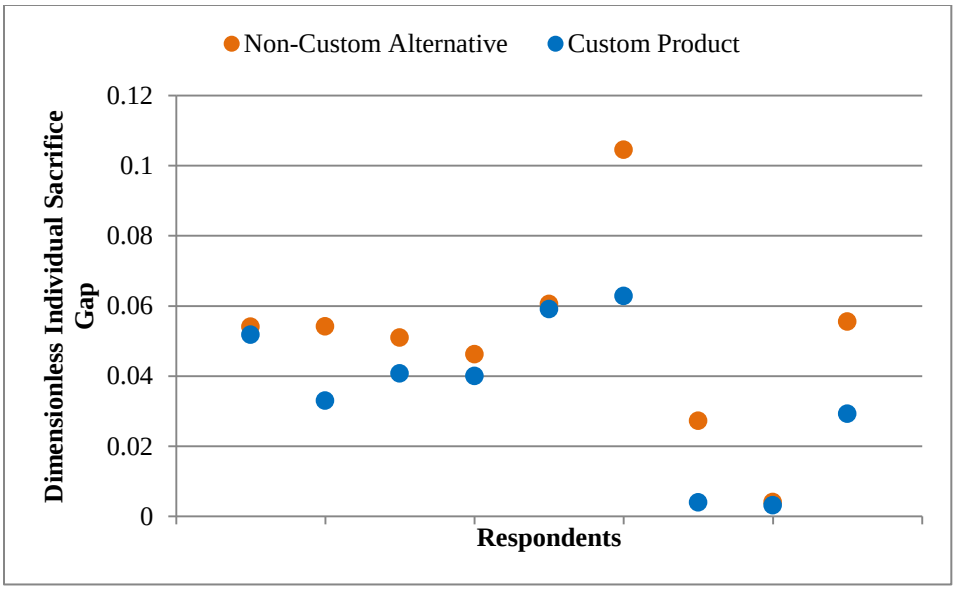

Figure 5.7: Type 4 Sacrifice Gap Fluctuation

The average fluctuation in sacrifice along the frontier is 0.0148 (σ = 0.0141), this is about half of the fluctuation for Type 3 respondents (μ = 0.0293, σ = .0230) who also exhibit switching behavior. This confirms that small changes (such as switching the availability of one level or adjusting the customization tax on a product line) can cause them to switch between products. Type 3 respondents experience similar choice behavior except they switch between custom products rather than between a custom product and a different market alternative.

Because their potential for sacrifice gap reduction is relatively low (compared to Type 1's and Type 3's) and because they switch between custom and non-custom products (unlike Type 3's who choose custom products regardless) adding complexity to a system to design

for Type 4 respondents is not the most effective means to gain long-term customer loyalty and retention. Even in the short term, there is no one Pareto configuration that appeals to all Type 4 respondents. Choice of a Pareto configuration, then, should not be centered on the choice behavior of these individuals. Rather they should be considered as part of the greater market through metrics such as aggregate contribution.

The insights gained from the respondent-centric analysis can be used in conjunction with the market-level metrics discussed in Chapter 4 (market average sacrifice gap, aggregate contribution, FCMSP, and build combinations) to build a base of information the firm can use to make decisions. An analysis of these market-level metrics as well as an exploration of how the information from the design space can be used is given in the following section.

5.2.3. FIRM IMPACT ANALYSIS

This section examines how the market level-metrics change along the Pareto Fontier and how these changes may affect a firms design decisions. If also explores how the information gained from the multi-objective design space may be used in the design process.

As in chapter 4, the following market-level metrics are used to assess the effects of the optimal product line configuration provided by the genetic algorithm on the firm: Sacrifice Gap, Aggregate Contribution, First Choice Market Share of Preference, and Build Combinations. These values are given as Table 5.10 below.

