Quantifying Perception-Based Attributes in Design: A Case Study on the Perceived Environmental Friendliness of Vehicle Silhouettes

by

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To the Great Master Designer of all - God

John 1:3

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CHAPTER I

Introduction

Design optimization problems have traditionally used engineering functionality attributes to inform the design of products and systems. However, the quantification and inclusion of subjective attributes has become a necessary part of the product design process. Numerous methods have been developed to model and quantify the subjective preferences of consumers and use them to inform design decisions. These methods have been applied to assess a variety of subjective design attributes such as aesthetics, beauty, luxuriousness, and sportiness to name a few. However, there is little research that attempts to quantify consumer judgments of environmental friendly design characteristics, including applicability to automotive vehicles. Methods such as Kansei engineering [*Nagamachi* (1995)] are used to assess emotional qualities of a product through the use of semantic word pairs and multivariate statistical analysis and engineers often use conjoint analysis [*Green and Srinivasan* (1990)] to quantify consumer preferences using utility functions. These methods are applicable to the current study, however they each have limitations. Kansei engineering measures consumer assessments of product characteristics, but does not assess consumer's actual choice [*Gonzalez et al.* (2010)]. Conjoint analysis is a useful tool for assessing consumer choice, but the number of attributes have to be kept low (no more than 6 attributes is ideal) in order to reduce the fatigue on subjects [*Green and Srinivasan*

(1990)]. Other conjoint methods, such as Adaptive Conjoint Analysis (ACA) is a solution for studies that have a higher number of attributes, but is challenging to implement and manage in a study using visual stimuli. Another issue with conjoint is that the products already exist and it is not a technique that can easily be used for new product design.

Quantifying subjective attributes is a challenging undertaking [*Orsborn et al.* (2009); *Petiot* (2005)]. This dissertation presents a particular approach to quantify subjective attributes, especially attributes that are not well established. Methods from psychology and engineering are integrated to create a rigorous method for assessing consumer preferences. This method is demonstrated using an automotive design problem where the objective is to investigate the visual styling cues that most readily convey environmental friendliness to consumers. The subjective judgments about these "green" styling cues are collectively referred to as perceived environmental friendliness (PEF). Measures of PEF are then included in an optimization framework where the objective is to maximize the fuel economy of vehicle designs, thus allowing for subjective preferences to be considered in the optimization problem. Previous work demonstrates the optimization of fuel efficient cars [*Frischknecht and Papalambros* (2008); *Michalek et al.* (2004)] but does not include empirically validated subjective attributes that express the styling cues that resonate with consumers. This dissertation shows how this can be done.

Traditional optimization models focus on the functional aspects of an artifact, and the designer has to rely on her own insight and intuition regarding consumer receptivity. The problem with doing design this way is that the goals of the designer may not align with the goals of the consumer. In other words, a designer may have the goal to design a car that looks "cool" but a consumer perceives the product to look "youthful"; or they may have the same goal but implement it differently. Both want youthful but the designer's idea of youthful isn't the same as the potential customer base. It is actually quite common for designers and consumers to perceive products differently [*Wolter et al.* (1989); *Krippendorff* (1989)]. This can pose a problem in the marketplace where consumers often use subjective reasoning to make decisions about products they purchase [*Creusen and Schoormans* (2005)]. If products do not appeal to consumers, then they may never be purchased. Consumers may start the decision process using objective thinking (e.g., "I need a fuel efficient car that gets at least 25 mpg"), but among many alternatives, a consumer may use apparently irrational decision making strategies to narrow down a choice (e.g., "I want to drive a car that actually looks green so that when people see me passing by, they will know that I care about the planet."). Including measures of PEF in the design optimization problem allows for objective and subjective attributes to be addressed simultaneously.

There is a number of motivators for this research and the selected case study. First, capturing subjective preference in product design is important for differentiating products in a competitive market. Second, designers often rely on intuition and experience to develop design concepts; the methods in this research provide a quantitative tool that designers can use to assist them in the design process in a way that supplements the intuitive approach. Third, there is a need to incorporate subjective preference in the design of fuel efficient vehicles where the inclusion of "green" styling presents an interesting problem for a number of reasons. Among these reasons is the fact that the concept of "green" is not as well established as say, the concept of luxury, so designers do not have much purchasing and market history to draw from. Furthermore, some consumers have the perception that one can recognize green technology if it is aesthetically unappealing [*Leader* (2008)]; a prevailing perception about green cars is that they are small and ugly. Yet, there are users that desire to make a statement by owning or driving a car that not only is environmentally friendly, but looks that way [*Heffner et al.* (2007); *Naughton* (2007)]. Lastly, the case study provides an opportunity to investigate whether or not there exist new automotive designs that would outperform those that exist on the market in terms of fuel economy and "green" styling.

1.1 Research Motivation

Designers often rely on intuition and experience to develop new design concepts. When designers seek inspiration to design for a certain expression (e.g., luxury), they use a number of methods. The use of semantic functions is a design strategy to create designs that "communicate" specific characteristics. These design characteristics will either "describe, signal, express, or indicate" [*Monö* (1997)] something to a consumer. Designers also review the history of a particular concept. However, when designing for a subjective attribute that is not well established in some contexts (e.g., "green"), there is a need for a more systematic approach for assessing these attributes. In the automotive industry, there is an increased interest not only in making more fuel efficient vehicles, but also in making them visually appealing in a way that conveys environmental consciousness [*Patton* (2007)]. Present day trends already show an increase in the number of fuel efficient, and electric hybrid vehicles being introduced in the market, and it is expected that by 2011 there will be 75 different hybrids on the market [*Naughton* (2007)]. Depending on market trends and government regulations, fuel economy may not be the only driver for the purchase of fuel efficient vehicles when the price premium paid for the new technology does not result in a timely payback in fuel cost savings. An article in the New York Times [*Patton* (2007)] highlighted some visual cues that various automakers have used to signal "greenness". They include: the "green-leaf" badge (Ford Motor Company's hybrids), the "green-line" badge (Saturn's hybrid called the VUE), a luminous green paint called "Jasper Pearl" (Toyota Camry hybrids), a general green badge (BMW 7-Series hybrid), characteristic silhouette (Toyota Prius) and another badge called "Hybrid Synergy Drive" (other Toyota Hybrids). Figure 1.1 provides examples of some of these visual cues. Designers at Toyota are using the approach of bringing a sporty look to next generation hybrid vehicles similar to Tesla Motors. It is suggested that adding a sporty look replaces the sense of green being a sacrifice in style and performance with one of indulgence and fun. These attempts are speculative at best and do very little to understand the effects that design features have on consumer perception and preference. Words, paint color, or badges alone are only sufficient for signaling the presence of a hybrid powertrain; as mentioned earlier, there is an interest in signaling more to the consumer than just having a hybrid vehicle. The styling of the car should communicate something about what it is. The use of semantics and other design strategies are necessary and can help consumers in the decision-making process [*Bloch* (1995); *Hirschman and Holbrook* (1982)] and give firms a competitive advantage [*Bloch* (1995); *Berkowitz* (1987)].

Figure 1.1: Examples of "green" visual cues (circa 2007)

Previous research has shown that people used subjective reasoning, including styling, as a determining factor for purchasing hybrid vehicles [*Heffner et al.* (2007)]. CNW Marketing Research indicated that among the top reasons consumers purchased a Toyota Prius was that it "made a statement about me" [*Maynard* (2007)], meaning it made a statement about how environmentally conscious they were. Quantifying the perception of green and understanding how people make judgments about green products will require an approach that goes beyond the use of words. This is mainly because green is still a relatively new concept and the process for selecting an appropriate and meaningful list of words may be a daunting task at this early stage, particularly because an established list of semantic expressions solely devoted to issues of "greenness" do not exist. Examining the influence of visual cues may be a more plausible way to begin this research exploration.

1.2 Proposed Methodology

The proposed methodology consists of several steps that will be discussed in greater detail in subsequent chapters. The first step in the research process involves the establishment of visual stimuli that participants will evaluate. The second step involves the development of a carefully constructed survey using the scientific method. The collected data are then analyzed using a combination of descriptive statistics and inferential statistics that provide insight on how to generate new designs based on the analyzed data. The resulting attributes are then integrated with engineering attributes within an optimization framework. Figure 1.2 shows a flow diagram of the overall flow of the methodology.

This methodology seeks to address three main research questions:

1. What physical attributes relate to one's perception of vehicle greenness?
2. What visual aesthetic characteristics are related to perception of greenness?
3. What are the tradeoffs between design variables that influence PEF and engineering criteria and how can we quantify them?

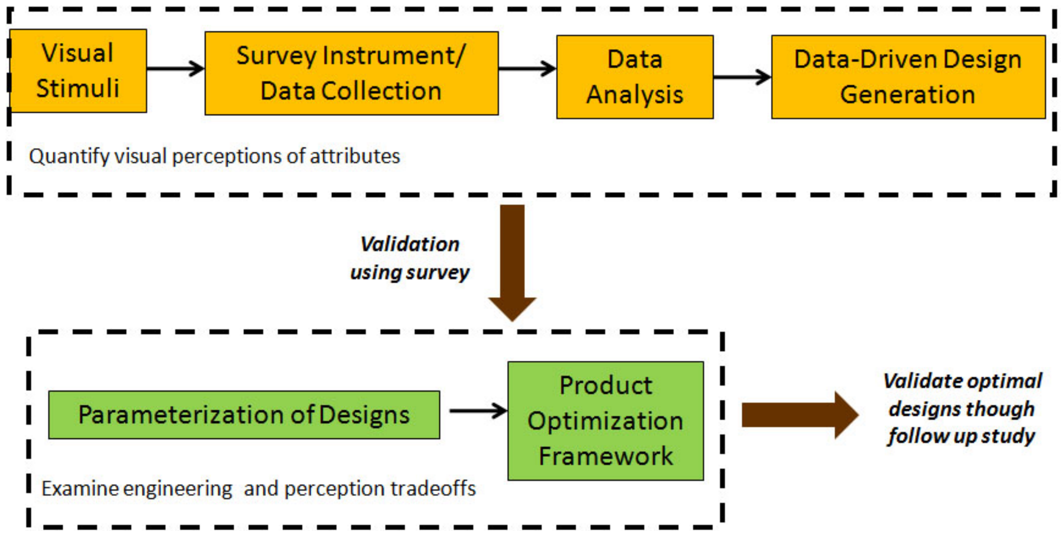


Figure 1.2: Flow diagram describing process for developing the methodology

1.3 Expected Contributions

The first contribution of this dissertation is the development a methodology that can be used to not only quantify a subjective attribute that is not well established, but to also identify the specific cues that influence these judgments when not known a priori. The details of the methodology include the use of methods from psychology and engineering as well as the statistical analysis techniques that rigorously link consumer judgment attributes to engineering attributes.

The second contribution of this work is that it demonstrates how one would quantify the specific psychological variable "perceived environmental friendliness" (PEF). Much of the previous work has developed methods to quantify aesthetics, general preference, and other concept-based attributes, as previously mentioned (e.g., luxury). However, there is no prior work to our knowledge that specifically attempts to quantify a PEF attribute in the context of automobile design.

The third contribution is to include the PEF subjective attribute in an engineering design optimization framework that designs fuel efficient vehicles. Previous works have used discrete choice to measure consumer preferences for fuel efficient vehicles [*Ewing and Sarigöllü* (2000)], and revealed preference data to develop interdisciplinary models for the design of fuel efficient vehicles [*Frischknecht and Papalambros* (2008); *Michalek et al.* (2004)]. These models do not incorporate empirically validated styling cues into their model. In the design optimization problem, this subjective attribute can be examined concurrently with objective attributes to see the tradeoffs that may exist between PEF shape characteristics, fuel efficiency and other performance criteria. This is demonstrated using the model developed in the dissertation work of Frischknecht [*Frischknecht* (2009)].

A fourth contribution is the development of two methods that can be used to generate new designs based directly on user data. The first is an algorithm based on a design of experiments technique where significant factors are identified through survey data. The second method is based on constraints in an optimization framework that determines the optimal values for the control points which, in turn, produce designs that have optimal PEF and fuel economy. This is novel in that the algorithm generates silhouettes that has rigorously incorporated engineering design criteria. Much of the previous work demonstrates how new designs can be generated by optimizing consumer preference while using engineering parameters and constraints to define their design space [*Orsborn et al.* (2009); *Swamy et al.* (2007)]. However these methods do not demonstrate how this is done concurrently in a broader engineering optimization problem.

1.4 Dissertation Overview

The remainder of this dissertation consists of the following: Chapter 2 provides background on prior research. Chapter 3 provides details of the methodology. Chapter 4 discusses the optimization studies performed and computed results. Chapter 5 summarizes the findings and places the dissertation conclusions in a broader research context.

CHAPTER II

Previous Research

Design is a decision making process that involves the knowledge and experience of the design engineer. The need to include subjective criteria is an important part of the process but the traditional engineering research paradigm does not provide a means for doing this. Methods from marketing and psychology provide models for assessing subjective attributes that engineers have adopted and integrated into the design process. This chapter provides background on methods for quantifying subjective attributes and discusses recent developments, evaluates those methods, and points to where new methods are needed.

2.1 Introduction

The engineering design research community has used demand, choice and preference models, such as the general class of utility models, to represent consumer choice. There is an analogous literature in psychology and marketing that has developed quantitative models for measuring attitudes, subjective dimensions, and perceptual attributes. Such models include factor analysis, multidimensional scaling, and various clustering models. These models have been shown to be good predictors of demand and choice, and so are relevant to decision-making models in engineering design [*Reid et al.* (2009)].

2.1.1 Discrete Choice Methods

Some popular methods used by engineering designers are discrete choice analysis and conjoint analysis. Discrete choice analysis is a statistical technique based on probabilistic choice models [*Ben-Akiva* (1985)]. It allows the development of models of consumer choice in order to predict the likelihood of choosing a specific option amongst alternatives. This method has been used in a number of applications including transportation design issues. Conjoint analysis is a method used to study the value that consumer's place on specific product features [*Sawtooth Software* (2009)]. Consumers are presented with a number of alternatives from which to choose that have specific attributes and levels, and conjoint analysis provides insight on the the tradeoffs people make between specific attributes thus enabling a research to make predictions about consumer choice. Both models capture consumer preference using a utility model.

2.1.2 Affective Design

Affective design is an area of research that deals with emotional aspects of design. A great review can be found in *Helander and Khalid* (2006). Kansei engineering is a classic approach for assessing the emotive or "feeling" qualities of a product [*Nagamachi* (1995)]. The goal of Kansei engineering is to translate consumer's feelings into product function and design [*Nagamachi* (2002)]. The technique consists of developing a word list that best describes the target feeling being designed for as a function of variations in specific product features. One can measure the Kansei using stimuli that can be assessed by any of the five senses. A majority of the previous work has been visual [*Achiche and Ahmed* (2008, 2009)] and tactile [*Choi and Changrim* (2007)].

Don Norman states that designs have three main categories: behavioral, visceral, and reflective [*Norman* (2004)]. The behavioral category involves how one can use an actual design. The visceral category involves the senses and preferences are usually assessed from a "gut level". The reflective category reflects the thoughts that the consumer has about how the product relates to themselves. Typical thoughts involve the sense of status or prestige that owning or using a product often brings. These three categories of design can best explain some of the research efforts that have been developed by the engineering design community shown in Figure 2.1.

2.2 Categories of Previous Research

When it comes to assessing subjective preferences, there are three main trajectories that previous engineering research methods typically follow as shown in Figure 2.1. They are: 1) Preference as a function of price, 2) preference with no consideration for price, and 3) the visceral judgments of specific emotive attributes of a design.

2.2.1 Preference as a function of price

The goal of the top trajectory is to quantify subjective preference with price being a factor. The typical stimuli that are used are a list of product attributes and the results are often used in marketing demand models that sometimes include optimization techniques and engineering criteria. MacDonald et al. quantifies consumer preference for environmentally friendly paper towels at a given price [*MacDonald et al.* (2007b)]. Specific attributes included recycled paper content, softness, absorbency, quilting, and strength. Conjoint analysis was used to quantify preference using a utility function that was a function of these product attributes. The work went beyond utility to assess how consumer's made decisions. Methods from psychology was used to identify crux and sentinel attributes, where crux attributes are those attributes that people want but cannot readily articulate (e.g., ability of paper towel to absorb water, crash-worthiness of a vehicle) and sentinel attributes are those that people perceive will provide the desired crux attribute (e.g., quilt pattern on paper towel, inclusion of airbags in vehicle). Engineering criteria was not considered in this model

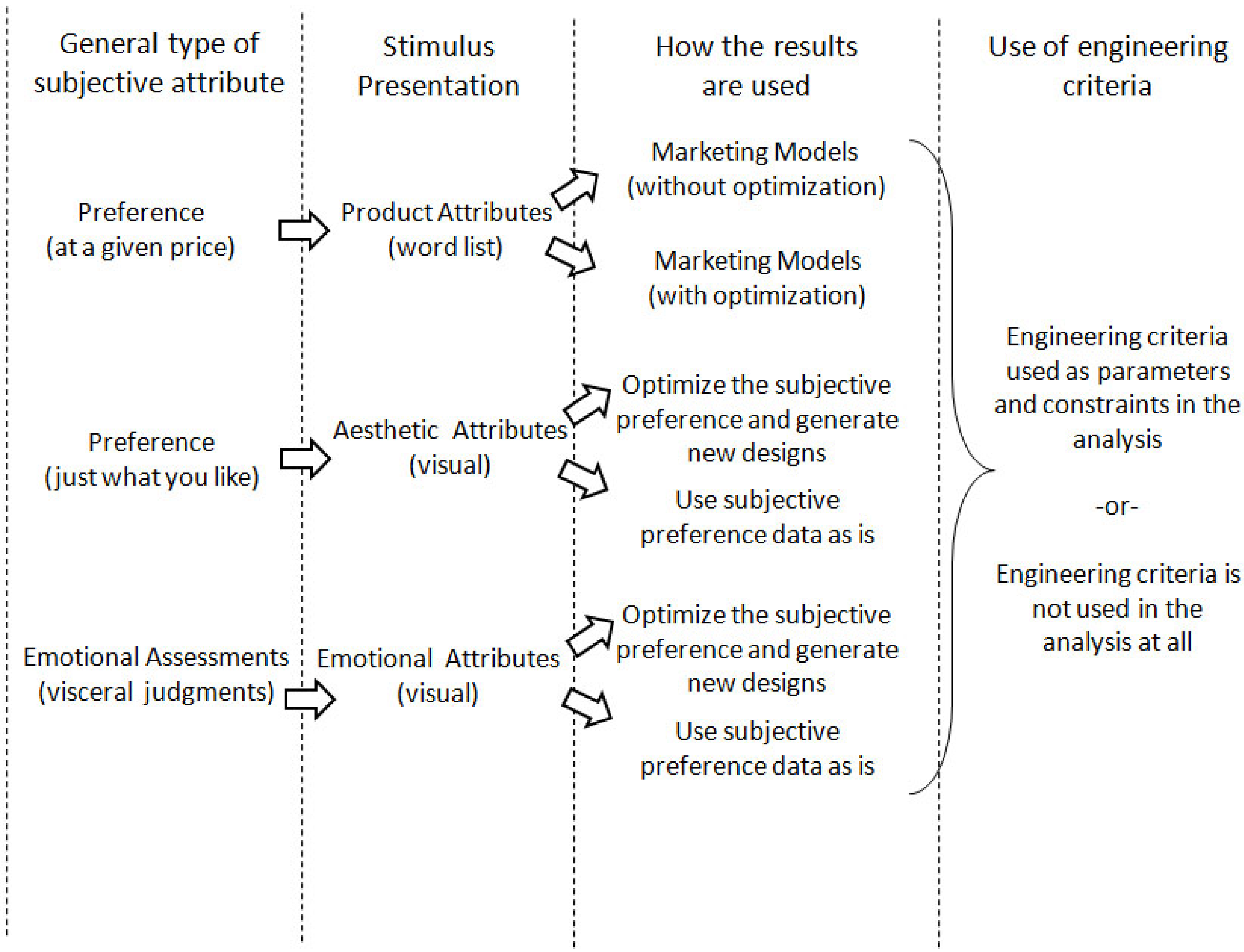


Figure 2.1: Visual summary of the previous work

and the marketing demand procedure did not incorporate optimization techniques.