Table 5.10: MOGA Firm Metrics

Index	Sacrifice Gap	Aggregate Contribution	FCMSP	Build Combinations
1	-0.00947	$13,661	58.05%	35,840
2	-0.00941	$13,661	58.05%	31,360
3	-0.00938	$13,678	58.05%	31,360
4	-0.00937	$13,701	58.05%	30,720
5	-0.00929	$13,721	59.02%	46,080
6	-0.00919	$13,863	59.02%	53,760
7	-0.00916	$13,924	59.51%	53,760
8	-0.00913	$13,934	59.02%	46,080
9	-0.0089	$13,939	58.54%	44,800
10	-0.00887	$13,961	58.54%	38,400
11	-0.00886	$13,965	58.54%	38,400
12	-0.00885	$13,989	59.02%	46,080
13	-0.00883	$14,035	58.05%	30,720
14	-0.00872	$14,038	58.05%	26,880
15	-0.00841	$14,079	58.05%	25,600
16	-0.00831	$14,081	58.05%	22,400
17	-0.00813	$14,104	58.05%	16,800
18	-0.0081	$14,123	58.05%	16,800
19	-0.00645	$14,124	58.05%	21,504
20	-0.00643	$14,128	57.56%	24,576
21	-0.0064	$14,133	58.05%	35,840
22	-0.00634	$14,169	58.05%	24,576
23	-0.00628	$14,261	59.51%	50,176
24	-0.00628	$14,307	59.02%	43,008
25	-0.00626	$14,328	59.51%	43,008
26	-0.00617	$14,334	58.54%	30,720
27	-0.00611	$14,374	58.54%	30,720
28	-0.00609	$14,378	58.54%	30,720
29	-0.00604	$14,448	58.54%	24,576
30	-0.00578	$14,459	58.54%	17,920
31	-0.00576	$14,478	58.54%	17,920
32	-0.00562	$14,486	58.05%	20,480
33	-0.00561	$14,486	58.54%	20,480
34	-0.00556	$14,515	58.54%	17,920
35	-0.00554	$14,535	58.54%	17,920
36	-0.00544	$14,554	59.51%	14,336
37	-0.00521	$14,641	58.54%	20,480

The customer impact analysis conducted above indicated that a sacrifice gap magnitude change of 0.00426 along the Pareto Frontier is inconsequential when compared to the magnitude of sacrifice gap reduction experienced by the hypothetical market. The reduction in market average sacrifice gap compared to the mass production market is between 0.0388 and 0.0336 for points 1 and 37, respectfully.

If only individuals who experience sacrifice gap reduction are considered (Type 1's, 3's, and 4's), the average sacrifice gap reduction is between 0.076 and 0.069; the range magnitude is 0.00753. Although reduction is higher and the range is greater, the difference in sacrifice gap reduction across the frontier is still minute when compared to the reduction seen at the market and individual level. Although there are several individuals who are more significantly impacted by changes in Pareto point selection (perhaps their sacrifice gap reduction changes from magnitudes in the tenths place to magnitudes in the hundreths place), the incremental increases and decreases of sacrifice gap along the frontier are balanced out on a market level. If the firm considers all individuals to be of equal weight in their design decisions, the Pareto configurations are nearly equivalent with respect to customer value. Because the fluctuations in market average sacrifice gap are minimal, the remaining metrics become more significant in the customization configuration design decision for this hypothetical market.

As stated above, the aggregate contribution range for the Pareto frontier is $980. This is not an inconsequential amount considering the hypothetical market is only comprised of 205 respondents. Divided evenly, this $980 represents a $4.78 difference in contribution per

respondent; this becomes more significant if the market size is in the thousands or millions. Aggregate contribution is, however, a short-term firm value metric. It does not take into account long-term measures of firm value that stem from decreased sacrifice gap such as customer good will, loyalty, or retention which may prove more fruitful in the long run. In addition, aggregate contribution only measures the financial impact of customization on the firm. It does not take into account the added system complexities that may make a highly profitable customization configuration infeasible.

The change in First Choice Market Share of Preference is also relatively small across the frontier (this was addressed in the Customer Impact section above). The change in FCMSP is 1.95%, this variation is caused by the 9 respondents classified as Type 4. The respondent impact analysis in the previous section indicated that the purchase behavior of Type 4 respondents is very sensitive to small changes in attribute availability, price structure, and accuracy of modeling assumptions. In addition, their potential for sacrifice gap reduction is relatively low. Since no custom configuration is able to capture all 9 of the incremental respondents and they have a low potential for loyalty and customer retention due to sacrifice gap decrease, design decisions should not be centered on this metric for this case study.

The firm metric that changes the most over the frontier is build combination magnitude. To re-iterate Chapter 4, build combination refers to the number of potential custom products that can be built from a particular configuration of attribute availability. The number of build combinations spans from 14,336 up to 53,760, a range of 39,424. Given that this hypothetical market scenario is based on the a company moving from mass production to

mass customization, making the jump from producing 1 product to producing even 14,336 potential products may be infeasible for the firm. Since the complexity associated with build combination magnitude is the metric that changes the most over the frontier (and one that may hinder the implementation of an optimal custom configuration) it is used as the basis for an exploration of how the data from the multi-objective design space can be used as part of the design process.

One way a firm may mitigate the increased complexity of the Pareto configurations is to move off the frontier to a point that offers less customer and firm value, but provides a more feasible solution. As an example, recall that there are 19 attribute levels that are available in all Pareto lines. If only these 19 attribute levels are offered, the objective function values are sub-optimal as shown in Figure 5.8. The blue dots are the original Pareto Frontier and the red dot is the configuration where only the 19 “always on” levels are offered.