The integration of optimization techniques in a demand model is demonstrated for the design of a universal motor in a decision-based design problem [*Wassenaar and Chen* (2003)]. In this work, discrete choice analysis is used to develop a demand model that considers four consumer attributes and several engineering attributes and constraints. The four consumer attributes are mass (kg), operating time (hr), power(W) and torque(Nm). Price is a fifth attribute that is considered in each of the choice sets presented to consumers. The engineering analysis provides functional relationship between these customer attributes and specific engineering design options. A multinomial logit model is used to model the choice behavior of the consumers. The form of the utility function is: $W = f(\beta_n, \mathbf{Z}_i)$, $\mathbf{Z}_i = (A_i, ..., A_j, S_1, ..., S_k, P)$ where A represents customer attributes, S represents observable socio-economic/demographic variables, and P is price. The subscript n corresponds to the n^{th} market segment and index i refers to the i-th alternative. Optimization techniques were used to maximize the expected utility of the net present value of profit subject to engineering constraints. The authors do not specify the optimization techniques used. This particular work demonstrates the modeling of consumer preference as a function of engineering criteria in a demand model.

This trajectory is analogous to the behavioral aspect of a design as described by Norman in that the methods seek to quantify the “utility” that consumers will get from a particular design. They are not particularly concerned with (or their models do not capture) other aspects of the decision.

2.2.2 Preference with no consideration for price

The second trajectory involves quantifying preference where price is not an important factor. The stimuli used are often visual and the results are used to optimize the subjective preference and generate new designs or use the result as is. This pathway is related to the reflective and/or visceral aspects of a design based on Norman's work.

A study was conducted that measured shape preference of bottles and used optimization techniques to examine the trade-offs between the form and engineering criteria [*Kelly and Papalambros* (2007)]. The methodology consisted of using conjoint analysis to assess preferences for bottle shapes. The bottles were described using a spline with 5 control points, 2 of which were variable and the other 3 were held fixed. A total of 16 shapes were presented to respondents. An optimization study was conducted to address the engineering goal of minimizing material volume, while maximizing shape preference. Although a variety of new designs were presented, the result was a shape very similar to a coca-cola bottle, which suggests that people may gravitate to shapes they are familiar with. The value of the control points for shape with minimal volume differed from that which was optimal for aesthetic preference, thus indicating the existence of a trade-off between consumer preference and engineering criteria. Kelly has also used interactive genetic algorithms (IGA) to assess preference for the bottle shapes [*Kelly* (2008)].

Other researchers have sought to quantify subjective preferences for automotive applications. Swamy et al. also presented work in a study that quantifies consumer's preference for the form of vehicle headlights [*Swamy et al.* (2007)]. In that work, preference is measured using conjoint analysis. The stimuli used were headlights based on the 2003 Honda Accord model. The shapes were created using Bezier curves with 4 control points (see Figure 2.2, left). The control points were reparameterized to represent a particular aspect of the shape, namely h and w represented size, α represented skewness and s represented sharpness. Other geometric dimensions were considered as parameters to ensure that the resulting shapes were within an acceptable range of values. These parameters set in the context of the headlight included: the grill width, track width, height of bumper, and height of the hood (see Figure 2.2, top-right). The authors developed a conjoint study with 72 questions, each with 3 alternatives as shown in Figure 2.2, bottom-right. A total of 18 engineering graduate students in mechanical engineering completed the survey. A random utility function was used to relate aesthetic headlight attributes to observed choices. Optimization was done to maximize the utility function. The specific optimization technique used was the coordinate descent method, which involves solving a multivariate problem by iteratively performing a univariate search along each direction [*Swamy et al.* (2007)]. A set of new β-values were found and when substituted into the utility function, they were able to achieve a max utility value of 9.18 as compared to 6.17 from the survey designs. The results were used to generate new headlight shapes based on this maximum utility function.

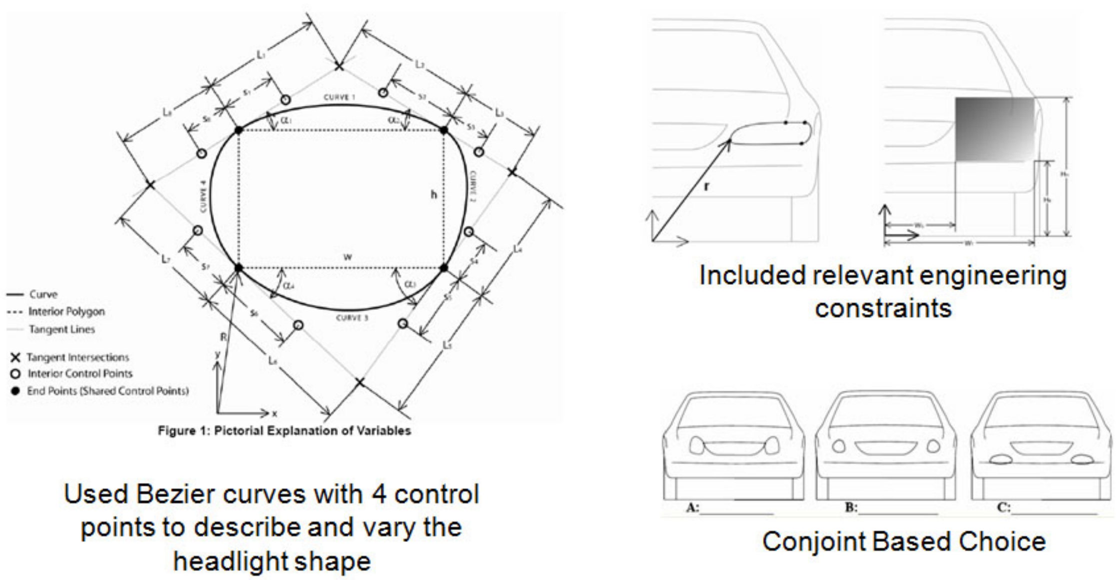


Figure 2.2: Descriptive visuals, taken from *Swamy et al.* (2007)

Orsborn et al. quantify the aesthetic form preference for a vehicle [*Orsborn et al.* (2009)], in a methodology consisting of the following steps: The first step is to determine the product space and use a generic form of the product. This generic form is then atomized (i.e., break the product down into smaller components). For example, product form can be broken down into product characteristics. Then each characteristic can be described using Bezier curves. Then the Bezier curves can be broken down into atomic elements, namely vectors, scalars, and angles (i.e., the "VSA" space). Consumer preference is quantified using a quadratic utility function and discrete choice conjoint analysis is used to determine the weights of the attributes included in the utility function. Each respondent participates in two surveys; the first one to determine the individual's unique utility function, and the second to verify that the utility function derived captured the preference of that individual (see survey question sample in Figure 2.3, right). The stimuli used was a set of 20 sports utility vehicles from the 2003 model year. Vehicles were selected that had blueprints of both front and side views and were proportionally consistent with the actual vehicle. Seven atomic attributes were selected including the x and z position of the cowl with respect to the ground, the x and z position of the top of the grill with respect to the cowl, the grill height, the position of the headlight with respect to the cowl and the height of the headlight(see Figure 2.3, left). A unique aspect of this work was the development of utility models on an individual level. Details of how utility models are used in an optimization framework was presented in a prior paper [*Orsborn and Cagan* (2009)].

In that work, the authors use a software agent approach to coordinate utility functions with shape grammars in order to automate designs preferred by consumers. Software agents provide a discrete architecture that facilitates future modifications [*Orsborn and Cagan* (2009)]. The authors demonstrate the use of software agent known as a "collaborative agent". Agents have the ability to generate designs, evaluate designs based on user preference, and optimize the design. Figure 2.4 shows the agent system structure and how it can be mapped to the atomic structure. The Manager Agent manages the design process and the product form. The Characteristic Agent(CA) designs a specific product characteristic. Shape rules are utilized to create character-

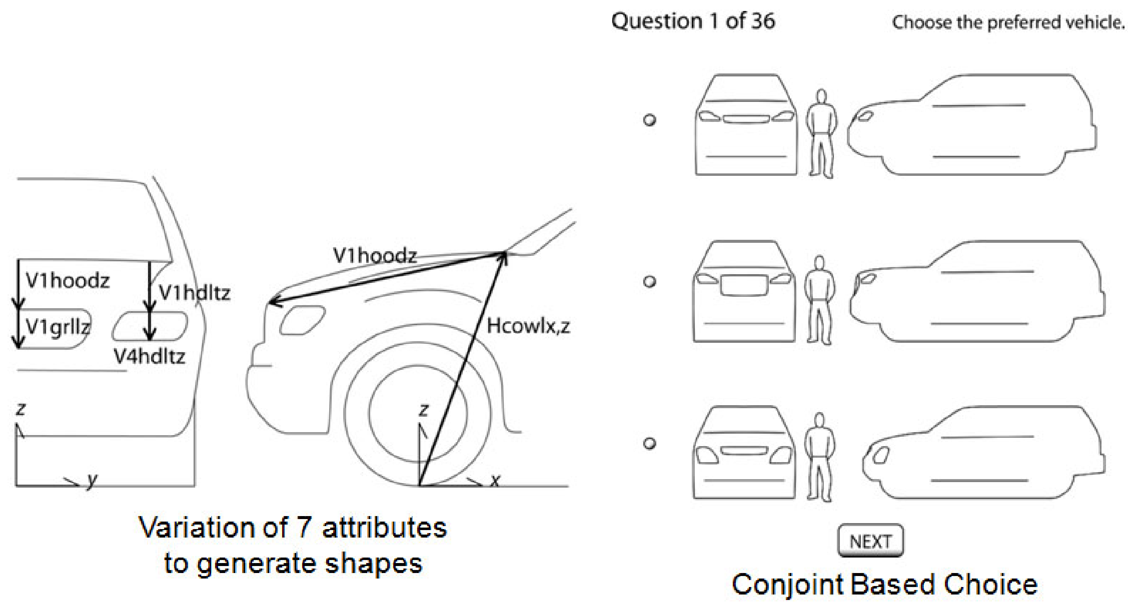


Figure 2.3: Descriptive visuals taken from *Orsborn et al.* (2009)

istic curves from which specific attribute values for vectors, scalars, and angles can be made known.

The agent system is used to optimize designs that maximize consumer's aesthetic utility function. The Manager Agent accepts five inputs that influences the optimization. Those five inputs are: Direction, Quantity, MaxLaps, PercentRestart, and Value. Direction determines the order in which the resulting designs will be sorted (e.g., best to worst, worst to best) based on the objective function. Quantity specifies the number of designs that will be created for each iteration. MaxLaps is the number of iterations that occur before the list of optimal designs is generated. PercentRestart indicates what percent of the previous design was used as the objective function. Value is the final variable used to inform the characteristics agent to use a separate internal optimization technique to find a parametric value for the attribute or randomly choose a variable within the constraints of the parametric range. This describes the general role of of the Agent System shown in Figure 2.5 of their general method. Additional processes between the three main systems (e.g., return design

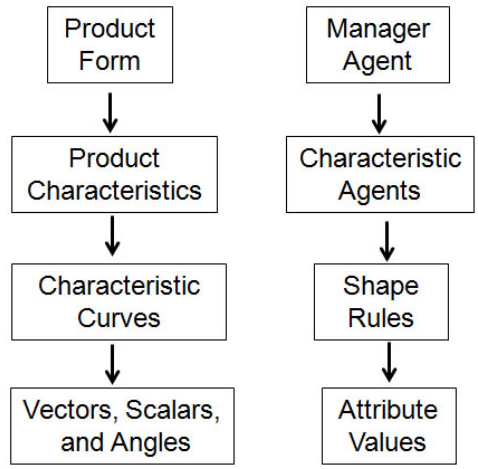


Figure 2.4: How atomic structure maps to agent structure, taken from *Orsborn and Cagan* (2009)

changes, choose rule, etc.) also work to support this iterative process. The result is an optimal utility function that has information about the product characteristics that best suits the preferences of the subject for which the utility function was optimized.

2.2.3 Emotional appraisal of designs

The third trajectory involves assessing consumer's emotional or visceral level appraisals for designs. Unlike the previous two, the subjective assessment is usually very specific going beyond mere preference, but wanting to know a specific subjective aspect of the design (e.g., how much a design conveys sportiness, massiveness, friendliness, youthfulness, etc.) This pathway primarily deals with the visceral aspect of a design but could also be reflective depending on the emotive quality being assessed.

A robust design technique was presented that assessed the "feeling" quality of a product and used vehicle profiles as a case study [*Lai et al.* (2005)]. The objective was to design a passenger car that targeted consumers who were 25-30 years old, white collar workers, married for 1-8 years, parents, and had a liking for outdoor life.

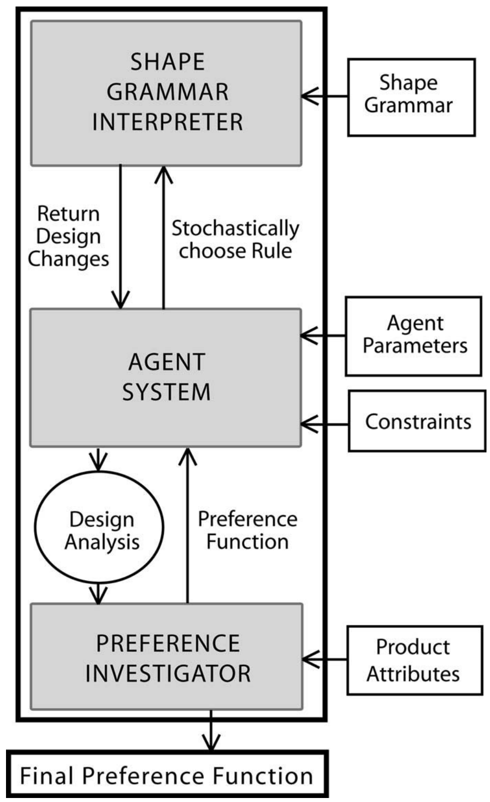


Figure 2.5: Overall method of the agent system, taken from *Orsborn and Cagan* (2009)

The specific feelings they wanted this new car to evoke was a sense of youthfulness, "outdoors" conveyance, and family. A semantic scale was developed for each one: Youthful-Mature, Field-City, and Personal-Family, respectively. In essence, the authors looked for designs on the lower end of the first two dimensions and the higher end of the third dimension. Three initial designs were created in the "traditional" sense by designers. The authors do not describe the specific method these designers used (e.g., hand sketch, CAD) but it appears that a software program was used. The study then implemented a method to design silhouettes that conveyed these feeling qualities using robust design. The study used stimuli based on 125 existing passenger car profiles. Profile design experts assisted with identifying the most important design factors to consider. They included 13 geometric relations as shown in Figure 2.6. They include: A) the ratio of the car's height to the car's length, B) the ratio of the chassis's height to wheel axles's height, C) the ratio of the wheel's diameter to car's height, D)the ratio of the fender's length to car's height, E) the ratio of the fore region's length to whole length, F) the ratio of front over-hang to car's length, G) the ratio of the apex's position on whole hood line, H) the gradient of fore windshield, I) The gradient of fore fender's bottom, J) the ratio of rear region's length to whole length, K) the gradient of the rear windshield, L) the gradient of the trunk's rear, and M) the gradient of rear fender's bottom. Each of these factors had 3 levels where the high is the maximum value from the original 125, the low is the minimum value, and the middle level is based on the average of the maximum and minimum values. The Taguchi design of experiments was used generating 27 different vehicles (see Figure 2.7). Each vehicle was placed on A4-sized cards, and a total of 27 participants rated the cards based on the feelings that were conveyed.

The results showed that factors A, D, E, F, H, K, L, and M were the most influential in their judgments and the corresponding levels. These significant factors were used to redesign the initial three silhouettes created by the designers. A follow

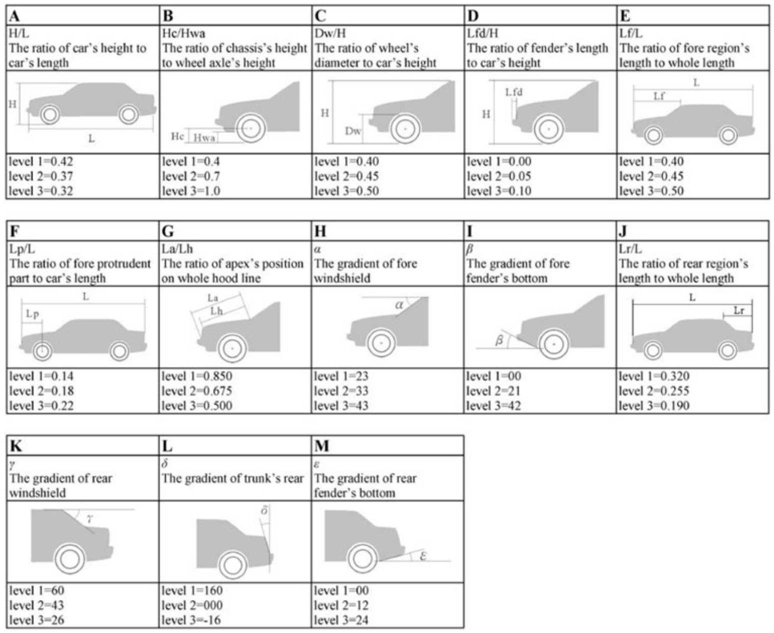


Figure 2.6: The 13 factors used, taken from *Lai et al.* (2005)

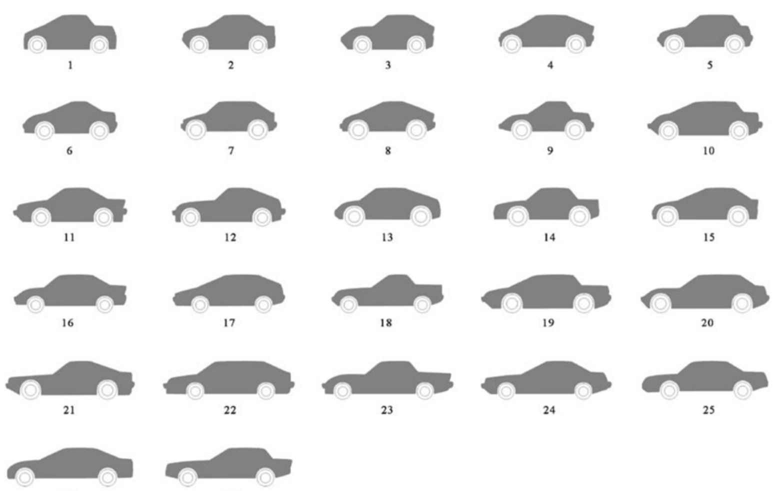


Figure 2.7: The 27 stimuli generated, taken from *Lai et al.* (2005)

up study was done with the subjects who evaluated the original profiles. Figure 2.8 shows the redesign (bottom row) of the initial three designs created using the traditional design method (top row). The analysis results indicate that the three new designs were significantly closer to the target feeling quality than the original designs.

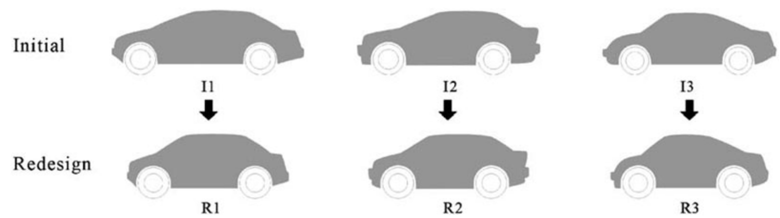


Figure 2.8: Three redesigns, taken from *Lai et al.* (2005)

Summary

The automotive examples presented here demonstrate how subjective attributes could be quantified using choice models and methods to assess the emotional aspects of designs.