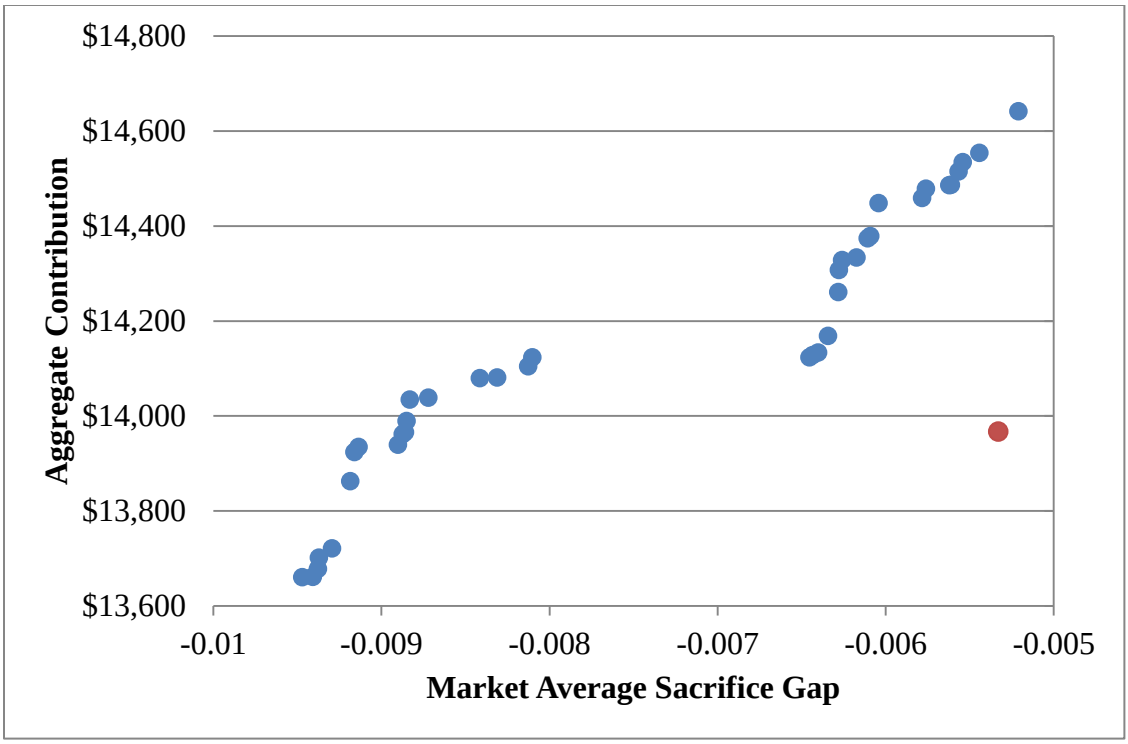

Figure 5.8: Sub-Optimal Solution Example

As expected, the sub-optimal configuration lies off of the Pareto Frontier. To determine the consequences of moving off of the frontier, the market-level metrics for this point are examined. A summary of the market level metrics for the sub-optimal point are given as Table 5.11.

Table 5.11: Sub-Optimal Point Market-Level Metrics

Sacrifice Gap	Aggregate Contribution	FCMSP	Build Combinations
-0.00533	$13,967	59.54 %	6,912

From a customer value standpoint, the sacrifice gap for the sub-optimal point is consistent with values seen on the frontier. In addition, the respondent impact analysis showed that, overall, the fluctuations in sacrifice gap across the frontier were inconsequential relative to their superiority to the mass production market. From an individual perspective, the sub-optimal line would decrease the sacrifice gap reduction for some respondents because certain levels that give them the highest net part-worth (the top of an respondent's hierarchy) may no longer be available. On the other hand, the reduction in customization tax due to the reduction in complexity would increase sacrifice gap reduction for others.

The aggregate contribution associated with this sub-optimal point is $13,967; this places it between index points 11 and 12 on the original Pareto Frontier. The market average sacrifice gap of this sub-optimal point is -.0053, placing it between points 36 and 37 on the original Pareto frontier. The aggregate contribution value for this point is $674 lower than the highest value on the frontier, but is also $306 higher than the lowest. FCMSP is consistent with points on the Pareto frontier as it falls within the range of values present in the original 37 points.

While the former three metrics remain consistent with the values seen on the Pareto frontier, the magnitude of build combinations drops drastically with this move off of the frontier. The number of build combinations associated with offering the 19 “always on” attributes in addition to the base product attributes is 6,912. This figure is 154% lower than the highest number of build combinations on the frontier (53,760) and 70% lower than the lowest number of combinations (14,336). This decrease in complexity without excessive compromise in other tabulated metrics indicates that moving away from the frontier may provide a more feasible solution.

Although the configurations on the Pareto frontier are optimal in terms of market average sacrifice gap and aggregate contribution, they may not be the best solution for a firm’s particular situation. The frontier does, however, provide a starting point from which other solutions may be explored.

The analysis conducted in this section provides a sample of how the information in the multi-objective design space may be used as part of the product design process. In reality, the data provided by the multi-objective optimization may be used in conjunction with other engineering design tools and methods to make the decisions necessary to define a custom product line. The benefit of using the data provided in this work is that it combines the value propositions of both the firm and consumer so that both parties are directly incorporated into the design process.

5.3. CHAPTER SUMMARY

This chapter began by presenting the procedure for using a multi-objective genetic algorithm (MOGA) to configure customization options that minimize market average sacrifice gap and maximize aggregate contribution in tandem. The procedure included instructions for objective function calculations as well as algorithm parameters used in this case study. The general process and context of the case study were provided in Chapter 3 and Chapter 4. After the procedure is presented, the resulting customization configurations were analyzed at an individual and at a market level.

At an individual level, purchase behavior along the Pareto Frontier was used to assess the preferences of the market. The 205 respondents were broken up into 4 segments for the analysis. Type 1 respondents chose the same custom product in all Pareto configurations. Type 2 respondents chose an outside (non-custom) alternative in all Pareto configurations, Type 3 chose a custom product in all Pareto configurations, but the product they chose varied. Finally, Type 4 respondents switched between a custom product and an outside alternative as the Pareto configurations varied.

A respondent's purchase behavior along the frontier as well as their mass production market sacrifice gap was tied to their magnitude of benefit from customization. Type 1 respondents and Type 3 respondents tended to have medium to high mass production sacrifice gaps and benefitted most from any Pareto configuration. Type 1's also tended to have less variation in sacrifice gap reduction from the mass production market because their optimal custom product was always available; this indicates that their preferences lined up well with those of the greater market. Type 2's exhibited the lowest average mass production

sacrifice gap and, thus, experienced no sacrifice gap reduction. Closer examination showed that these respondents tended to be content with their product choice in the mass production market and would, therefore, be very difficult for a firm to capture without the introduction of different attribute levels or a drastically reduced price structure. Type 4's tended to have the least potential sacrifice gap reduction magnitude (not considering Type 2's), which resulted in switching behavior along the frontier.

Respondent-level analysis also showed which respondents would be most sensitive to the assumptions in the model. If respondent experienced a low magnitude of sacrifice gap reduction, their real-world purchase decision is more likely to deviate from the model. This highlights the need for further inquiry into customer purchase behavior modeling such as integration of stated and revealed preferences in consumer decision models.

Looking at the behavior of individual sacrifice gap over all the Pareto configurations, there appears to be a ceiling to how low a respondent's sacrifice gap can drop given a particular set of attribute levels and a static price structure. This is expected. As a respondent's product approaches optimality within a given market construct, it is more and more difficult to raise the utility of their Best Available alternative and thereby decrease their sacrifice gap.

The relationship between customer loyalty/retention and sacrifice gap reduction was discussed at multiple junctures of the analysis. Although the relationship is reinforced narratively, there is not quantified correlation in the current body of work. A numerical investigation of how sacrifice gap magnitude and sacrifice gap reduction from the outside

market is related to customer loyalty would be a useful tool to determine the effect of sacrifice gap on the firm in the long-run.

Once sacrifice gap was examined on an individual level, insights from the analysis were used in conjunction with market-level metrics to discern the impact of switching between Pareto configurations on the firm. Starting with market average sacrifice gap, the magnitude of variation across the frontier is minute relative to the magnitude of sacrifice gap reduction from the mass production market. Although there are some respondents who are sensitive to changes in Pareto configuration, the effect is balanced out within the overall market.

Build combinations are the metric that varied most over the Pareto Frontier. The minimum number of build combinations is 14,336 and the highest is 53,760. In this hypothetical market scenario, the firm is attempting to offer customization from a mass production product line; therefore even the least complex Pareto point may be infeasible. Mitigating build combination complexity was then used as an example for how the data acquired in the multi-objective optimization may be used within the design process.

A sub-optimal point in the design space that offers only the “always available” attribute levels was examined for this example. This point is analyzed using the same market-level metrics (sacrifice gap, aggregate contribution, FCMSP, and build combinations). Analysis of this point showed that points off of the Pareto Frontier may be more appropriate in some situations. It also showed that in this market scenario sacrifice gap is relatively constant close to the frontier. It is unclear if this would be the case in a more crowded

marketplace or when the competition is modeled as dynamic rather than static. This is another area of future work.

In conclusion, sacrifice gap was used to both design and assess optimal customization offerings in a hypothetical market. Assessment of market preferences at a respondent level showed how the data from the optimization and the sacrifice gap metric itself can be used to help a firm better understand its customer base. An assessment of market-level metrics was then conducted. This assessment showed how firms can determine which metrics vary most along the frontier and how the data acquired from the multi-objective design space can be used as a part of the design process. The ability to combine this data with other engineering design tools and methods is also noted.

CHAPTER 6: CONCLUSIONS AND FUTURE WORK

This chapter revisits the research questions presented in Chapter 1.The approach proposed in Chapter 3 is analyzed in the context of the case studies executed in Chapters 4 and 5 to determine if the questions have been successfully answered. General conclusions regarding the approach and areas of future work related to the research questions are noted.