The next section will discuss early attempts to assess consumer judgments on green products.

2.3 Consumer Judgments on Green Products

Efforts to quantify how products convey environmental friendliness are extremely limited. A study conducted by *Ewing and Sarigöllü* (2000) used discrete-choice analysis to assess consumer preferences for fuel efficient vehicles. The study asked participants about their preferences for hypothetical vehicles described using words. The following 6 attributes were included in their study: purchase price, repair and maintenance costs, the maximum distance traveled on a full tank or charge (i.e., cruising range), refueling time, acceleration, and emissions. A focus group helped to verify the choice of attributes and levels included in the study. The environmental attitudes of the respondents were also assessed. The study found that although individuals were interested in fuel efficient vehicles, they were not willing to trade-off standard vehicle performance measures for range, acceleration, and refueling time. Results also suggest that imposing regulations is not enough to make such vehicles marketable; increasing gas prices and commute time were ineffective. The work does not discuss the subjective aspects of design that are important to consumers.

Research conducted by *MacDonald et al.* (2007a) assesses the effects of environmentally friendly product features and how people make decisions about these products. The objective of that study was to understand and demonstrate the inconsistencies that exist in consumer preference data. Several inconsistencies were defined, but of particular interest in the present discussion are those related to "across-user" inconsistencies that are typical in design work. Specifically, they are: comparative inconsistency, external inconsistency and internal inconsistency. Of most relevance to environmentally friendly product choices are external inconsistencies, which occur when a group of subjects show a mismatch between stated preferences (in a preference elicitation procedure) and revealed preferences (gathered from purchase history). The term 'external' is used because it requires the examination of preferences that were made outside of the preference elicitations tasks used in the study. Within external inconsistencies are three preference construction phenomena that decisions about green products are often subject to: social desirability bias, embedding, and pseudo-sacredness. Social desirability bias occurs when people tend to provide answers to survey questions according to what seems acceptable whether it's a social norm or to please the survey researcher. Embedding occurs when a person states they are willing to pay a price premium for a product when the reality is they would only add the specific amount to their entire grocery bill and not for a single product. Pseudo-sacredness occurs when an individual's values for the environment are manifested as sacred in preference elicitation, i.e. they will not trade them for other desirable qualities; but in another context, their values are traded-off [*MacDonald et al.* (2007a); *Thompson and Gonzalez* (1997)].

The study examined how subjects constructed preferences about environmentally friendly paper towels. The authors assessed whether people perceive a link between recycled paper content and environmental friendliness. A discrete choice survey was used and examined four main attributes of paper towels: strength, softness, absorbency, and recycled paper content. The survey was administered by an external agency and a total of 217 respondents participated. When subjects were asked the price they would be willing to pay for a paper towel of average strength, softness, and absorbency, and 0% recycled paper content, 60 of the 217 respondents stated they would not buy the paper towel for any price due to lack of recycled paper content and/or concerns for the environment. This is an example of a stated preference. In another section of the study, 52 of those same 60 respondents reported buying a paper towel brand that had 0% recycled paper content. This is an example of a revealed preference. Thus, this example demonstrates an external inconsistency due to the contradiction of preferences exhibited by the 52 respondents under different scenarios. Although the results are insightful and interesting, the study was based primarily on verbal descriptions of the stimuli and does not examine how these preferences would change if consumers had to make a decision based on visual attributes. In other words, there is still room to answer the question: how would subjects' judgments change if they were presented with images of the various paper towel products that were visually manipulated according to the attributes that were examined (or if they were given an opportunity to interact with the paper towel, such as pick up a spill)? Nonetheless, this research provided an empirical basis for understanding how consumers make choices about environmentally friendly products. Unfortunately, the results cannot inform green styling of automobiles.

2.4 Gaps in the Literature

The previous work presented demonstrated the different ways to quantify subjective attributes. The methods presented along the first trajectory of Figure 2.1 provides a means for developing demand models of consumer preference as a function of price. Engineering criteria can be included in an optimization framework that maximizes profit. These results will provide the combination of product attributes that are optimally designed in terms of engineering criteria as well as for the profitability of the firm. This approach is limited in that they typically rely on a list of words as a stimuli and do not provide visual information. Thus, they cannot assess the visceral aspects of the products.

The second trajectory demonstrates methods for quantifying aesthetic preference using utility functions and other methods from psychology. Visual information is presented to the user to assess the reflective and/or visceral aspects of the design. Consumer preference is captured in the form of a utility model that is function of the specific product attributes or design features under investigation. The surveys can provide the relative weights to be assigned to each design feature to understand the value that individual place on them. A variety of optimization methods can be applied to maximize the utility thus providing the optimal values for the design features that are the most preferable to the user and in turn, generate new designs. The examples presented focused on consumer preference. They did not ask about specific emotional attributes (e.g., luxury, cool, etc.) although their methods are capable of doing so. However, the limitation with these methods is that they do not demonstrate the integration of these subjective attributes into a broader engineering optimization model, such as the methods of the first trajectory.

The methods along the third trajectory demonstrate the quantification of the emotional appraisals or "feeling" sense that products convey. Visual information is presented to the user to assess the visceral aspects of a design. The methods in this trajectory can be used to assess PEF in a general sense. But they do not integrate engineering design criteria in their models and are not able to provide information about consumer choice. The prior efforts to quantify consumer judgments on green products represent early attempts to understand subjective judgments about green products. However, they are not directly applicable for quantifying green styling cues (i.e. PEF) in the context of automotive design.

This dissertation fills a gap in the literature in that it presents a methodology that can be used to achieve the goals of all three trajectories discussed here and provides another example of consumer judgments on green but in the context of automobile styling. Chapter 3 demonstrates the general methodology for quantifying PEF using methods from psychology and engineering. The approach considers consumer choice and a model is developed that characterizes judgments of PEF as a function of the design features of the silhouette. In Chapter 4, the model is then integrated into a broader optimization framework that develops a fuel efficient vehicle. This bi-objective optimization problem demonstrates how one could integrate the subjective PEF attribute while concurrently designing for the objective design attribute of a fuel efficient vehicle.

CHAPTER III

Quantifying Perceived Environmental Friendliness

This chapter presents the steps in the study of the effects that changes in the physical characteristics of a vehicle have on perceptions about environmental friendliness. It addresses two of the three main research questions: What physical attributes relate to one's perception of vehicle greenness? What visual aesthetic characteristics are related to perception of greenness? Some of the material presented in this chapter is based on a 2009 publication by Reid, Gonzalez, and Papalambros [*Reid et al.* (2009)].

3.1 Introduction

Engineering functionality attributes have long been used in design optimization of artifacts and systems. Our ability to quantify the value of engineering attributes, such as weight or stress, as functions of the design variables, allows their inclusion in a mathematical design optimization model. We do not possess the same ability to quantify subjective design attributes, specifically those that are based on people's perception, henceforth called perception-based or perceptual attributes. Perceptual attributes are design properties that can influence people's judgments about objective qualities such as safety and weight. People make judgments on these attributes with little or no quantitative information. For example, a vehicle is perceived as safe without knowing safety metrics such as crash test ratings and number of airbags; or an object is perceived as heavy without knowing its actual weight. People often use heuristics to make decisions when they do not have enough information to make those decisions [*Tversky and Kahneman* (1974)]. Heuristics refer to mental shortcuts or rules of thumb that people use to make subjective judgments when information or time is limited.

Quantifying subjective attributes and the attendant user preferences for them are important in product design. Functionality and usability seem no longer sufficient in a product's success [*Helander and Khalid* (2006)]. As product variety and maturity increase in the marketplace, the emerging product differentiators are the subjective responses to the product as experienced by the customer [*Henson et al.* (2006)]. It is now well accepted that, to make appealing designs, designers should include characteristics that are visceral or engage the senses [*Norman* (2004)]. Likewise, the inclusion of semantic functions in the design process helps to produce designs that "signal, indicate, express, and describe" [*Monö* (1997)].

The automotive industry, vehicle users, and governments have become increasingly concerned about environmental issues in the production and use of automobiles. There is increased interest not only in making more eco-friendly vehicles, but also in making them visually appealing in a "green" way [*Patton* (2007)]. It is expected that by 2011, there will be 75 hybrid powertrain models available in the US market [*Naughton* (2007)]. Depending on market conditions and government regulations, fuel economy may not be the only impetus or motivator for the purchase of hybrid or electric vehicles when the price premium paid for the new technology does not result in a timely payback in fuel cost savings. In addition, increasing gas prices is not enough to make fuel efficient cars marketable [*Ewing and Sarigöllü* (2000)]. There may be additional factors that motivate people to purchase eco-friendly vehicles.

Some motivators were identified in a semiotic study on early adopters of hybrid vehicles [*Heffner et al.* (2007)]. The study showed that many of them purchased hybrid vehicles for reasons beyond fuel economy, including ethics, concern for others, personal or national independence, and individuality. Many adopters did not perform "rational" analyses such as break-even time or annual fuel savings. Rather, purchase decisions were driven by subjective preferences. Some early adopters specifically identified the distinct styling of their hybrid vehicle being a primary rationale for their choice and enjoyed the attention that driving such a unique-looking car attracted. The specific design factors (i.e., visual cues) were not identified. Nonetheless, the literature shows that people's own reasoning about their behavior and choices are not always in sync with what actually determines their behavior and choice [*Nisbett and Wilson* (1977); *MacDonald et al.* (2007a)]. People may want to drive a car that conveys to the world that they are eco-friendly and are proud of it. Design attributes have meaning to the consumer beyond their objective value.

The remainder of this chapter will discuss the details of the experiment conducted to quantify this attribute, validation of the results, and an algorithm that was developed to generate new designs.

3.2 Experiment for Quantifying PEF

This study examines the relationship between vehicle design features and perceptions of environmental friendliness. The study will also correlate these measures with environmental consciousness scales and judgments of vehicle familiarity. The primary aim of the study is to investigate the effects that variations in vehicle shapes have on perceptions about the environmental friendliness (PEF) of a vehicle.

The visual stimuli were created through a design of experiments (DOE) approach and data collected through a survey instrument that lead to the creation of new designs. The new designs were validated with additional survey data collection. Validated designs were parameterized and integrated into a design optimization model that included typical engineering attributes. The optimization will be discussed in Chapter 4.

3.2.1 Stimuli Creation

The first step in the methodology is to create the visual stimuli that will be used in the experiment. The stimuli were created using minimal extraneous detail in order to have greater control over the factors that may influence judgments. The benefit to using simplified representations (i.e., silhouettes) is that it is consistent with what designers use in industry at the conceptual stage of design. It also allowed us to examine the phenomenon before moving to more realistic and more complicated 3-D models.

A number of methods for creating automotive shapes have been proposed. Kokai et al. describe developing 3-D renderings from conceptual designs based on deformation gradients [*Kokai et al.* (2007)]. Shape grammars have been used to create a variety of automotive shapes and brand identities [*Orsborn et al.* (2006); *McCormack and Cagan* (2004); *Pugliese and Cagan* (2002)]. These researchers used existing vehicles as the basis for development of methods that in turn could create new vehicles.

In this study, we were motivated to produce original designs of vehicle silhouettes and were not limited to existing vehicles. The stimuli included visual included visual information about the wheels and the front windshield to help orient the direction of the vehicles.

Figure 3.1 shows a parameterized vehicle silhouette where the numbered points are varied along the x and y directions creating 14 factors. A 15th factor operates on the entire silhouette by controlling the smoothness of the splines. A Taguchi design was used to keep the number of vehicles small and to avoid taxing the research subjects by presenting too many stimuli. This Taguchi design with 15 factors produced 16 silhouettes (Table 3.1), which allowed us to explore a broad range of variations with

Veh.No.	P1x	P1y	P2x	P2y	P3x	P3y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	curv
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	2	1	1	1	2	1	1	1	1	2	2	2	2	2
3	1	2	2	2	2	1	1	1	1	2	1	1	2	2	2
4	2	1	2	2	2	2	1	1	1	2	2	2	1	1	1
5	2	1	1	2	2	1	1	2	2	1	1	2	1	2	2
6	1	2	1	2	2	2	1	2	2	1	2	1	2	1	1
7	2	2	2	1	1	1	1	2	2	2	1	2	2	1	1
8	1	1	2	1	1	2	1	2	2	2	2	1	1	2	2
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
10	1	2	2	1	2	2	2	1	2	1	1	2	1	2	1
11	2	2	1	2	1	1	2	1	2	2	2	1	1	2	1
12	1	1	1	2	1	2	2	1	2	2	1	2	2	1	2
13	1	1	2	2	1	1	2	2	1	1	2	2	2	2	1
14	2	2	2	2	1	2	2	2	1	1	1	1	1	1	2
15	1	2	1	1	2	1	2	2	1	2	2	2	1	1	2
16	2	1	1	1	2	2	2	2	1	2	1	1	2	2	1

Table 3.1: Binary code in Taguchi design of experiments and corresponding [x,y] points on Figure 3.1 as coded by the first 14 factors. The 15th factor called ‘curv’ controls the curvature of the overall vehicle.

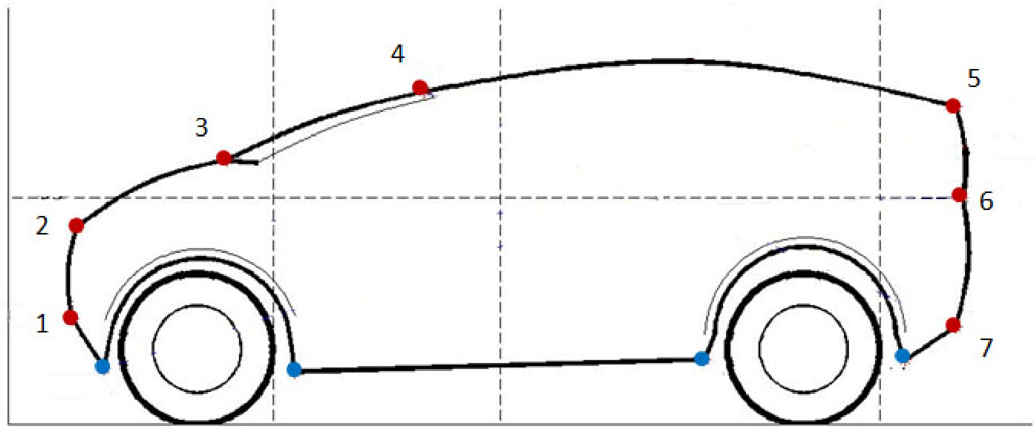


Figure 3.1: Sample silhouette (not from DOE). Points 1-7 were varied; all other points were held fixed.

a low number of stimuli. A 17th vehicle, not part of the DOE, with the silhouette of a 2007 Toyota Prius, was included in the set presented to participants as a 'plant' (see Figure 3.2 for a complete set). We wanted to test whether people would choose and rate highly a silhouette that resembles the most commonly purchased "green" vehicle in the present market.

Algorithm used to create stimuli

The algorithm implemented in Matlab outputs silhouettes by connecting piecewise polynomials as a function of a set of control points. Figure 3.1 shows 7 control points. Between each point is a curve where each curve is generated by a total of 3 points: the starting point (x), the ending point (z) and a middle point (y). In Figure 3.1, the points highlighted are described in Matlab as x and z points for each curve; y is not visible on the curves. As can be seen, some points that are x points for one curve can be z points for another curve. For example, Point 2 is the x Point for the curve between Points 2 and 3, but Point 2 is the z point for the curve between Points 1 and 2. In essence, each curve is a polynomial with two pieces connected:

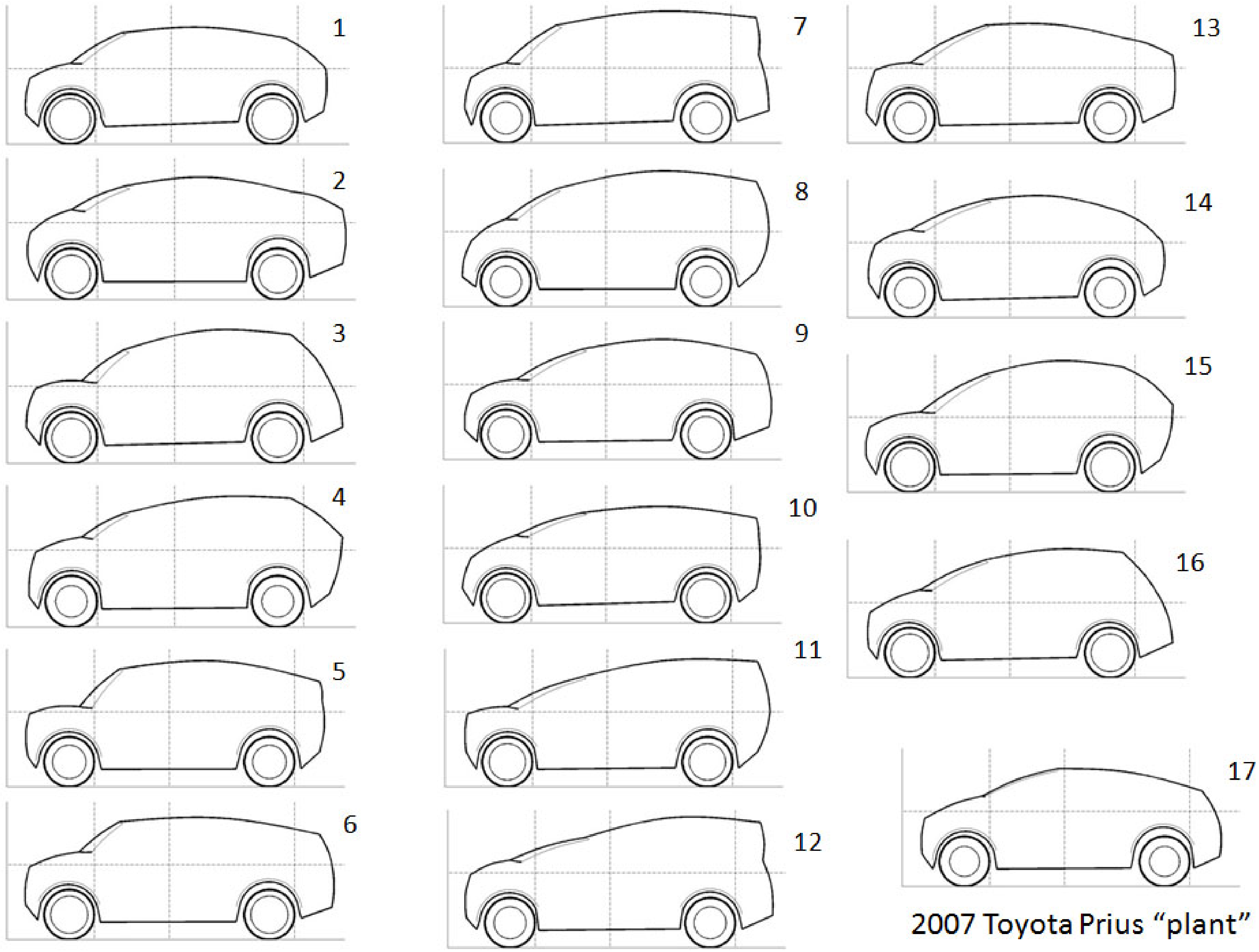


Figure 3.2: Set of 16 vehicles generated using the DOE in Table 3.1; the 17th vehicle is the 2007 Toyota Prius plant.

xy and yz. The curvature is adjusted by moving the middle point y from its original position (on the line xz) along some predefined direction with some step size.

3.2.2 Survey Instrument

A survey was designed and administered using the Sawtooth software http://www.sawtoothsoftware.com [*Sawtooth Software* (2009)]. This software facilitates developing and launching web-based surveys as well as surveys that can be conducted on a computer without an Internet connection. Additional details about the survey instrument can be found in Appendix B.