6.1. RESEARCH QUESTIONS

The research questions posed in Chapter 1 look to fill knowledge gaps between engineering and marketing disciplines. In particular, this work looks to more directly incorporate customer preference information into the engineering design process and push the market towards a more complete fulfillment of mass customization. This goal is broken into two steps: 1) translating customer sacrifice gap into a numerical form and 2) using this metric in the mass customization design process.

The first question looks to quantify how well a product concept or alternative in the market meets the first tenet of mass customization, “what the customer wants exactly;” this represents a measure of customer value. The distance between “what the customer wants exactly” and “what the customer settles for” is referred to as sacrifice gap. Although this concept is notably important in both marketing and engineering literature, the absence of a numerical measure provides the motivation behind the first research question:

How can sacrifice gap be empirically defined using quantified customer choice data?

The approach in Chapter 3 of this thesis addresses the first question by examining the two terms in the accepted definition of sacrifice gap in the context of engineering design, and numerically defining them in terms of respondent preference information taken from conjoint analysis surveys. The numerical definitions proposed in Table 3.6 require that the mathematical representations of respondent preference information are on an individual-level, but can accommodate multiple model types (HB, ICE, etc). In addition, since the "what the customer wants exactly" configuration is based only on feature utilities, it is consistent throughout the design process. Once these two terms are numerically defined, their difference is taken to be a respondent's sacrifice gap; this is given as Equation 3.4.

The concept of sacrifice gap, like mass customization, is focused on the needs and wants of the individual customer. As such, the quantitative definition given as Equation 3.4 can be readily used to assess how much sacrifice a single respondent possesses. Although individual preferences are a central concern in the concept of mass customization, the ability to apply it to an entire market is what differentiates it from craft production. Measuring proximity to mass customization, then, requires the quantification of sacrifice on a market-level. This is a challenge because the customer preference modeling technique used in this work does not typically allow for comparison of individual value metrics across respondents. To mitigate this concern the individual sacrifice gap values calculated using Equation 3.4 are normalized by dividing them by a particular respondent's overall range of utility value. This is similar to calculating the importances for a particular attribute and is given as Equation 3.5. Normalizing respondent sacrifice gap values in this manner places all respondents on the same, normalized scale and allows for respondent sacrifice gap values to be aggregated.

Calculation of market average sacrifice gap for use in optimization problems is given as Equation 3.6.

Quantification of customer sacrifice on a market-level provides a metric, whose narrative definition is rooted in marketing literature, that can be used as a customer preference measure in engineering design. Engineering product design has primarily approached the mass customization challenge of providing the customer "exactly what they want" by creating product line variety at low cost. Metrics to design and assess product line design such as component commonality, complexity, and cost are common; however, the design field has seen a recent research push toward incorporation of consumer preferences into engineering design. Similar to the sacrifice gap metric from Equations 3.4, the methodologies in these works use demand modeling techniques that have been established in the marketing domain (such as discrete choice analysis). Use of demand modeling techniques have provided avenues for optimizing product families using metrics such as aggregate contribution, expected profit, and market share. Each of these metrics incorporates customer preference information indirectly, however. That is, the objectives in many of these works focus on firm-based value metrics that require customer demand models as an input. The absence of works that directly incorporate customer preferences into the design process lead to the second research question:

How can sacrifice gap be leveraged as a customer-centric metric to guide product architecture decisions towards mass customization?

The work in this thesis looks to build on the body of engineering design research by incorporating customer preferences directly into the design process using the quantified sacrifice gap metric. Two case study formulations using an MP3 player are used in this work to demonstrate the use of sacrifice gap as an objective function. The case study in Chapter 4 designed a product line by optimizing the available feature level configuration to minimize market average sacrifice gap. The purpose of this first case study is to observe how the metric behaves within a product line design problem. Sacrifice gap was lowered while aggregate contribution and market share of preference were increased through implementation of the optimal custom configuration. The optimization also reflected the trade-off between feature and price utility customers exhibit in a real world purchase decision and confirmed that some individuals benefit more from customization than others. Finally, the analysis of Chapter 4 confirmed that aggregate contribution and sacrifice gap are competing objectives in the optimal space and are therefore appropriate objective functions to define a multi-objective design space in Chapter 5.

Chapter 5 builds on the case study in Chapter 4 by introducing a second, firm-centric, metric into the optimization problem. Incorporating firm and consumer interests in tandem provides a more realistic scenario, and the larger information base provides additional insight into how firm and consumer interests interact. The optimization yielded a Pareto frontier of points that simultaneously maximize aggregate contribution and minimize market average sacrifice gap.

Analysis of the Pareto Frontier at a respondent level showed how a firm may use the data from the multi-objective space as well as the sacrifice gap metric itself to better understand the market. Correlations between mass production sacrifice gap, purchase behavior along the frontier, and sacrifice gap reduction were drawn. In addition, the analysis helped identify individuals that are most sensitive to assumptions of the model and highlighted the need for further inquiry into customer purchase choice modeling. Motivation for future work into the numerical relationship between customer loyalty/retention and sacrifice gap was also noted.

Analysis at a market level showed that examination of the change in market average sacrifice gap, aggregate contribution, FCMSP, and build combinations across the frontier can help a firm determine which metrics should be considered most important in product design decisions. Highlighting build combinations as a potential hindrance to optimal configuration implementation, its minimization is used to show how the data from the multi-objective space may be used as part of the greater product design process.

In conclusion, the narrative definition of sacrifice gap given in literature was translated into numerical quantities that can assess an individual's proximity to mass customization using customer preference data (RQ 1). The individual-level metric was then normalized over a particular respondent's scale of utilities so that comparisons across individuals in the market were possible. This normalization allowed for the aggregation of sacrifice gap across the market, this in turn allowed for the calculation of a market average sacrifice gap that can be used in product design problems for mass customization.

The normalized, market average sacrifice gap metric was used to both design and assess optimal customization offerings in a hypothetical market (RQ 2). Assessment of market preferences at an individual level showed how the data from the optimization and the sacrifice gap metric itself can be used to help a firm better understand its customer base while an assessment of market-level metrics showed how firms can determine which metrics vary most along the frontier and how the data acquired from the multi-objective design space can be used as a part of the design process. The ability to combine this data with other engineering design tools and methods is also noted.

6.2. FUTURE WORK

The approach outlined in Chapter 3 and the case study execution in Chapters 4 and 5 have answered the research questions posed at the outset of this thesis. This work has also led to multiple follow-up questions that provide opportunities for future research.

The quantification of sacrifice gap proposed in Equation 3.4 is heavily dependent upon the accuracy of the customer preference part-worths obtained through conjoint analysis surveys and mathematical modeling of data (HB modeling in this case). Although these methods are established in marketing literature and are gaining prevalence in engineering literature, their use in mass customization-specific problems is largely untested. For sacrifice gap to be considered an effective and accurate metric, the accuracy and consistency of consumer preference value models must be further explored.

The magnitude and behavior of sacrifice gap is also dependent upon the assumptions make in this work (such as the first choice decision assumption when determining the Best

Available alternative). The comparison of stated and revealed preference data for customer purchase decisions could help refine customer decision models. The assumption of linear interpolation between price points in the discrete choice survey (recalling that price points were often $100 apart) is another assumption that should be investigated further. In future work, researchers may consider narrowing the range of prices on the survey to get more granular price points (thereby improving the accuracy of the linearly interpolated part-worths) or modeling the behavior of price utilities between points using a different type of function (such as spline, for example).

Regarding the formation of "what the customer wants exactly" in the sacrifice gap metric, the customer's ideal product is held constant throughout the product design process. In reality, the configuration of a respondent's ideal product will change over time as their wants and needs change. Examining the ideal products for the same respondent over multiple generations of a product (and therefore repeated acquisition of preference data through conjoint surveys) could hold valuable insights into how customer preferences change, and how and when attributes move from being compensatory to non-compensatory.