Inspired by previous work [*Karana* (2007)] two hypotheses were tested with this survey instrument:

1. Subjects will assign higher perceived environmental friendliness (PEF) ratings to vehicle designs that have less abrupt line changes than those that have discontinuities or have a boxy shape.

2. Subjects will assign higher PEF ratings to vehicle designs that are also perceived as being inspired by nature compared to vehicles that are perceived low on Inspired By Nature (IBN).

Vehicles that have less abrupt line changes include vehicles 1, 2, 9, 10, 13, 14, and 15. Those that have more discontinuities or a boxy shape include vehicles 3, 4, 5, 6, 7, 8, 11 12 and 16.

The independent variables were the 15 factors that vary the shapes of the silhouettes. The dependent measures in the survey included self-report measures on perceived environmental friendliness (PEF), the likelihood that the silhouettes were Inspired By Nature (IBN), the degree of familiarity (FAMT) of each of the silhouettes, personal preference (PREF) and the degree of eco-consciousness of participants (based on [*Thompson and Barton* (1994)]). These dependent variables were ratings on a 7-point Likert scale except for the preference measure, which was based on selecting the top two favorites. The IBN variable was also measured using a sorting task where the online subjects selected the vehicles they thought were likely inspired by nature. The in-person subjects were given a stack of 17 cards to sort into two categories: Likely Inspired by Nature and Not Likely Inspired by Nature. Each card displayed one of the vehicles. The variables IBN, FAMT, and PREF were used as covariates to examine individual difference effects in the PEF comparisons and nature judgments. These variables were selected based on feedback from pilot studies and from colleagues.

The survey was designed using five main parts. The first part of the survey consisted of questions about PEF and Preference. The second part assessed Familiarity. The third part consisted of questions that assessed the eco-consciousness of the subjects. The fourth part examined IBN and the fifth part was the sorting task for the in-person subjects or an extra set of questions for the online subjects. A sample of the question format for a rating task is shown in Figure 3.3.

For the rating tasks, each of the 17 vehicles was shown one at a time in randomized order. For the preference task, a total of six trials of six vehicles were presented to subjects also in randomized order. Each vehicle was shown twice and two vehicles were shown three times to balance the choice sets.

Figure 3.4 gives examples of how each of the questions was worded. Subjects were also provided a list of assumptions that applied to all vehicle designs in the study:

For all the vehicles shown, assume that all:

- *have excellent fuel economy*
- *have clean emissions*
- *have an equal number of doors*
- *carry the same number of passengers*

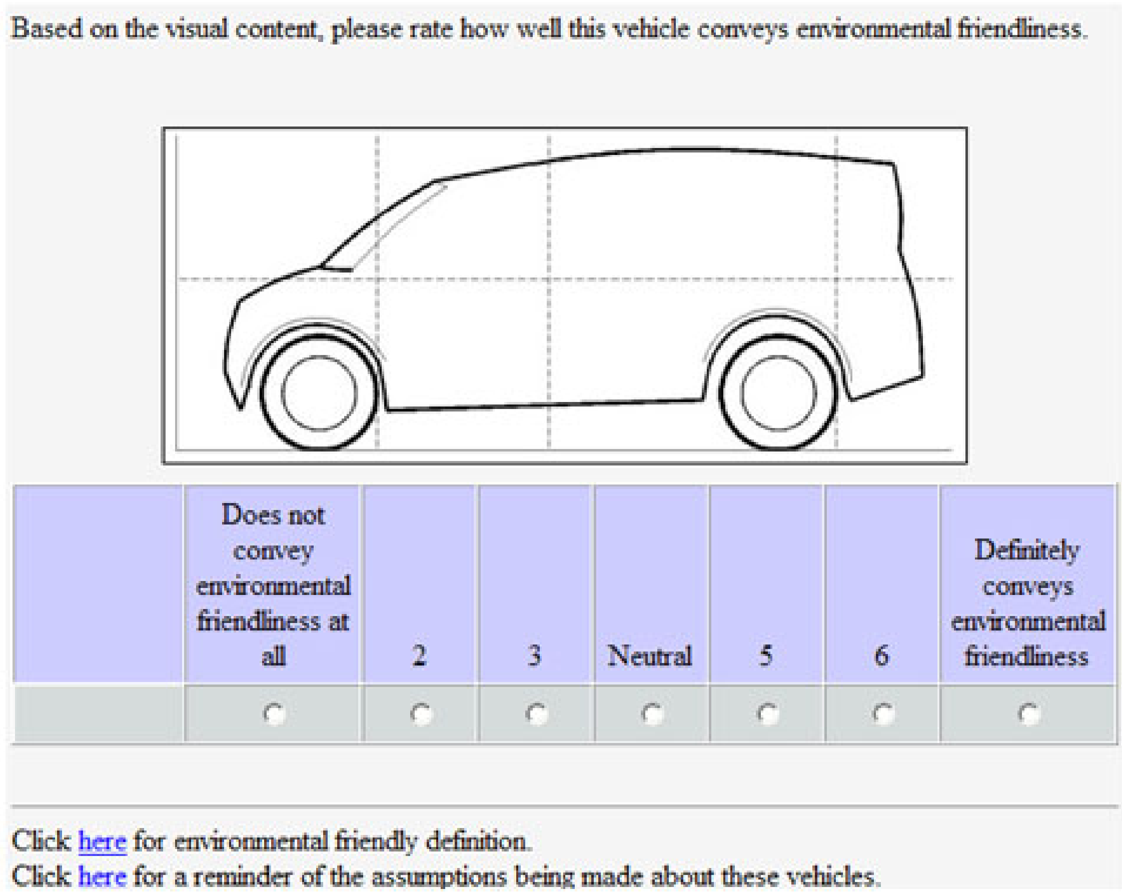


Figure 3.3: Example of rating task survey question. Shown here is a question from the PEF rating task

- *are equally priced*
- *belong to the same vehicle class (i.e., are cross-over vehicles)*

For the PEF portion of the survey, a working definition for environmental friendliness was also provided:

> *Environmental friendliness is a term used to describe products, ideas, or concepts that have minimal to no impact on the environment (i.e. air, water, land and natural resources). Examples of negative impacts on the environment include water pollution, the removal of resources from nature that once removed cannot be replaced, and the release of air pollutants that*

Dependent Measure	Wording of questions
PEF (rating)	Based on the visual content, please rate how environmentally friendly the vehicle appears to be.
PREF (choice)	Please select 2 vehicles you like the best.
FAMT (rating)	Please rate how much this design shape looks like a vehicle you may encounter in your daily life.
IBN (rating)	Using the scale below, please rate how much you think the vehicle shape below was inspired by shapes found in nature.
IBN (sorting)	**Online subjects (select from screen):** Please select all the vehicle shapes you think were LIKELY to be inspired by nature (Just try your best. There are no wrong or right answers.) **In-person subjects stated orally (using a stack of 17 cards):** In front of you are a stack of cards showing the vehicles that you just saw. Similar to the last section of the survey, please sort the cards into two stacks where one is "Likely Inspired by Nature" and the other is "Not Likely Inspired by nature"

Figure 3.4: Question wording within the main survey sections

reduces the ozone layer which protects us from the harmful rays emitted from the sun.

Design of the Sorting Task

The cards were created using 4 x 6 inch index cards with printouts of the vehicle images placed on the center of the index cards (see Figure 3.5). They were also laminated to provide some rigidity. Each card was numbered on the back to facilitate coding. Two bins were provided wherein subjects could place the cards according to the two categories. The motivation for this sorting task was based on feedback from pilot studies where subjects' feedback suggested a need to make that task a bit more enjoyable and less mundane.

Figure 3.5: Set up of the sorting task.

Participants

A total of 195 participants participated in this study (98 females, 96 males, with one subject who did not identify gender) ranging in age from 18 to older than 70 years. Subjects under age 18 were not allowed to participate in this study. Although the survey was web-based, there were 93 subjects who completed the study in-person with the experimenter present and another 102 who participated online without the experimenter present. Table 3.2 summarizes the demographic information.

Gender			Age Groups			
F	M	N/A	18-30	31-50	51-70	70
50%	49%	1%	32%	32%	29%	7%

Table 3.2: Demographic information of the 195 respondents

Although the survey was web-based, there were several motivations for testing some participants in-person:

- Subjects are more likely to commit to completing a survey if they schedule a time than just doing it on a whim such as when a survey link goes out to a mass-email list. People often click on survey links of this kind during "idle time" and then quit when the idle time runs out.

- Positive results were observed doing pilot study with lab mates. People seemed to have fewer issues of distraction and fatigue because they blocked the time to do the study.

- Subjects without a computer can be in the study because the experimenter provided one.
- If subjects had questions during the survey or ran into problems, they were assisted immediately to aid in the successful completion of the survey. It is possible that a person working remotely would just quit.

The in-person subjects were recruited using newsletters, email, a fundraiser, and sitting with a laptop in public places with a sign up saying "Participate in a survey on vehicle design, $5.00 gift card for your time". The public places included Primo Coffee on Whitaker Road in Ypsilanti, Burt's Caf in the Shapiro Library, the Ypsilanti District Public Library, and the Baltimore Washington International Airport (researcher had a long layover and did an interview there). Care was taken to get permission to solicit subjects at each of these establishments.

In-person subjects were compensated with a $5.00 gift card that was appropriate to the location. For example, subjects on the University of Michigan's North campus and at the Ypsilanti District Library could choose from Target, Kroger, or Quiznos. Interviewees on Central Campus could choose $5.00 gift cards to Starbuck's, Espresso Royale, and Jimmy Johns. Subjects at Primo Coffee only had the option of receiving a Primo Coffee gift card since this business allowed recruitment in their establishment. In all other locations, a Starbuck's card was offered because people can easily find one. Those at the fundraiser donated the value of the gift card to the cause.

For the online survey, Luth Research (http://www.luthresearch.com) managed and conducted the study using subjects from their network. Luth Research is a marketing research company founded in 1977 and located in San Diego, California. Respondents were informed of the inclusion criteria and received a standard compensation rate of $2.00 for surveys approximately 20 minutes long.

Procedure:

In-person subjects who responded to the solicitation coordinated with the experimenter to schedule a time and meeting place. For University of Michigan North Campus students, the typical meeting place was in a lab in the Duderstadt Center or at a table near MUJO's Coffee stand. Once the subjects arrived, they were thanked for their time and briefly oriented on the task. The experimenter sat nearby in case the subjects had questions. In-person subjects were also given a hard copy of the environmentally friendly definition and list of assumptions because it was observed that although a link was provided in the survey, subjects did not always click the link. When subjects were done with the computer portion of the survey, they completed the sorting task. Subjects were provided with a stack of 17 cards and were told to place the cards into one of the two bins labeled "Likely Inspired by Nature" or "Not Likely Inspired by Nature" as shown in Figure 3.5. When the subjects were done, they were allowed to ask questions and they were debriefed about the purpose of the study. They were then asked to choose a $5.00 gift card of their choice or given one (e.g., subjects at Primo Coffee). For accounting purposes, subjects also completed a form with their name, contact information, and the gift card they received.

In place of the card sort task, the online subjects were given an extra section of the web-based survey where they chose the silhouettes that were "Likely Inspired by Nature". The silhouettes that were not selected were classified as "Not Likely Inspired by Nature" for the purpose of the analysis.

Data Analysis:

The data from the online and in-person administrations were combined because there was little difference between the two administrations. Descriptive and inferential statistics were used to analyze the data. The means and standard deviations of all the rating questions were computed. Subjects were presented with the option of choosing the two vehicles they liked the best. These data were analyzed by computing the number of votes that were given to each of the vehicles that subjects voted for as their top two.

A two-sample t-test was used to test the differences between the control point values that were high and low. This analysis was done for each of the dependent variables to determine which factor level was most significant in the judgments. In addition, ANOVA also tested main effects and interactions between any pairs of x and y control points.

3.2.3 Results

Descriptive statistics assessed which vehicles received the highest ratings on PEF and how much participants thought the shapes were IBN. Vehicle 14 ($M = 5.12$, $SD = 1.38$), Vehicle 2 ($M = 4.56$, $SD = 1.45$) and Vehicle 17 ($M = 4.61$, $SD = 1.42$) were perceived as the most environmentally friendly. Figure 3.6 shows a scatterplot of the percent votes for shapes that appear to be inspired by nature (IBN) from the sorting task and mean ratings of perceived environmental friendliness.

The same vehicles were also perceived as inspired by nature with similar ratings. Measures of preference were computed by counting the number of times each vehicle was selected as one of the top two favorites that each person had. Vehicles 14 and 17 were the most preferred vehicles with 72% and 78% of the participants choosing these among the silhouettes they liked best. Figure 3.7 shows a scatterplot of the preference (%vote) versus perceived environmental friendliness (mean ratings on a scale of 1-7).

The benefit of using silhouettes that varied on 15 factors is that one can identify the factors that influenced these judgments. Individual factors were tested using two-

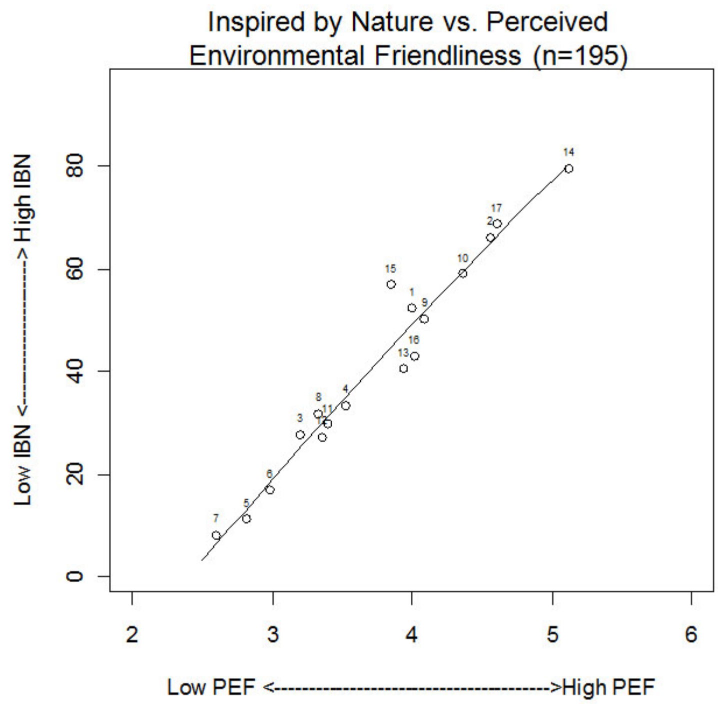


Figure 3.6: Scatterplot showing the correlation between votes on silhouettes inspired by shapes in nature (IBN) and perceived environmental friendliness (mean ratings on both variables)

sample t-tests to identify the specific level (high or low) of the factors that significantly influenced these judgments. The binary value of each factor, called the "high" and "low" conditions, was used as the grouping for the t-test. For example, vehicles 1 - 8 have a low value for the x coordinate of Point 4 (P4x) and Vehicles 9 - 16 have a high P4x value (see Table 3.1).

The results indicate that P4x and P5x had a significant effect on PEF and IBN judgments. Moving Point 4 in the x-direction affects the angle of the front windshield and moving Point 5 in the x-direction affects the angle of the back end. The t-test identified that when P4x and P5x are high and low respectively, the vehicles are seen as being more inspired by nature and environmentally friendly. A high P4x and a low P5x make the vehicle appear more curved and smooth and less boxy.

Factor 15 controls the smoothness of the entire vehicle but did not lead to signifi-

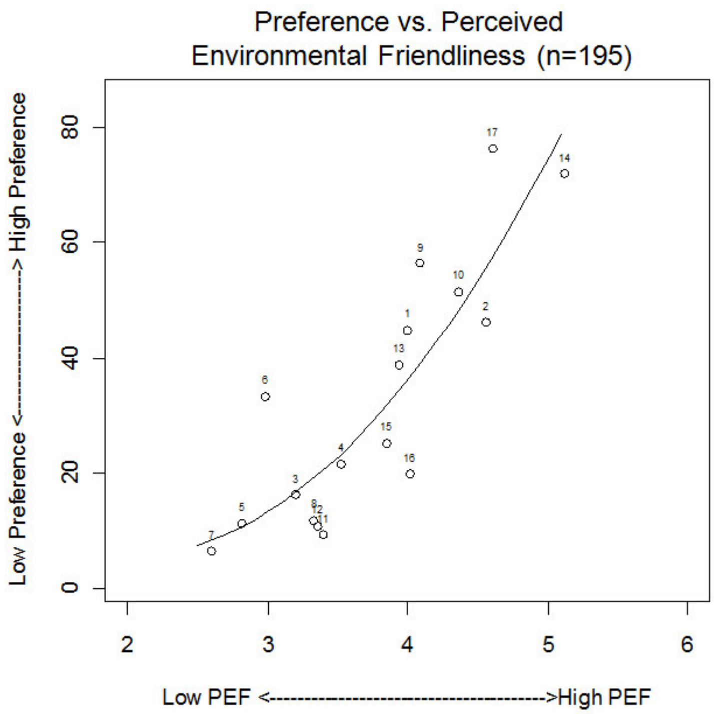


Figure 3.7: Scatterplot showing the correlation between judgments on preference and perceived environmental friendliness (mean ratings on both variables)

cant differences in ratings. The values selected for Factor 15 do not produce sufficient variation that can be detected visually. This can be seen by comparing the eight silhouettes with low values on F15 (i.e., Vehicles 1, 4, 6, 7, 10, 11, 13, 16) to the eight with high values on F15 (vehicles 2, 3, 5, 8, 9, 12, 14, 15) as seen in Figure 3. In addition, the combination of the other 14 factors influences the curved and boxy perception of the silhouette as seen in the combination of P4x and P5x in the perceptions of PEF and IBN.

Factors associated as pairs in x-y coordinates were analyzed together in a two-way ANOVA, which assesses both main effects and interactions between factors. Higher order interactions were not possible in the present Taguchi design. Factor 15 was excluded from the ANOVA because it was not a member of an x-y pair. When examining the factors that influenced judgments on PEF, the two-way ANOVA yielded a significant main effect on P4x and the interaction effect between P4x and P4y. There were also main effects on P5x and P5y. None of the other ANOVA results on PEF reached statistical significance.

Similarly, several factors influenced the IBN rating and sorting judgments. Points 2, 4, 5, 6, and 7 had significant effects, either on an individual factor or the interaction between factors.

Table 3.3 shows a complete summary of the ANOVA results for PEF and IBN.

The results indicate that changes in the appearance of the windshield (variations of point 4), the height and shape of the back end (variations of point 5, 6 and 7) and the height and shape of the front end (point 2) influence the IBN judgments. When these points combine to produce silhouettes that smooth and continuous transitions between lines, the silhouettes are rated as being more inspired by nature.

The PEF and preference means are highly correlated, $r(15) = 0.85$, $p < 0.01$ (See Figure 3.7). Because the points that influence PEF are a subset of those that influence IBN, it is expected that there will be an overlap in vehicles judged as being more environmentally friendly as well as inspired by nature, which is consistent with our second hypothesis. There is a very high correlation between PEF and IBN (sorting), $r(15) = 0.98$, $p < 0.01$ (Figure 3.6) and between PEF and IBN (rating),$r(15) = 0.95$, $p < 0.01$.

Measures of familiarity did not correlate well with measures of preference. This suggests that what subjects preferred was unrelated to what they rated as familiar.

3.2.4 Discussion

The trend displayed in the Preference vs. PEF plot suggests that the vehicles rated as being relatively high on PEF were also most preferable and the ones that were low on PEF were least preferable. Questions that the results raise include: Did people prefer certain vehicles because they truly liked them? Did they choose because the shapes looked more realistic? Do they like these vehicles because they were primed

Factor No. On Table 1	Point On Fig.2	PEF	IBN (rating)	IBN (sorting)
P1x	1	$F(1,1) = 0.14, p = 0.717$	$F(1,1) = 0.08, p = 0.786$	$F(1,1) = 0.01, p = 0.920$
P1y	1	$F(1,1) = 0.12, p = 0.736$	$F(1,1) = 0.20, p = 0.661$	$F(1,1) = 0.37, p = 0.556$
P1x:P1y	1	$F(1,1) = 0.24, p = 0.635$	$F(1,1) = 0.02, p = 0.877$	$F(1,1) = 0.17, p = 0.688$
P2x	2	$F(1,1) = 0.02, p = 0.903$	$F(1,1) = 0.16, p = 0.694$	$F(1,1) = 0.00, p = 0.993$
P2y	2	$F(1,1) = 0.90, p = 0.361$	$F(1,1) = 2.06, p = 0.174$	$F(1,1) = 1.86, p = 0.196$
P2x:P2y	2	$F(1,1) = 4.21, p = 0.061$	$\mathbf{F(1,1) = 6.95, p = 0.020}$	$\mathbf{F(1,1) = 4.92, p = 0.045}$
P3x	3	$F(1,1) = 0.04, p = 0.839$	$F(1,1) = 0.00, p = 0.947$	$F(1,1) = 0.01, p = 0.916$
P3y	3	$F(1,1) = 2.18, p = 0.163$	$F(1,1) = 0.92, p = 0.355$	$F(1,1) = 1.49, p = 0.245$
P3x:P3y	3	$F(1,1) = 0.08, p = 0.780$	$F(1,1) = 0.27, p = 0.614$	$F(1,1) = 0.26, p = 0.616$
P4x	4	$\mathbf{F(1,1) = 8.38, p = 0.013}$	$F(1,1) = 4.19, p = 0.061$	$\mathbf{F(1,1) = 6.82, p = 0.022}$
P4y	4	$F(1,1) = 0.41, p = 0.535$	$F(1,1) = 0.01, p = 0.905$	$F(1,1) = 0.38, p = 0.547$
P4x:P4y	4	$\mathbf{F(1,1) = 8.17, p = 0.013}$	$\mathbf{F(1,1) = 8.95, p = 0.010}$	$\mathbf{F(1,1) = 8.57, p = 0.012}$
P5x	5	$\mathbf{F(1,1) = 5.83, p = 0.031}$	$\mathbf{F(1,1) = 8.94, p = 0.010}$	$\mathbf{F(1,1) = 5.81, p = 0.032}$
P5y	5	$\mathbf{F(1,1) = 5.86, p = 0.031}$	$\mathbf{F(1,1) = 6.52, p = 0.024}$	$F(1,1) = 4.25, p = 0.060$
P5x:P5y	4	$F(1,1) = 0.44, p = 0.518$	$F(1,1) = 0.05, p = 0.821$	$F(1,1) = 0.29, p = 0.599$
P6x	6	$F(1,1) = 0.01, p = 0.937$	$F(1,1) = 0.45, p = 0.512$	$F(1,1) = 0.05, p = 0.827$
P6y	6	$F(1,1) = 0.53, p = 0.478$	$F(1,1) = 1.22, p = 0.290$	$F(1,1) = 0.49, p = 0.497$
P6x:P6y	6	$F(1,1) = 4.09, p = 0.064$	$\mathbf{F(1,1) = 6.70, p = 0.022}$	$F(1,1) = 4.48, p = 0.054$
P7x	7	$F(1,1) = 0.40, p = 0.538$	$F(1,1) = 0.69, p = 0.422$	$F(1,1) = 0.94, p = 0.349$
P7y	7	$F(1,1) = 0.08, p = 0.788$	$F(1,1) = 0.43, p = 0.523$	$F(1,1) = 0.30, p = 0.594$
P7x:P7y	7	$F(1,1) = 4.07, p = 0.065$	$\mathbf{F(1,1) = 6.45, p = 0.025}$	$\mathbf{F(1,1) = 4.72, p = 0.049}$

Table 3.3: ANOVA summary of main effects and two-way interaction effect for measures of PEF, IBN(rating), and IBN(sorting). Items with $p < .05$ are significant

in the survey about environmental consciousness issues? Are we witnessing a form of social-desirability bias in these choices where people are "preferring" the vehicles that look more environmentally friendly because they want to please the experimenter?

I conjecture that people were probably driven by silhouettes that they genuinely liked and that looked the most familiar to them. Bloch states that behavioral responses to designs take place along an approach-avoidance continuum [*Bloch* (1995)]. He discusses this in the context of purchasing situation where approach behaviors include extended viewing, touching a product, seeking out information, or actually making a purchase. Approach behaviors are based on positive feelings about a product. On the contrary, avoidance behaviors, based on negative feelings, include distancing oneself from a product. Crozier states that people will most like objects and places that are moderately familiar and will be more averse to the novel and the over familiar [*Crozier* (1994)] so it is also possible that familiarity had an implicit role in the judgments. Kelly also found that in his coke bottle shape studies, that although presented with a number of novel designs, individuals gravitated towards a shape that was most familiar to them - the traditional coca-cola bottle shape [*Kelly* (2008)].

3.3 Data-Driven Design Generation

The results provide insight on how the manipulation of specific control points influence judgments about PEF and IBN. This information can be used to create new silhouettes predicted to have higher PEF or IBN ratings than those in the original set. In this sense, the design of the present survey extends traditional survey methods which are designed to evaluate existing designs. Indeed, the goal in the present research was to use survey methodology as a tool in the design process to generate new candidate designs. A set of new designs was generated based on the user-driven data for both IBN and PEF vehicles. These designs essentially represent "interpolation" within the set. Extrapolations are possible, but would need to be validated with a follow up study.

Factors	Low	High	p-values	Binary Code
P1x	39.04	40.19	0.91	2
P1y	36.22	43.01	0.52	2
P2x	37.95	41.28	0.75	2
P2y	45.96	33.27	0.22	1
P3x	41.92	37.31	0.66	1
P3y	34.62	44.62	0.34	2
P4x	30.96	48.27	0.08	2
P4y	43.21	36.03	0.50	1
P5x	49.94	29.29	0.03	1
P5y	46.99	32.24	0.15	1
P6x	38.53	40.71	0.84	2
P6y	41.41	37.82	0.73	1
P7x	44.23	35.00	0.38	1
P7y	40.58	38.65	0.86	1
cur	35.38	43.85	0.42	2

Figure 3.8: Results of two-sample t-test for the IBN measure (sorting). Low = mean rating when factors are low and High = mean rating when factors are high

To create higher IBN vehicles, the factor levels with the highest means based on the two-sample t-test and ANOVA were used to describe each of the factors. Figure 3.8 provides results from the two-sample t-test and shows the corresponding binary code that was generated based on the survey data. In the binary code column, a value of 1 is recorded when the mean rating in the "Low" column was higher than that of the "High" column and a value of 2 is recorded when the mean rating in the "High" column was higher than that of the "Low" column.

This binary code is converted into specific values that correspond to each control point. For example, the two possible values for P1x are -1.75 and -1.65, which corresponds to low and high, respectively. These values are passed to the MATLAB algorithm that generates new designs.

	P1x	P1y	P2x	P2y	P3x	P3y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	cur
IBN1	2	2	2	1	1	2	2	1	1	1	2	1	1	1	2
IBN2	2	2	2	1	1	2	2	1	2	1	2	1	1	1	2
IBN3	2	2	2	1	1	2	2	1	1	2	2	1	1	1	2
IBN4	2	2	2	1	1	2	2	1	2	2	2	1	1	1	2
IBN5a	2	2	2	1	1	2	1	1	1	1	2	1	1	1	2
IBN5b	2	2	2	1	1	2	2	2	1	1	2	1	1	1	2
IBN5c	2	2	2	1	1	2	1	2	1	1	2	1	1	1	2
IBN6a	2	2	1	1	1	2	2	1	1	1	2	1	1	1	2
IBN6b	2	2	2	2	1	2	2	1	1	1	2	1	1	1	2
IBN6c	2	2	1	2	1	2	2	1	1	1	2	1	1	1	2
IBN7a	2	2	2	1	1	2	2	1	1	1	1	1	1	1	2
IBN7b	2	2	2	1	1	2	2	1	1	1	2	2	1	1	2
IBN7c	2	2	2	1	1	2	2	1	1	1	1	2	1	1	2
IBN8a	2	2	2	1	1	2	2	1	1	1	2	1	2	1	2
IBN8b	2	2	2	1	1	2	2	1	1	1	2	1	1	2	2
IBN8c	2	2	2	1	1	2	2	1	1	1	2	1	2	2	2

Figure 3.9: Table of binary code used to generate new IBN designs

The factors represent x and y coordinates of a point, and so both factors are varied even if one factor in the pair is not statistically significant. Figure 3.9 provides a sample of the possible ways to manipulate the most statistically significant factors. The binary code on the last column of Table 5 provides the baseline from which new designs are generated. In Figure 3.9, these values are stored in the first row labeled IBN1, which generates "IBN1" in Figure 3.11.

The cells that are darkened in Figure 3.9 represent the factors that were varied to create new designs. These factors were selected because they had at least one measure that was significant at the 0.05 confidence level based on the two-sample t-tests and ANOVA results. There are many possible combinations of factor levels that could lead to new designs, but only 15 are shown. These 15 are based on changing the x and y values of each significant control point. For control points that had a main effect on one member of the x-y pair, the other member was varied. For example, Point 4x was shown to be significant, but not Point 4y. However, Point 4y was also varied since it is a member of the x-y pair that describes Point 4. Varying values of the x and y coordinates of more than two control points at a time would generate combinations beyond the 15 shown.

Each of the binary code strings was used in the algorithm to generate the corresponding silhouette to create a variety of designs. The designs that had a back end that looked too boxy or had abrupt changes in lines were excluded because the data showed that vehicles that were boxy in the back were rated as less inspired by nature and not perceived as environmentally friendly, as discussed earlier. In general, the code produces many designs, but some can be eliminated because they lead to patterns known not to fit the criteria derived from the survey data.

	P1x	P1y	P2x	P2y	P3x	P3y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	cur
V14	2	2	2	2	1	2	2	2	1	1	1	1	1	1	2
PEF1	2	2	2	2	1	2	1	2	1	1	1	1	1	1	2
PEF2	2	2	2	2	1	2	2	2	2	1	1	1	1	1	2
PEF3	2	2	2	2	1	2	1	2	2	1	1	1	1	1	2
PEF4a	2	2	2	2	1	2	1	1	1	1	1	1	1	1	2
PEF4b	2	2	2	2	1	2	2	1	1	1	1	1	1	1	2
PEF4c	2	2	2	2	1	2	1	2	1	1	1	1	1	1	2
PEF5a	2	2	2	2	1	2	2	2	2	1	1	1	1	1	2
PEF5b	2	2	2	2	1	2	2	2	1	2	1	1	1	1	2
PEF5c	2	2	2	2	1	2	2	2	2	2	1	1	1	1	2
PEFc1	2	2	2	2	1	2	1	1	2	1	1	1	1	1	2
PEFc2	2	2	2	2	1	2	2	1	2	1	1	1	1	1	2
PEFc3	2	2	2	2	1	2	1	2	2	1	1	1	1	1	2
PEFc4	2	2	2	2	1	2	1	1	1	2	1	1	1	1	2
PEFc5	2	2	2	2	1	2	2	1	1	2	1	1	1	1	2
PEFc6	2	2	2	2	1	2	1	2	1	2	1	1	1	1	2
PEFc7	2	2	2	2	1	2	2	1	2	2	1	1	1	1	2
PEFc8	2	2	2	2	1	2	2	1	2	1	1	1	1	1	2
PEFc9	2	2	2	2	1	2	1	2	2	2	1	1	1	1	2

Figure 3.10: Table of binary code used to generate new PEF designs

To create the designs with higher PEF, the binary code of vehicle 14 was used as a reference and Factors P4x, P4y, P5x and P5y were varied based on the results of the inferential statistics. Since PEF involved only 4 control points, 18 possible combinations were generated. Figure 3.10 shows the 18 possible variations that can be achieved from the data. Similar to the ideal IBN vehicles, those that deviated from the survey results (i.e., boxy back end) were not considered.

In Figures 3.9 and 3.10, the first few rows represent factors selected using the two-sample t-tests (i.e., IBN1 - IBN4 and PEF1 - PEF3). The other rows are based on results from the ANOVA that identify other factors that were statistically significant. For example, IBN5a - IBN5c represent a 5th category of vehicle that is varied based on P4x and P4y only.

3.3.1 Validation Study

A validation study was conducted using 3 of the 5 samples shown in Figure 3.11 to verify that these vehicles were rated by research participants as higher in PEF and IBN than the silhouettes in the original set. The samples were limited to 3 so as to manage the length of the survey. Vehicle PEF4a was used as Vehicle 18, IBN7a as Vehicle 19, and PEF4b as Vehicle 20. The three vehicles that had the least apparent sharp corners or boxy appearance were selected, since the data indicated such features are associated with lower PEF. We predicted that each of these vehicles would show the highest ratings in their respective scales (e.g., vehicles PEF4a and PEF4b would be rated highest on PEF, IBN7a would be rated as highly inspired by nature).

Gender			Age Groups			
F	M	N/A	18-30	31-50	51-70	70
24	21	1%	47.8%	43.5%	10.9%	0%

Table 3.4: Demographic information of the 46 respondents

A total of 46 new survey respondents participated in this validation study. These subjects were recruited from an engineering course and using Facebook. Table 3.4 lists the demographic information of the respondents.

The same survey design for the first study was used, except for the inclusion of the three new vehicle designs. Each of the main sections now had 20 vehicles for subjects to judge. Figure 3.12 indicates that the new Vehicle 19 is rated relatively high in PEF as well as in preference. Vehicle 19 has approximately the same PEF rating and lower PREF score than Vehicle 14, one of the original designs.

We predicted that Vehicle 19 would be rated the highest in IBN measures. Figure 3.13 shows that Vehicle 19 is rated second highest to another new vehicle, Vehicle 20. Again, this can be expected because the factors that influence judgments about IBN also include factors that influence PEF.

As before, inferential statistics were used to assess the factors that influenced the

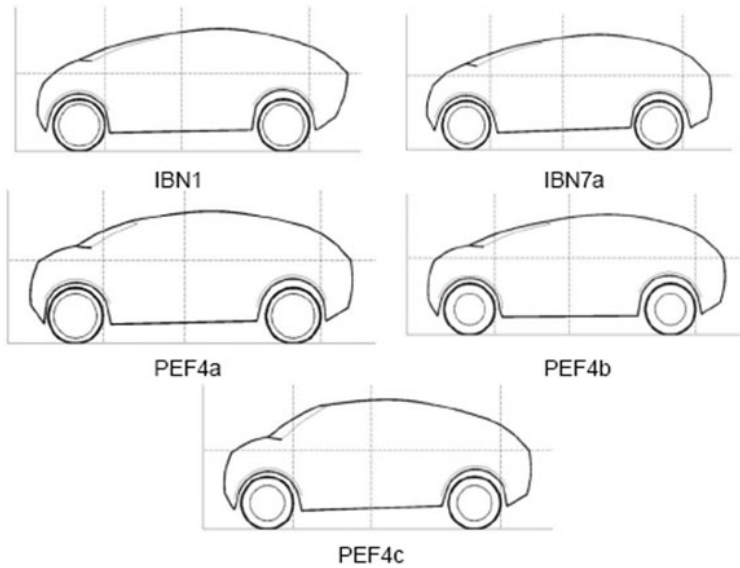


Figure 3.11: Examples of vehicle silhouettes developed form the survey data. See Figures 3.9 and 3.10 for binary code used to create these vehicles

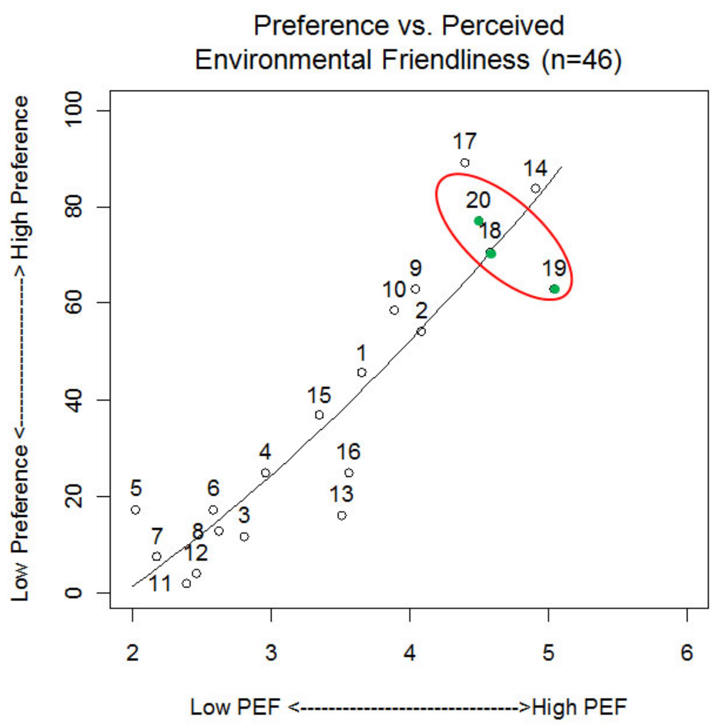


Figure 3.12: Scatterplot showing the correlation between preference and PEF (mean ratings on both variables). Vehicle 19 is relatively higher on PEF than some of the original designs

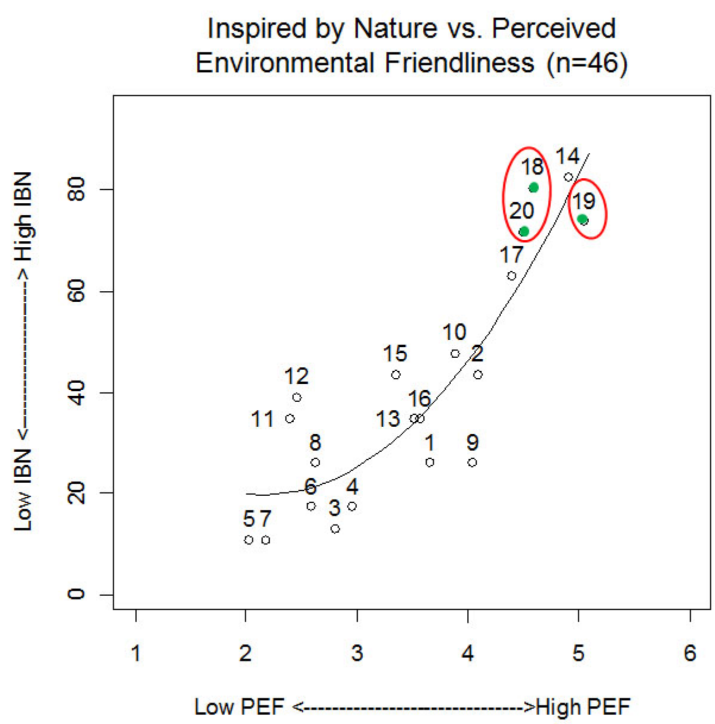


Figure 3.13: Scatterplot showing the correlation between IBN and PEF (mean ratings on both variables). Vehicles 19 and 20, which are new designs, are rated as more IBN and are relatively higher on PEF than the original designs and the Toyota Prius (Vehicle 17)

judgments. For PEF, the two-sample t-tests identified that low values for P5x and P5y have a significant effect on the judgments; the ANOVA showed significance on interactions between P4x and P4y, main effects on P5x and P5y, interactions between P2x and P2y, and interactions between P1x and P1y.

For IBN (rating), the two-sample t-test identified significance when there were low values for P5x and P5y and high values for P3y and the curvature factor. Similarly, the IBN (sorting) indicated significance when P1y, P3y, and P4x were high and when P3x, P5x, P5y, and P7x were low. Figure 3.14 summarizes the results of the two-sample t-tests for PEF and IBN. For the IBN (rating), the ANOVA indicated a main effect on P5x. For the IBN (sorting), there were main effects on P3x, P5x and P7x, and interactions between P1x and P1y.