This work assumes a compensatory decision making process for all respondents; this assumption is highly integrated in the formulation of sacrifice gap and the optimization problems that follow. Although this is a common assumption, its validity should be further investigated in the context of product design. It is possible that a customers' optimal product (the product they would choose in a product purchase decision) could be better modeled through a combination of compensatory and non-compensatory features. A more accurate

model of the consumer decision making process would then lead to a more accurate solution to the product design problem.

Another question resulting from this work is how to best represent the individual-level sacrifice gaps (from Equation 3.4) on a market-level. This work uses the market average sacrifice gap of all respondents to address this question, but this is not the only possible representation. Other representations may only include individuals who experience a change in sacrifice as the objective function, build in a consideration for distribution of individual sacrifice gap, or consider sacrifice gap reduction as opposed to sacrifice gap magnitude.

From a firm perspective, a profit measure such as aggregate contribution may not be the only value proposition they consider. Al optimal product lines showed a large increase in complexity, which may be unattainable for some firms. This concern could be mitigated in future inquiry by using points that are close to, but not on the Pareto frontier or by incorporating a complexity measure such as build combinations as an objective function in the MOGA.

In the case studies, the cost of customization was passed directly to the consumer by way of a customization tax that stayed constant throughout the optimization process. This cost was incorporated into the sale price of the products and helped determine which configurations were optimal. This optimization problem could be reversed, however, to help a firm with a set product line configuration determine a customization tax structure for their products.

Within the case study analysis, the connection was drawn between increased customer loyalty/retention and sacrifice gap. Although this relationship is described narratively, the current body of work does not contain a numerical correlation between the two. Since this work defines sacrifice gap numerically, future work could attempt to correlate a respondent's sacrifice gap with their loyalty and retention tendencies using real world purchase data. This future work could examine how sacrifice gap decrease relative to the competitive market, magnitude of sacrifice gap, and changes in sacrifice gap over time effect loyalty and retention.

Although this work focuses on using sacrifice gap as an objective in product line optimization, its uses in the design realm are certainly not limited to this application. Ferguson et al. (2010) noted that there is a lack of metrics that assess customer readiness for mass customization [23]. Because sacrifice gap measures how close a product in the market is relative to "What the customer wants exactly" (the first tenet of mass customization), it may be possible to relate sacrifice gap to mass customization readiness in a market. Hart (1995) reinforces this notion by attributing the success of mass customization as dependent upon "customer customization sensitivity"; this, in turn, is a function of sacrifice gap [17].

In addition, the analysis in Chapter 5 showed that the data from the multi-objective space may be alternative method for segmenting a market. Whereas current techniques focus on customer wants and needs, segmentation could also be conducted using differing levels of sacrifice or purchase behavior along the frontier. These are just two examples of potential extensions that use the metric proposed in this thesis.

This work is the first to numerically define and use sacrifice gap as a customer preference metric in engineering design problems. As such, its full potential and diversity of uses within the product design process are yet unknown. Further refinement of the metric and development of applications for it is another subject of future work.

6.3. CHAPTER SUMMARY

This chapter revisits the two research questions posed in Chapter 1 to verify that the investigation conducted in this thesis answers them. This work has answered the first question by formulating an empirical definition of consumer sacrifice gap using discrete choice analysis and HB modeling techniques developed in the marketing discipline. The second question is addressed by applying this metric to a product line design problem for mass customization. A single-objective and multi-objective optimization is conducted, and the results analyzed in the scope of firm metrics, engineering design, and consumer interests.

This work provides a foundation for further inquiry into the uses of quantified sacrifice gap in the context of engineering design for mass customization. Several areas of future work were identified in the process. These areas are verifying the accuracy of data used to quantify sacrifice gap, modeling of the consumer decision making process, representing individual sacrifice on a market-level, and using sacrifice gap in the product design process.

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