	PEF	IBN-sort	IBN-rating
P1y	-	high	-
P3x		low	
P3y	-	high	high
P4x	-	high	-
P5x	low	low	low
P5y	low	low	low
P7x	-	low	-
cur	-	-	high

Figure 3.14: Summary of significant ($p < .05$) factors on the two-sample t-test for the validation study ($n = 46$)

The PEF and preference measures are highly correlated, $r(18) = 0.91$, $p < 0.01$ (Figure 3.12). Correlations also exist between PEF and IBN (sorting) $r(18) = 0.73$, $p < 0.01$ (Figure 3.13) and also between PEF and IBN (rating) significant, $r(18) = 0.88$, $p < 0.01$.

3.4 Using the data for Chapter 4

The results of this experiment provide some insight on the types of vehicle silhouettes that people associate with being environmentally friendly, the specific control points that significantly influenced the judgments, and the value of the level (i.e., "high" or "low) for those control points.

A model for PEF was developed using a regression analysis of the 10 most significant factors based on the survey results (see Appendix A for details). A combination of main effects and interactions were significant. A model that includes both main effects and interactions is shown in Equation (3.1).

$$PEF = \beta_{01} + \beta_{ix}P_{ix} + \beta_{iy}P_{iy} + \beta_{kx}P_{kx} + \sum(\alpha_{jxy}P_{jx}P_{jy}) \tag{3.1}$$

where $i = 5$, $j = 2, 4, 6, 7$, $k = 4$, and β_{01} is the intercept. A model that just considers the main effects is shown in Equation (3.2).

$$PEF = \beta_{02} + \sum(\beta_{ix}P_{ix} + \beta_{iy}P_{iy}) \tag{3.2}$$

where $i = \{2, 4, 5, 6, 7\}$ and β_{02} is the intercept for this model.

The main effects model, Equation (3.2) will be used in the optimization studies presented in chapter 4. This model was chosen because the design algorithm to create ideal PEF and IBN vehicles were based on main effects.

3.5 Discussion

This chapter presented a methodology for studying the perceived environmental friendliness of vehicle silhouettes. Analytical capabilities from both engineering and behavioral science were integrated.

We showed that perception-based attributes can be systematically quantified and used to develop new designs, some of which outperform existing 'green' vehicles, in terms of ratings of inspired-by-nature and perception of environmental friendliness. This ability to capture preference and evaluation beyond the confines of a typical marketing approach, such as conjoint analysis, is important for design studies. The proposed approach explored a set of designs that were not derived from existing vehicle models as done previously [*Dagher and Petiot* (2007); *Swamy et al.* (2007)].

Both main effects and interactions were examined to provide insight about how the factors may be influencing people's judgments. Previous work considered main effects only and acknowledged the need to examine interactions in studies of this kind [*Kokai et al.* (2007); *Orsborn et al.* (2006)]. Extensions of the current work on a binary code system can define distance metrics (e.g., the Hamming distance) that can be incorporated into an engineering optimization framework, and used to generate and choose new designs [*Hamming* (1950); *Daintith* (2010)].

The results are consistent with the hypotheses that were posed about the vehicle silhouettes. The first hypothesis stated:

> Subjects will assign higher perceived environmental friendliness (PEF) ratings to vehicle designs that have less abrupt line changes than those that have discontinuities or have a boxy shape.

Self-reports from subjects also indicate that some respondents based their judgments of environmentally friendliness on silhouettes that looked less boxy and had lines that were smoother. Though this result may seem obvious, the results quantitatively support this where the top 3 vehicle silhouettes: Vehicle 14 ($M = 5.12$, $SD = 1.38$), Vehicle 2 ($M = 4.56$, $SD = 1.45$) and Vehicle 17 ($M = 4.61$, $SD = 1.42$) are from the set with less abrupt changes in lines (see subsection 3.2.2). The second hypothesis stated:

> Subjects will assign higher PEF ratings to vehicle designs that are also

perceived as being inspired by nature compared to vehicles that are perceived low on Inspired By Nature (IBN).

The results showed there was a strong correlation between measures of PEF and IBN for both the first study and the validation study.

Unlike previous work, this study consisted of a very diverse subject pool, largely external to the university and engineering. Much of the prior studies recruited small samples of students from within their engineering departments and had a sample of up to 30 subjects [*Lai et al.* (2005); *Swamy et al.* (2007); *Orsborn et al.* (2009); *Achiche and Ahmed* (2008)]. Previous work primarily solicited subjects within their universities and their departments. The benefit of recruiting subjects external to the university and from a diverse population is that one can ensure a good mix of educational backgrounds, age-groups, geographic locations, all of which could influence judgments. This ensured that our results would be reflective of a diverse set of individuals and the range of preferences they represent.

3.6 Limitations

A general limitation in this work is that perceptions can change with time and this can certainly be true about 'green' perceptions. One extension is to embed the survey in a longitudinal design to allow modeling of changing perception over time. A further limitation is that automobile silhouettes are useful during the early conceptual stage, and later stages of development require more visual information, such as 3D body shapes. The method can be further extended by allowing for more complicated DOEs that permit testing of higher order interactions of the design factors. The combination of 3D body shapes with the ability to examine higher order interactions between factors will provide a rich framework in which to implement perception-based attributes in engineering design.

The experiment itself can be improved. The creation of the stimuli was done using a DOE to generate different combinations on the 15 variables to create each of the silhouettes. Only 2 levels for each factor were used, which limits the richness of the algorithm (e.g., can't assess non-monotonicity). The use of 3 levels would have provided more combinations from which subjects could choose, thus providing a finer resolution for assessing the judgments. In other words, the inclusion of a third level would help to assess if there were some mid-points that were more preferable. The reason the study used factors with two levels was to minimize the demand on the subjects. The decision was to have the first study include a broad range of control points to identify the critical ones for PEF. Future studies can limit the number of factors and increase the number of levels to three or even four. Although each combination of the two levels produced a silhouette that approximated a cross-over vehicle, there were some combinations of variables that produced silhouettes that looked more like an SUV. Furthermore, although subjects were given a list of assumptions to keep in mind, there is no guarantee that they referred to the list. For some of the in-person interviews, the experimenter noticed that some subjects never clicked the link to read the list of assumptions throughout the survey section that provided it. Perhaps they remembered them from the screen or simply resorted to their natural heuristics. Proportionality is an important factor that was not considered in this experiment but may have had some influence. Although subjects were told to assume that all the shapes were cross-over vehicles, there were some shapes whose proportions resembled a minivan or SUV. Although not directly related to proportionality, a recent study provided a means to measure some geometric relations that may provide some insight on features of the silhouette, though not directly related to proportionality [*Achiche and Ahmed* (2008)]. The geometric parameters included were the ratio of lines to curves (LCR) defined as $LCR = NL/(NC + NL)$ where NL is the number of lines and NC is the number of curves, the ratio of acute angles and obtuse angles (AOR), defined as $AOR = NAA/(NAA + NOA)$, where NAA is the number of acute angles and NOA is the number of obtuse angles. The authors also included a regularity level (RL) to compute the symmetry where a max value of 3 included all three planes of symmetry, $RL = \sum_1^3 R_i/3 \times 100$. The study assessed the "aggressiveness" of the forms. Forms that had more curves than straight lines were "friendly". Forms with more straight lines than curves were "aggressive". In essence, low LCR, AOR, and RL values equate to designs being friendly. A good follow up study would be to examine these ratios for each of the silhouettes and see which ones correlate to the trend in environmentally friendly judgments to better support the hypothesis.

CHAPTER IV

Engineering Optimization Study

The previous chapter discussed some motivators for quantifying the PEF attribute and its relevance to the automobile industry. Among them were consumers wanting to make a statement and the desire for automakers to differentiate their products as increasing numbers of fuel efficient vehicles saturate the market. The previous chapter also demonstrated that subjective attributes such as PEF can be quantified using standard techniques from the behavioral sciences. This chapter demonstrates how to use the PEF attribute in an optimal design framework and demonstrates the trade-offs that exist between performance and PEF attributes. A modified version of the model developed by *Frischknecht* (2009) is the basis of the optimization studies presented here. A methodology by which subjective attributes such as PEF can be included in an optimization framework is presented.

4.1 Introduction

Engineering optimization models typically focus on functional or objective design criteria. Engineers are not trained on how to include subjective criteria in the design process. The problem with doing design in this way is that the goals of the engineering designer may not align with the goals of the user. For example, a designer may have the goal to design a car that looks “cool” but a user perceives it to look "sporty". It is quite common for designers and consumers to perceive products differently [*Wolter et al.* (1989)]. This can pose a problem in the marketplace where it is well established that consumers often use subjective reasoning to make decisions about products they purchase, and if products don't appeal to consumers, then they may never be purchased. Consumers may start the decision process using objective attributes (e.g., "I need a fuel efficient car that gets at least 25 mpg") but among many alternatives, a consumer may use subjective attributes to narrow down a choice set (e.g., "I want to drive a car that looks green so that when people see me driving by, they will know that I care about the planet").

This situation poses a challenge to designers and engineers because what typically happens in automotive design is that engineers inform designers (stylists, for body design) of the necessary constraints to create a shape for the components of the vehicle [*Lewin* (2003)]. An additional challenge is how to quantify styles in ways that are explicit and produce repeatable results.

Efforts to include consumer preference and other subjective attributes in optimization models have been previously expended [*Thurston* (1991); *Kelly and Papalambros* (2007); *Orsborn et al.* (2009)]. However, the opportunity to include "green" styling criteria in optimization models for fuel economy has not been explored.

Design optimization is a decision-making process that involves the development of models that describe the artifact in question. The models used are often based on fundamental engineering principles and can only model the functional aspects of the artifact. This approach allows for the design of functional products and systems that meet specific design criteria. Important to this design process is the inclusion of other aspects of the system that exist, but must be quantified using methods from other disciplines.

The design of a fuel efficient vehicle requires methods from multiple disciplines. Michalek developed a model that combines engineering, marketing, and policy models to describe the impact of multiple stakeholder decisions on the design of a fuel efficient vehicle [*Michalek et al.* (2004)]. Follow up research conducted by Frischknecht expanded the models developed by Michalek as well as Georgiopoulos [*Frischknecht* (2009); *Georgiopoulos* (2003)]. Frischknecht's framework forms the basis of the optimization studies conducted here.

The remainder of this chapter consist of the following: Section 4.2 provides an overview of the framework that was developed by Bart Frischknecht and his accompanying MATLAB algorithm; Section 4.3 discusses model development; Section 4.4 presents the optimization studies conducted with the models; Section 4.5 shows a parametric study on PEF bounds to generate Pareto points; Section 4.6 discusses the desired optimal silhouettes; Section 4.7 and 4.8 give an overall discussion of the results and their limitations, respectively.

4.2 Background on the Framework

Frischknecht established a methodology that uses quantitative models to aid the decision making process based on two main interests of a firm: maximizing profit, a private interest, and maximizing sustainability, in the form of fuel consumption, which represents a public interest. This is achieved using an enterprise-wide tradeoff model where these competing interests are balanced with product design and price as primary decision variables. Figure 4.1 shows this decision-making framework with the inclusion of perceptual attributes, which are a function of the firm's decision variables [*Frischknecht et al.* (2009)]. This model can be used to examine scenarios for a single firm or multiple firms using a game theoretic model. Figure 4.1 shows the framework when multiple firms are taken into consideration.

Quantitative models are developed for each aspect of the product design process. Engineering design is described using a vector of performance criteria described as $\mathbf{z} = \mathbf{f}(\mathbf{x})$, where $\mathbf{x}$ are product design variables. The main design variables are related

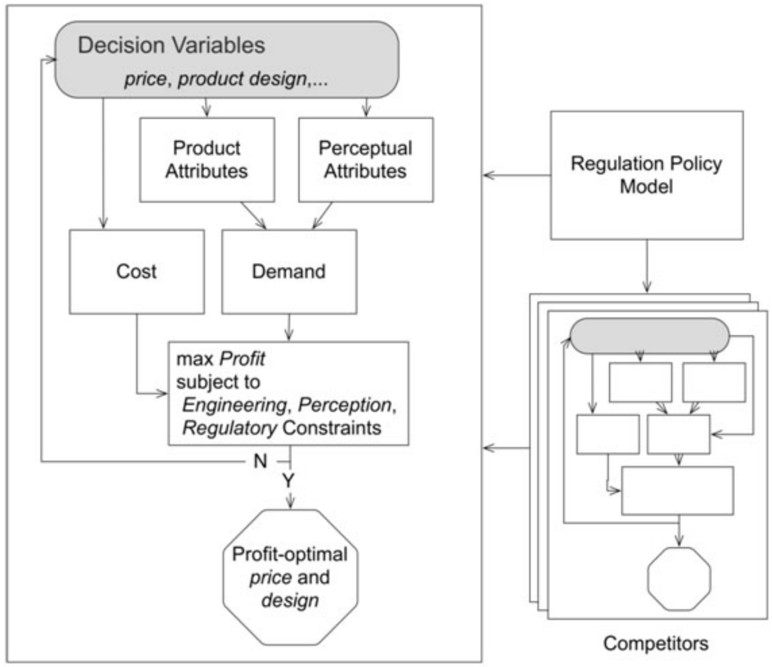


Figure 4.1: Flow diagram of Block-M decision-making framework

to engine performance and vehicle geometry. A consumer demand model is used for the marketing portion of the model where demand Q_j for product j is a function of its utility: $Q_j(\mathbf{U}_{ij}); i = 1, \ldots, I; j = 1, \ldots, J$, where $U_{ij} = u(\boldsymbol{\alpha}(\mathbf{z_j}), p_j)$ is the utility of consumer i as function of product attributes $\boldsymbol{\alpha}(\mathbf{z_j})$ at a given price, p_j. These three models are combined into a single formulation used to model the U.S. automotive market including regulatory constraints. The general form of the model is shown in Equation (4.1).

$$
\begin{aligned}
\max_{p,\mathbf{x}} \quad & \pi(p, \mathbf{x}; \mathbf{v}) \\
\text{subject to:} \quad & \textit{engineering constraints} \\
& \textit{regulatory constraints}
\end{aligned}
\tag{4.1}
$$

where π is the firm's profit function, the maximization objective as a function of the design variables $\mathbf{x}$ and price p, with a set of fixed parameters $\mathbf{v}$. The next few subsections discuss details of this model that are relevant to the studies conducted in this chapter.

4.2.1 Modeling Product Attributes

Product attributes $\boldsymbol{\alpha}$ are modeled as functions of product design variables. There are seven main design variables considered in this model: engine bore, x_{EB}; final drive, x_{FD}; engine bore to stroke ratio, x_{EBS}; vehicle length, x_{L103}; width, x_{W105}; height, x_{H101}; and wheelbase, x_{L101}.

It is assumed that the engineering models of vehicle performance are sufficient for describing the relationship between product design decisions and product attributes. The model is based on five-passenger mid-size crossover vehicles. The main product attributes examined include: fuel economy, acceleration, range, crashworthiness, and cargo capacity. Three powertrain options are considered including: gasoline spark-ignition internal combustion engine, gasoline turbocharged direct-injection internal combustion engine, and a split-mode hybrid vehicle design with a battery for energy storage, a gasoline internal combustion engine, and two electric machines for battery charging and locomotion.

4.2.2 Specific Vehicle Characteristics

The main vehicle characteristics considered are powertrain specification, packaging, and safety. Of specific interest here are powertrain and packaging. Details of safety will not be considered here.

4.2.2.1 Powertrain

Three models for powertrains are considered: spark-ignition (SI), gas turbo direct injection (GTDI) and hybrid-electric. A combination of software simulation tools, modeling, and experimental data are used to create models for each of these engines. Of interest is the SI powertrain because all the models developed later will be based on this powertrain. The model for this particular powertrain was developed using powertrain specs and vehicle parameters for a model similar to or the 2007 Ford Edge. Five performance tests were done to assess the US city driving cycle and the US highway driving cycle, which is used to calculate combined fuel economy, and an acceleration test was used to compute the vehicle's top speed and the time required to accelerate from 0 to 60 mph.

4.2.2.2 Packaging

Packaging is part of the design process that considers how people and other components will fit into a vehicle structure. In the model, packaging was based on simple assumptions about vehicle geometry, which includes engine length and cargo volume index behind the 2nd row seating, among others. Mass properties of the vehicle were considered, including vehicle curb weight, gross vehicle weight rating, and minimum required payload capacity. The curb weight was estimated using a regression based on 2005 light duty trucks from Ward's automotive yearbook [*Wards Communications* (2006)].

4.2.3 Modeling Consumer Preference

New models for consumer demand were developed using a large number of vehicle alternatives (473 models) to permit finer product differentiation between alternative vehicles. An ideal-point model is used to capture consumer preference for vehicle size defined as $length \times width$. The consumer demand model was developed based on existing consumer data for those that purchased cross-over vehicles and only focused on the product attributes of interest to consumers: those vehicles that existed at the time of purchase.

4.2.4 Summary

The optimization framework developed by Frischknecht provides a quantitative basis for studying the influence of marketing, engineering, and economic decisions for the design of fuel efficient vehicles, from the perspective of a single stakeholder: the firm. The model can examine both private and public objectives of the firm, to maximize profit and minimize environmental impact through fuel efficiency. The current model is set up to consider product attributes, consumer demand, and cost. The product attributes focus primarily on performance criteria and include a simple formulation for styling considerations of the consumer defined as $length \times width$. The model is structured to study changes in the market under different scenarios.

The remainder of this chapter will discuss changes that were made to Frischknecht's model to accommodate perceptual attributes as a decision variable of the firm. The models developed focus mainly on the impact of including perceptual attributes on the design of a fuel efficient vehicle, where profit is not an objective. The premise for this formulation is to understand the impact of styling criteria for PEF on "actual" environmental friendliness defined as fuel economy. Frischknecht's model provides a basis for studying a number of different aspects of vehicle design, although in the following we concentrate on the impact of design changes on the design of fuel efficient vehicles. Future research can examine the role of PEF on profit, but a more complete demand model needs to be developed for such a study.

4.3 Model Developments

The present research addresses the interaction between product and perceptual attributes. Figure 4.2 shows a diagram that specifies the decision variables of the firm, namely price, powertrain specifications, geometry and styling. Three variables directly impact functional criteria (i.e., fuel economy, acceleration, size) and visual preference (i.e., perceptual attributes) namely PEF in this particular study.

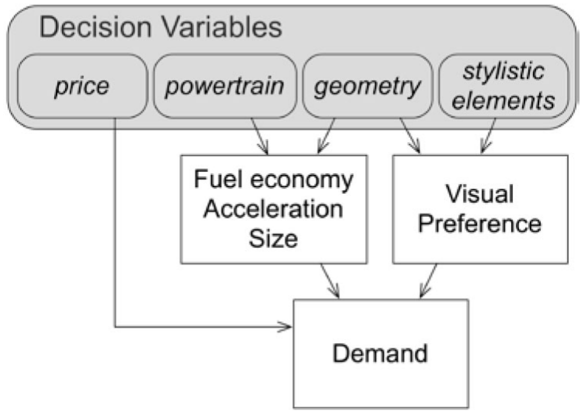


Figure 4.2: Flow diagram showing the role of perceptual attributes

The formal representation of this model is shown in Equation (4.2).

$$
\begin{aligned}
\max_{\mathbf{x}} \quad & FE(\mathbf{x};\mathbf{p}) \\
\text{subject to:} \quad & \textit{engineering constraints} \\
& PEF \textit{ constraints}
\end{aligned}
\tag{4.2}
$$

The objective is to maximize fuel economy (FE) with respect to design variables $\mathbf{x}$ and given some parameters $\mathbf{p}$, subject to engineering constraints and constraints imposed by PEF.

4.3.1 Geometry Considerations

The vehicle silhouettes studied in Chapter 3 provide limited information on the various dimensions that exist on actual vehicles. However, dimensions for length, height, and approximate cargo volume can be readily identified. The Society of Automotive Engineers (SAE) J1100 handbook provides standards on motor vehicle dimensions [*SAE International* (2005)]. Those that are relevant to the silhouette include: $L101$, the length of the wheelbase; $L103$, the overall length of the vehicle; $L104$, the distance from the center of the front wheel and the bumper where the engine is placed (i.e., the front overhang); and $H101$, the overall vehicle height. Figure 4.3 shows the SAE dimensions on the vehicle silhouette. Other dimensions of interest include the track width (W101) and body width (W105). These dimensions are held constant across all vehicle silhouettes.

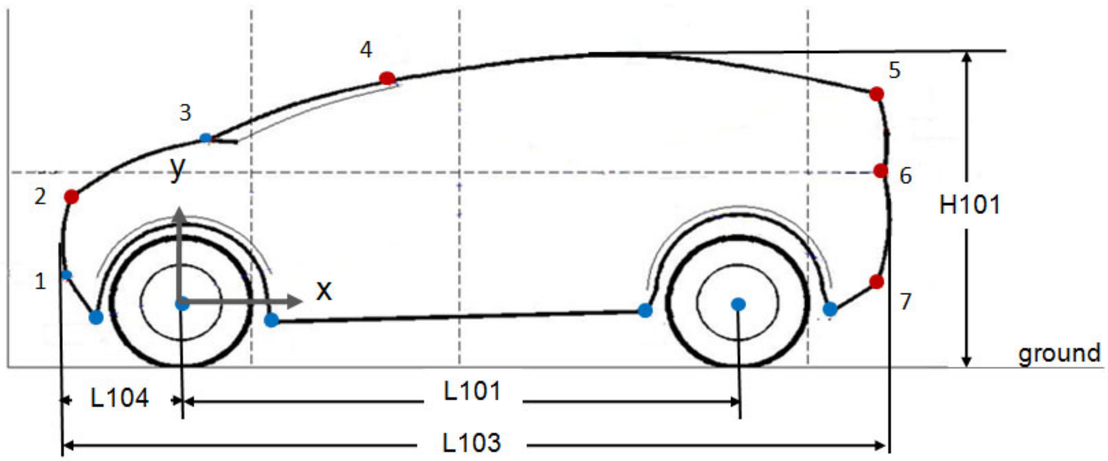


Figure 4.3: SAE dimensions used to describe the silhouette geometry

We now develop a connection between the silhouette used in Chapter 3 and the quantitative framework needed for the present optimization model. Upon inspection, the dimensions $H101$ and $L103$ can be written as functions of the control points and other points along the spline used in Chapter 3. They are defined as Euclidean distances between the extreme points of the silhouette. It was observed that using Points 1 and 6 provided the best estimate for the overall vehicle length as shown in Equation (4.3). A constant C is included in both models which includes scaling and a conversion factor to put the dimensions in units of mm, as will be discussed further below.

$$L103 = ||x_{P1} - x_{P6}|| \times C \tag{4.3}$$

The highest point of the vehicle may vary as new designs are generated. There are three variations that have been observed: when Point 4 is higher than Point 5, when point 5 is higher than point 4, and when point between them (a mid point not visible) are higher, as shown in Figure 4.3. Equation (4.4) is used to compute the overall height which requires the identification of the highest point, P_{top}.

$$H101 = ||y_{P_{top}} - ground|| \times C \tag{4.4}$$

The identification of point P_{top} is done easily for designs already generated. However, this poses a problem when the highest point is not already known prior to optimization. The engineering model requires a minimum height for the vehicle that allows a driver or passenger to sit. Since P_4 is located in the region just above the driver seat, we set $P_{top} = P_4$ to ensure that the seating criteria are met (see Section 4.4). Equation (4.5) will be used in the model.

$$H101 = ||y_{P4} - ground|| \times C \tag{4.5}$$

The model developed by Frischknecht used vehicle characteristics for mid-size crossover vehicles. A scaling factor of 1.21 was used to ensure that the dimensions of the silhouette were within the acceptable range with respect to the upper and lower bounds in the model. This factor was included in the parameter C in Equations (4.3)-(4.5).

The dimensions $H101$ and $L103$ provide the geometric basis for studying the influence of PEF on the design of a fuel efficient vehicle.

4.3.2 PEF Model

The analysis presented in Chapter 3 allows for a PEF regression model to be developed based on the most significant factors that influenced PEF. Recall that the

Control Point	Coefficient	Value
	intcpt	18.53631801
$P2x$	β_1	0.742725625
$P2y$	β_2	-1.019072917
$P4x$	β_3	0.640592125
$P4y$	β_4	-0.76652625
$P5x$	β_5	-0.44144525
$P5y$	β_6	-0.719213594
$P6x$	β_7	0.065708437
$P6y$	β_8	-0.27742225
$P7x$	β_9	-0.41492225
$P7y$	β_{10}	0.14402375

Table 4.1: List of beta values for PEF model

x and y coordinates of Points 2, 4, 5, 6, and 7 were the most significant. The model of PEF can be described as shown in Equation (A.1).

$$PEF = \beta_{02} + \sum_{i=2}^{7} (\beta_{ix} P_{ix} + \beta_{iy} P_{iy}) \tag{4.6}$$

where $i = 2, 4, 5, 6, 7$ correspond to the control points and β_{02} is the intercept. The coefficients and their control points are listed in Table 4.1. A regression was run using the most significant controls points of the 16 vehicles as descriptors and the mean ratings as predictors (see Appendix A for details). This model has a $R^2 = 0.85$ correlation with actual values. Equation (A.1) will be used in a bi-objective optimization of a fuel efficient vehicle.

4.3.3 Fuel Economy Model

The fuel economy of a vehicle depends on a number of factors including vehicle weight, powertrain specification, and drag coefficient. Corporate Average Fuel Economy (CAFE) is a government standard based on the sales-weighted average fuel economy that an automaker's fleet of passenger cars and light trucks sold in the US achieves in any given model year [*NHTSA* (2004); *EPA* (2004)]. Based on the CAFE standards, a model for fuel economy was created by Frischknecht using the powertrain simulation package *Cruise* [*AVL* (2008)]. Performance tests are computed for the US city driving cycle Equation (4.7), and the US highway driving cycle Equation (4.8). The two measures are used to compute combined fuel economy of a vehicle based on 2006 EPA reporting methods which give a weight of 55% to city driving and 45% to highway driving, Equation (4.9).

$$MPGCycUSCity = \frac{1}{\frac{1.609344 CycUSCity}{100\times 3.786235}} \tag{4.7}$$

$$MPGCycUSHwy = \frac{1}{\frac{1.609344 CycUSHwy}{100\times 3.786235}} \tag{4.8}$$

Details of how the values for $CycUSCity$ and $CycUSHwy$ are calculated are discussed in Frischknect's PhD dissertation [*Frischknecht* (2009)]. They were developed using polynomial surrogate models obtained from *Cruise* simulations. The specific vehicle characteristics that influenced these models include: engine bore, engine bore to stroke ratio, final drive, H101, L101, L103, W105, and coefficient of drag,C_D. The first seven of these characteristics are design variables used in the model and the drag coefficient is set as a parameter. It can be generally stated that $CycUSCity$ and $CycUSHwy$ are expressed as functions $f(\mathbf{x}, p)$ where $\mathbf{x}$ is a vector of the seven vehicle characteristics, namely $\mathbf{x} = [x_{EB}, x_{EBS}, x_{FD}, x_{H101}, x_{L101}, x_{L103}, x_{W105}]$ and p is a parameter for the drag coefficient. Equations (4.7) and (4.8) are combined to compute the overall fuel economy, Equation (4.9),further below.

$$CombinedFuelEconomy = \frac{1}{\frac{0.55}{MPGCycUSCity} + \frac{0.45}{MPGCycUSHwy}} \tag{4.9}$$

4.3.4 Summary

This subsection presented the geometry considerations, the PEF model developed, and the fuel economy model previously developed by Frischknecht. The next subsection will discuss how these models are used in an optimization framework.

4.4 Optimization Studies

Three optimization studies are now conducted and compared. The first two are single objective (SO) optimization studies that maximize fuel economy without PEF constraints. This first study presents the results from using the original fuel economy model developed by Frischknecht. The second study assesses the performance of a revised fuel economy model modified to include replace L104 and H101 with Equations (4.3) and (4.5), respectively and is used as a basis for comparison of subsequent optimization studies. The third study maximizes fuel economy subject to a PEF constraint. The purpose of this study is to examine the tradeoffs that exist between fuel economy and PEF. The second study provides an additional means for creating new designs that are optimized both for fuel economy and PEF considerations. The third study is followed by a parametric study on the PEF bound to generate a Pareto tradeoff representation for maximizing both the fuel economy and PEF.

A SO optimization problem seeks to minimize or maximize a single design objective while satisfying the constraints of the artifact or process being designed. Such problems typically have a single solution that represents a compromise between all objectives [*Ngatchou et al.* (2005)]. MO optimization problems can be represented as a SO problem by assigning weights to each objective and summing the product of the weights and each objective [*Papalambros and Wilde* (2000)]. A limitation with this approach is that the relative importance of each objective must be known a priori and requires several iterations so that trade-offs become more apparent [*Ngatchou et al.*

(2005); *Papalambros and Wilde* (2000)].

A common approach for studying MO optimization problems is by identifying the Pareto set of solutions. A solution belongs to the Pareto set if one objective cannot be improved without causing one or more of the other objectives to deteriorate. Figure 4.4 shows the Pareto set of solutions for a bi-objective maximization problem, characteristic of what will be studied in later sections. The darkened region represents the "efficient frontier" of the feasible space and is also known as the Pareto-optimal set.

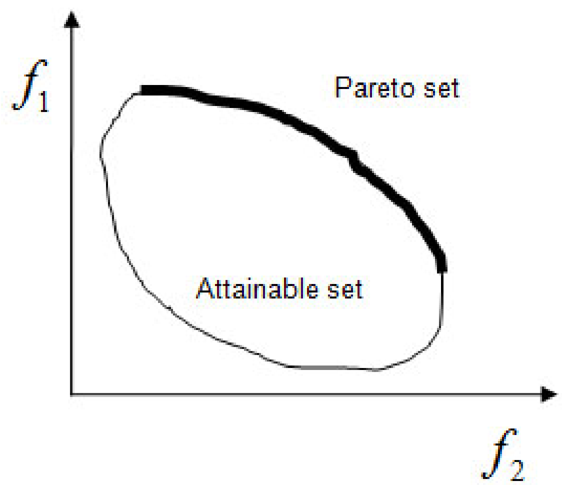


Figure 4.4: Pareto set for a bi-objective maximization problem

The specific approach used here to generate Pareto points is to optimize one objective while using the second objective as a constraint. Here, fuel economy is maximized subject to a constraint that ensures a maximum PEF value. Section 4.4 shows the results for the first two studies; Section 4.4 shows the results for the third study.

Single Objective: Maximizing Fuel Economy

Two SO optimization studies were conducted using the original fuel economy model developed by Frischknecht as described in Section 4.3 and a modified version of this model which replaces L103 and H101 with Equation 4.3) and (4.5), respectively. The objective is to maximize fuel economy with respect to design variables $\mathbf{x}$ and parameters p, subject to only engineering constraints as shown in Equation (4.10).

$$\begin{aligned} \max_{\mathbf{x}} \quad & FE(\mathbf{x};\mathbf{p}) \\ \text{subject to:} \quad & \textit{Engineering constraints} \end{aligned} \tag{4.10}$$

The design variables of interest are engine bore, x_{EB}; final drive, x_{FD}; engine bore to stroke ratio, x_{EBS}; vehicle length, x_{L103}; width, x_{W105}; height, x_{H101}; and wheelbase, x_{L101}. Recall that in the modified model, x_{L103} and x_{H101} are defined as functions of control points $P6x$ and $P4y$, respectively, see Equations (4.3) and (4.5). This allowed the computed positions of the control points to dictate the values for $H101$ and $L103$ thus capturing the influence of PEF in the model. The variable for the wheel base, x_{L101}, was included as a parameter in the model.

These dimensions serve as inputs to a number of other design criteria including cargo volume, speed, and vehicle mass, which in turn impacts safety criteria and vehicle center of gravity. Therefore, changes in these variables will impact not only fuel economy but other vehicle aspects as well. The x and y coordinates of the control points from the PEF function are included as variables. Table 4.2 shows the complete set of variables considered.

Equations (4.11) - (4.27) list the constraints in the original fuel economy maximization model. They represent performance criteria and other vehicle characteristics that are typical for a crossover vehicle. Specifically, the constraints consider: safety, Equations (4.16) and (4.18); performance, Equations (4.11), (4.25), and, (4.27); geometry, Equations (4.22), (4.13), (4.14), (4.20), (4.20), and (4.21); and cargo volume, Equations (4.14) and (4.15). Other constraints in the Frischknecht model were relaxed

Variable	Description	Lower Bound	Upper Bound
x_{EB}	Engine Bore	86	100
x_{FD}	Final Drive	1.1	4.0
x_{W105}	Width of the Track	1600	2000
x_{EBS}	Engine Bore Stroke Ratio	0.95	1.18
x_{P2x}	x-coordinate of point 2	-1.6	-1.4
x_{P2y}	y-coordinate of point 2	1.6	1.9
x_{P4x}	x-coordinate of point 4	2.0	3.0
x_{P4y}	y-coordinate of point 4	3.0	4.1
x_{P5x}	x-coordinate of point 5	8.5	10.0
x_{P5y}	y-coordinate of point 5	3.2	4.0
x_{P6x}	x-coordinate of point 6	10.0	10.5
x_{P6y}	y-coordinate of point 6	2.0	2.5
x_{P7x}	x-coordinate of point 7	10.1	10.5
x_{P7y}	y-coordinate of point 7	0.3	0.4
x_{H101}	Vehicle height, a $f(x_{P4y})$	1600	1930
x_{L103}	Vehicle length, a $f(x_{P6x})$	3556	5080
x_{L101}	Wheelbase parameter	2286	3048

Table 4.2: List of design variables and their bounds

to allow for a greater degree of design freedom.

Table 4.2 shows the lower and upper bounds for the design variables listed.

$$
\begin{aligned}
g_1 &= 5\% - Grad65Tow \leq 0 && (4.11)\\
g_2 &= 13^\circ - A107 \leq 0 && (4.12)\\
g_3 &= 12^\circ - A147 \leq 0 && (4.13)\\
g_4 &= 29 \text{ ft}^3 - CVI \leq 0 && (4.14)\\
g_5 &= CVI - 60 \text{ ft}^3 \leq 0 && (4.15)\\
g_6 &= Rollover - 0.1 \leq 0 && (4.16)\\
g_7 &= 50\% - 100\,(1 - CG_{long} - L104/L101) \leq 0 && (4.17)\\
g_9 &= MinCrushSpace - CrushSpace \leq 0 && (4.18)\\
g_{11} &= (2TireFlop + 2MidRailWidth + EngLength + 50.8) && \\
&\quad -(W105 - 254) \leq 0 && (4.19)\\
g_{12} &= L101 + L104 - L103 \leq 0 && (4.20)\\
g_{14} &= MinSitHeight - H101 \leq 0 && (4.21)\\
g_{30} &= (TireDynRollRad + 10 * 25.4) - L104 \leq 0 && (4.22)\\
g_{34} &= MinCargoMass - VehCargoFullMass \leq 0 && (4.23)\\
g_{37} &= AccelTestFront - 9.81 * MaxAccelTestFront \leq 0 && (4.24)\\
g_{39} &= Acc3050Tow - Max30to50 \leq 0 && (4.25)\\
g_{44} &= MPGConstraint - CombinedMPG \leq 0 && (4.26)\\
g_{45} &= MinTopSpeed - MaxTopSpeed \leq 0 && (4.27)
\end{aligned}
$$

The results of the optimization are shown in Table 4.4. The first column labeled as “MPG only-original” contain the results of the model developed by Frischknecht. The initial values for the variables are shown in Table 4.3.

In Table 4.4, it can be observed that the combined fuel economy is 23.21 mpg with

x_{EB}	x_{FD}	x_{EBS}	x_{L103}	x_{W105}	x_{H101}	x_{L101}
-0.150285714	0.5	-0.244484848	0.086666667	0.40	0.4488	0.277997365

Table 4.3: Initial values for the seven design variables

			Study 1	**Study 2**
Description	Variables	Units	MPG only original	MPG only revised
Objective	Combined FE	mpg	23.21	23.61
	MPG City	mpg	21.84	22.13
	MPG Hwy	mpg	25.13	25.71
Design Variables	L103	mm	4712.6	4420.0
	W105	mm	1885.8	1881.3
	H101	mm	1703.6	1703.6
	Eng Bore	mm	87	86
	Eng Bore Stroke	-	1.05	1.18
	Final Drive	-	3.62	3.59
	L101	mm	2752.3	3009.5
Performance Measures	Accel:from 0-60 mph	sec	7.96	9.71
	Max Speed	mpg	115	129.3
	Tow Grade	degrees	5	5
	CVID	ft^3	29	29

Table 4.4: Results of the single objective optimization to maximize fuel economy with two model variants (studies 1 and 2)

the city and highway fuel economy being 21.84 mpg and 25.13 mpg, respectively. The geometry variable values are overall vehicle length, $L103 = 4712.6mm$, track width, $W105 = 1885.8mm$, overall height, $H101 = 1703.6mm$ and wheelbase, $L101 = 2752.3mm$. Performance variable values are time to accelerate from rest to 60 mph of 7.96 seconds, maximum speed of 115 mph, tow grade of 5 degrees, and a minimum cargo volume of 29 ft^3.

In this model, there were six active constraints. Note that a constraint is active when it's removal can affect the value of the optimum [*Papalambros and Wilde* (2000)]. These active constraints are max gradeability, which estimates the percent grade achievable at 65 mph while towing a trailer (Equation (4.11)), minimum cargo volume (Equation (4.14)), rollover score (Equation (4.16)), minimum seating height (Equation (**??**)), front wheel clearance (Equation (4.22)), and minimum top speed (Equation (4.27)).

The results of the revised model are listed in the second column under the heading "MPG only-revised". The combined fuel economy is 23.61 mpg with the city and highway fuel economy being 22.13 mpg and 25.71 mpg, respectively. Compared to the original model, the revised model achieves better fuel economy. This is due to changes in the geometry, i.e., the overall length $L103 = 4420mm$, track width, $W105 = 1881.3mm$, and the wheel base $L101 = 3009.5mm$, which is a parameter for the revised model. The value of the overall height remains the same.

Note that Table 4.2 shows the acceptable range for these geometric dimensions. The values obtained indicate smaller sized cross-over vehicles are designed in the revised model. The wheelbase parameter $L101$, is on the higher end of the acceptable range. The vehicle front overhang is the dimension $L104$ shown in Figure 4.3. The value for $L104$ is obtained by subtracting the wheelbase from the overall length (i.e., $L104 = L103 - L101$). With an overall shorter vehicle length and an overall longer wheelbase, we find that $L104$ will be smaller thus reducing the space for the engine. This necessitates a design that uses the smallest engine possible, hence the engine bore and engine bore-to-stroke ratio hit their lower and upper bounds, respectively.

Like the original model, several constraints were active. Table 4.5 lists the constraints that were active for the original and revised fuel economy models. Note here that some of the same constraints are active for both models. For the revised model, g_{30}, the front wheel clearance and g_{45}, the minimum top speed become inactive; the lower bound constraint on the engine bore and the upper bound constraint on the engine bore-to-stroke ratio become active.

These results provide a baseline of how the fuel economy model performs under the conditions presented. We now examine how the design changes with the inclusion

Constraint	Original Model	Revised Model
g_1: TowGrad65	active	active
g_4: MinCVID	active	active
g_6: Rollover Score	active	active
g_{14}: MinH101	active	active
g_{30}: Tire Dynamic Roll	active	inactive
g_{45}: MinTopSpeed	active	inactive
Lower Bound on Engine Bore	inactive	active
Upper Bound on Engine Bore-to-stroke	inactive	active

Table 4.5: Summary of constraint activity in original and revised fuel economy models

of PEF as a constraint.

Maximizing Fuel Economy with a PEF Constraint

The objective of this third study is to maximize fuel economy with respect to design variables $\mathbf{x}$ and parameters $\mathbf{p}$, subject to engineering constraints and PEF constraint based on Equation (A.1).

The inclusion of a PEF constraint ensures that vehicle designs will satisfy the visual requirements necessary to capture the "green" styling cues required by the consumer. The intent is to concurrently consider objective and subjective attributes in the optimization by imposing PEF as a constraint.

The highest attainable value obtained from the PEF model, Equation (A.1), is 4.7314. This value is obtained by setting all the control points to their upper or lower bounds for variables that had positive or negative coefficients respectively. Therefore, the PEF constraint is set to be at a value lower than that, specifically 4.5:

$$g_{47} = 4.5 - \sum_{i=2}^{7} \beta_{ix} P_{ix} + \beta_{iy} P_{iy} \leq 0 \tag{4.28}$$

where $i \neq 3$. A constraint was placed on x_{P4y} and x_{P5y} to allow x_{P4y} to have more freedom since it directly affects $H101$, Equation (4.29):

$$g_{48} = x_{P5y} - x_{P4y} \leq 0 \tag{4.29}$$

Further discussion on the selection of the PEF lower bound at 4.5 is given in the next section. The high and low levels for each control point from Chapter 3 were used as upper and lower bounds as shown in Table 4.2. Recall these levels were used in the Design of Experiment to generate the original 16 vehicles shapes as well as the 3 silhouettes used in the validation study (i.e, Vehicles 18-20). It was found that there were no feasible solutions using the original bounds for the control points due some of the constraints that were a function of H101. As a result, the original bounds on P4y were relaxed to $3.2 \leq P4y \leq 4.1$ and the lower bound on P6x was relaxed to 10 in order to accommodate the geometry and performance constraints in the model. The original bounds for P4y were $3.4 \leq P4y \leq 3.7$ and the original lower bound on P6x was 10.1.

The results of the third optimization study are presented in Table 4.6 along with the two previous ones: The results from the two optimization studies discussed in Section 4.4 and the results for the revised fuel economy model with a constraint on PEF with two different lower bounds, 4.5 and 4.731.

Since the PEF constraint was not used in Study 2, only two of the values of the control points are shown since they are functions of H101 and L103. The other eight control points are not shown because their values depend on PEF.

Upon inspection of Table 4.6, it can be seen that there is no change in the fuel economy with the inclusion of the PEF constraint as defined in Equation (4.28). However, the model was re-run with a larger PEF bound: $4.731 - PEF \leq 0$. Recall that the maximum achievable value for PEF was 4.7314. The results are listed in the column labeled "MPG with 4.731-PEF" and it can be seen that as PEF increased, the fuel economy decreased. There are a number of explanations for this. First, the overall length increased from $L103 = 4420mm$ to $L103 = 4550mm$. This length changed as a result of the value for P6x increasing, almost hitting its upper bound. Note the arrows located next to each of the control points from P2x to P7y. An up arrow indicates the value of the control point should increase in order to maximize PEF; a down arrow indicates the value should decrease to maximize PEF. This is in accordance to the signs of the coefficients in Table 4.1.

It seems counterintuitive that a more PEF vehicle would get longer when heuristics seem to tell us that a smaller car is more green. Recall that one of the conclusions of Chapter 3 was that vehicles that had more curved lines were perceived to be more environmentally friendly than those with abrupt changes. An increase in P6x would cause the segment between Point 5 and Point 6 to stretch and produce more of a smooth curve. Vehicle shapes that had lower P6x values tended to make the segment from Point 5 to 6 get boxy. In the study presented in Chapter 3, there were only 2 possible values for P6x: 10.1 or 10.5. Some of the best PEF vehicles, such as vehicles 10, 14, 19, 20, had P6x values of 10.1 and only one PEF vehicle had a P6x value of 10.5. The highest value obtained with the max PEF constraint is 10.442 and the lowest value is 10.095, which are very close to the original values. Figure 4.5 below provides a visual of the tradeoffs that exist with changes in the overall length.

Further, the case"MPG with 4.731-PEF" leads to a vehicle that has a longer length and is slightly wider than the case of "MPG with 4.5-PEF" model. As a result, there is a slight decrease in the fuel economy since the increase in these dimensions increases the vehicle mass. The increase in the vehicle mass also affects some of the performance measures shown in the table, namely, it produces a decrease in the maximum speed and an increase in the time to accelerate from 0 to 60 mph. The increase in the length and width of the vehicle adds more volume to the cargo area, noted as the CVID,

			Study 1	**Study 2**	**Study 3a**	**Study 3b**
Description	Variables	Units	MPG only original	MPG only revised	MPG with 4.5-PEF	MPG with 4.731-PEF
Objective	Combined FE	mpg	23.21	23.61	23.61	23.59
	MPG City	mpg	21.84	22.13	22.13	21.91
	MPG Hwy	mpg	25.13	25.71	25.71	25.43
Design Variables	L103	mm	4712.6	4420.0	4420.0	4549.6
	W105	mm	1885.8	1881.3	1881.3	1885.5
	H101	mm	1703.6	1703.6	1703.6	1703.6
	Eng Bore	mm	87	86	86	86
	Eng Bore Stroke	-	1.05	1.18	1.18	1.18
	Final Drive	-	3.62	3.59	3.59	3.64
	P2x(↑)	-	-	-	-1.443	-1.4
	P2y(↓)	-	-	-	1.602	1.6
	P4x(↑)	-	-	-	2.756	3.0
	P4y(↓)	-	-	3.915	3.915	3.915
	P5x(↓)	-	-	-	8.519	8.5
	P5y(↓)	-	-	-	3.202	3.2
	P6x(↑)	-	-	10.095	10.095	10.442
	P6y(↓)	-	-	-	2.027	2.0
	P7x(↓)	-	-	-	10.1	10.1
	P7y(↑)	-	-	-	0.397	0.4
Performance Measures	Accel:from 0-60 mph	sec	7.96	9.51	9.51	9.62
	Max Speed	mpg	115	129.3	129.3	128.5
	Tow Grade	degrees	5	5	5	5
	CVID	ft^3	29	29	29	35
Parameters	L101	mm	2752.3	3009.5	3009.5	3009.5

Table 4.6: Optimization Study Results. The arrows indicate the direction of variable values under max PEF conditions

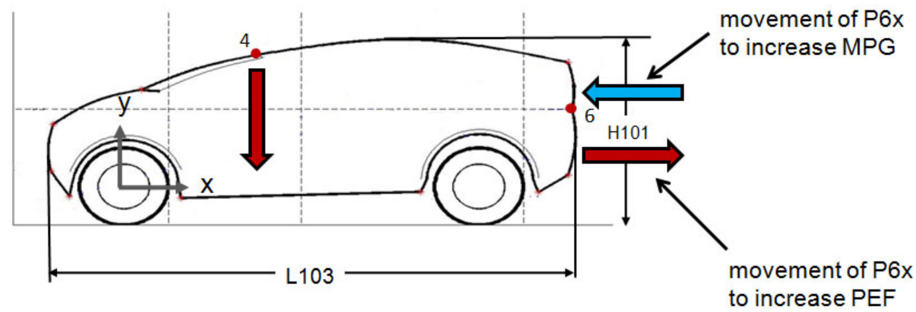


Figure 4.5: Pictorial representation of tradeoffs between PEF and MPG through P6x

and the tow grade remain unchanged.

Monotonicity Analysis is a technique that provides a means for identifying constraint activity, reducing the problem to search for fewer variables in a limited feasible region and also provides insight to the designer, thus negating the need for extensive experience [*Papalambros and Wilde* (1979)]. Monotonicity Analysis predicted that several constraints would be active, see Appendix D. Those constraints include the upper and lower bound for the engine bore, engine bore-to-stroke ratio, respectively, and some of the same non-linear constraints that were active in the single objective optimization discussed in Section 4.4. Table 4.7 summarizes the constraint activity for the optimization studies presented here and Table D.1 in Appendix D has the complete monotonicity table that was used.

4.5 Parametric Study on PEF: Pareto Points

In design optimization problems, parameters are values that are set by the designer in order to proceed with model development [*Papalambros and Wilde* (2000)]. The values selected are set for the particular application under study and are not based on any underlying phenomenon. A parametric study is needed to examine how changes in those parameter values affect the optimum to ensure its validity. In Section 4.4, changes to the PEF constraint influenced the value of the optimum which indicates

Constraint	MPG with 4.5-PEF	MPG with 4.731-PEF
g_1: TowGrad65	active	active
g_4: MinCVID	active	inactive
g_6: Rollover Score	active	active
g_{14}: MinH101	active	active
g_{47}: PEF constraints	active	active
Engine Bore	LB active	LB active
Engine Bore-to-stroke	UB active	UB active
P2x	-	UB active
P2y	-	LB active
P4x	-	UB active
P5x	-	LB active
P5y	-	LB active
P6y	-	LB active
P7x	UB active	UB active
P7y	-	UB active

Table 4.7: Summary of constraint activity between original and revised fuel economy models

the need for a parametric study. In a bi-objective problem $\max_{f_1,f_2}$, Pareto points can be completed by solving the problem $\max_{f_1}, sub.to.f_2 \geq \mathbf{F_2}$ for different values of the parameter F_2. We follow the approach here.

A parametric study is conducted on the PEF constraint by varying the minimum value of PEF from 3.5 to 4.731. Figure 4.6 shows the results. The complete details have been included in Appendix D.

It can be seen that changes in the PEF constraint do not affect the optimum fuel economy when the PEF bound goes from 3.5 to 4.7. During this range, several constraints are always active: Grad65Tow, Rollover, and MinH101. The PEF constraint has conditional activity with respect to control points that hit their bounds and during instances where the optimizer finds a combination of values that produce an exact minimum PEF value (see Appendix D). The lower bound on the engine bore variable and the upper bound on the engine bore-to-stroke ratio also remain active. The changes in the vehicle geometry influence these values to hit their bounds in order

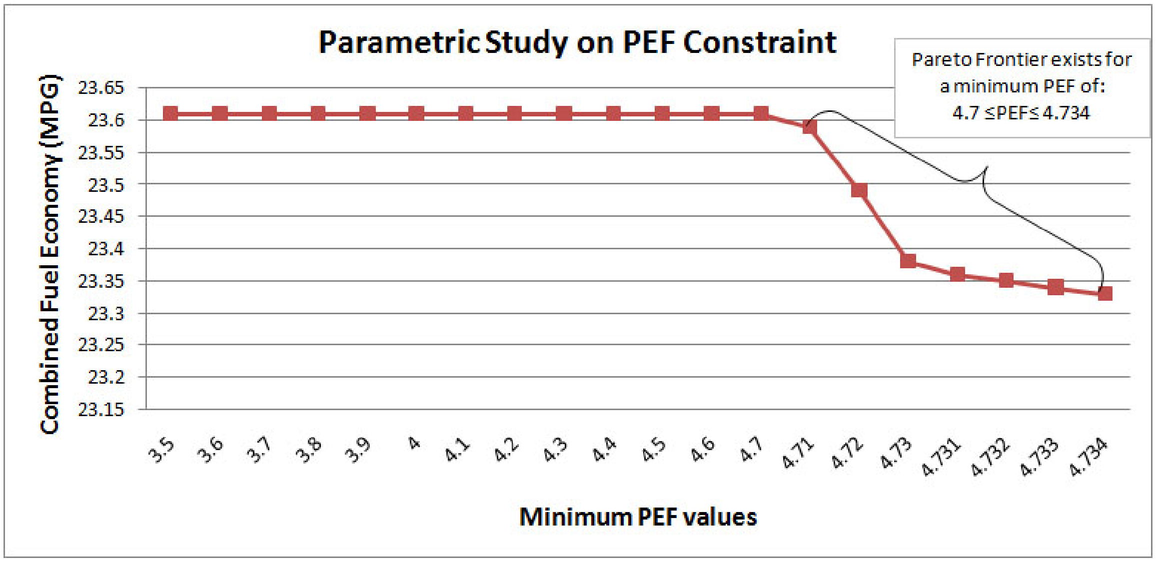


Figure 4.6: Results of a parametric study done on the PEF constraint

to make a smaller engine. Notice the difference in the values for the L104 between the original fuel economy model and those of the revised model. The reduced amount of space in the front requires that the design uses the smallest engine possible.

When the PEF bound value is varied from 4.71-4.734, there is a tradeoff that takes place between PEF and fuel economy. As PEF increases, the fuel economy decreases. The main variable influencing this tradeoff is P6x which affects the length. In essence, as the length of the vehicle increases, PEF increases, and as expected the fuel economy decreases. In this range, the PEF constraint becomes active and dominates the minimum cargo volume constraint, which becomes inactive. The minimum cargo volume constraint is no longer active because the increased length provides additional volume thus ensuring that the minimum cargo volume requirement is met. These results are consistent with what was predicted using monotonicity analysis (see Appendix D for details). It was shown that the PEF constraint and the minimum cargo volume constraint would have conditionally activities with respect to P6x and that the eight control points that are not part of the optimum will hit their bounds.

The points with PEF bound above 4.7 in Figure 4.6 represent Pareto points for the problem $\max_{MPG,PEF}$. It appears this Pareto set is nonconvex, which requires further investigation.

4.6 Optimal Silhouettes

The optimization study provided another method for generating new silhouettes. Recall from Chapter 3 that a silhouette can be generated using fourteen x and y coordinate values with a 15th variable that controls the curvature. The results of the survey was used to provide the acceptable bounds for generating new silhouettes.

The values of the control points in Table 4.6 are used to generate new designs that consider fuel efficiency. The other five variables are held fixed as parameters. Figure 4.7 shows a silhouette using the control points identified in the "MPG with 4.5-PEF" and Figure 4.8 shows the "MPG with 4.731-PEF" silhouette. As expected from the values of the control point, it can be seen that the two figures look very similar, though the slight increase in P6x in the "MPG with 4.731-PEF" shape creates a point in the backend.

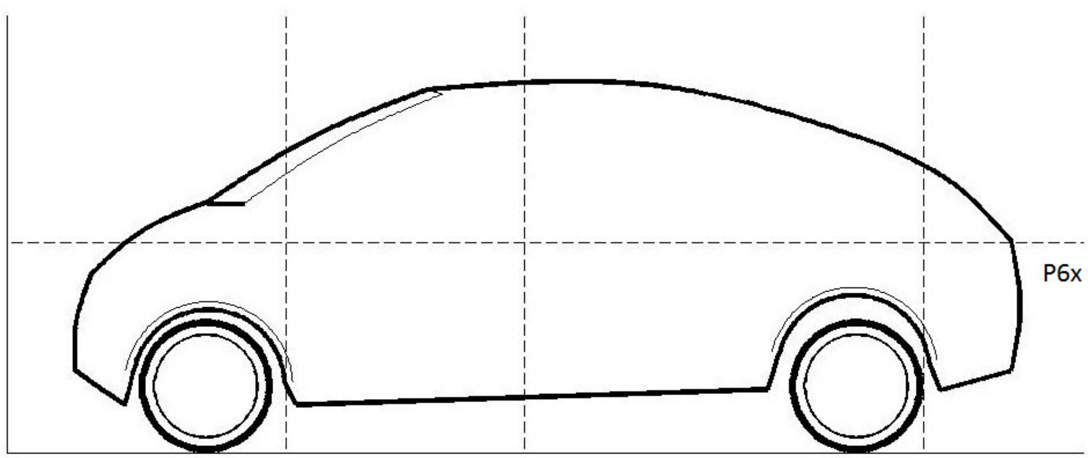


Figure 4.7: Silhouette with Maximized Fuel Economy $PEF \geq 4.5$ as a constraint

A silhouette was not included for the "MPG only-revised" case because the values

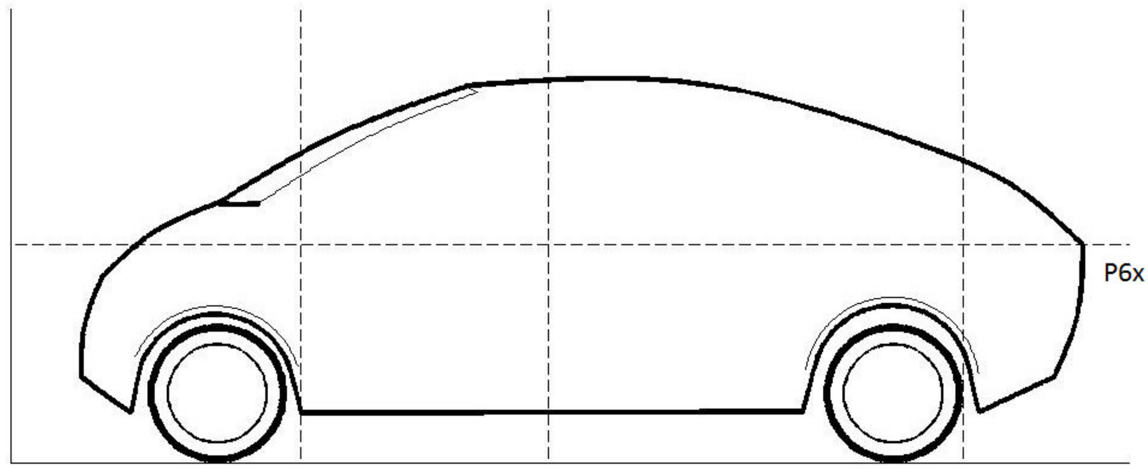


Figure 4.8: Silhouette with Maximized Fuel Economy and 4.731-PEF as a constraint

of the control points were not dependent on PEF conditions. However, Figure 4.7 effectively is the "MPG only-revised" silhouette since it achieves the same fuel economy of 23.61 mpg.

4.7 Discussion

This chapter demonstrated how PEF could be included in an optimization model that takes a rigorous approach at designing a fuel efficient vehicle. PEF was included into the model by mapping the control points to geometries considered in the model through the overall height dimension, H101 and the overall length dimension, L103. It was observed that the revised fuel economy model ("MPG only-revised") produced a more fuel efficient vehicle than the original fuel economy model ("MPG only-original"). The improvement in fuel economy was directly related to changes in the geometry, where L103 decreased and the wheel base, L101 increased. This led to reduced length in the front-overhang, L104, and thus reduced the amount of weight on the front tire. H101 had a single optimal value and did not change between the models. Appendix C shows that H101 has very little impact on the overall fuel economy computation, contributing only one term to the polynomial.

The PEF constraint had varying effects on the fuel economy depending on what its minimum value was. A first result showed that increasing PEF caused a decrease in fuel economy. A parametric study was done to the examine the effects of varying the the minimum value of PEF. The study showed that when PEF's minimum value was in the range from $3.5 \leq PEF \leq 4.7$, it achieved the same fuel economy: 23.61 mpg. However, when the minimum PEF value was in the range from $4.71 \leq PEF \leq 4.731$, there was a tradeoff between PEF and fuel economy, indicative of a Pareto tradeoff; as PEF increased, the fuel economy would decrease. The achievable fuel economy for in this model ranged from 23.3-23.6 mpg.

The PEF constraint and the minimum cargo volume constraint had conditional activities with respect to L103. In the range where PEF was between 3.5 and 4.7, the minimum cargo volume constraint was active and dominated the PEF constraint which was inactive. The value of L103 was towards its lower bound thus indicating that the shorter vehicle length reduced the cargo volume available. The PEF constraint became dominant in the range where PEF was from $4.71 \leq PEF \leq 4.731$ and the minimum cargo volume became inactive. The value of L103 in this range moved towards its upper bound, thus increasing its length and providing more room for cargo and exceeding the minimum cargo volume constraint.

Optimal silhouette designs were generated based on PEF and the fuel economy. The survey results provided the acceptable range of values for each of the ten control points that were included in the model to ensure that PEF optimal designs would be generated. Two of the control points, P4y and P6x, were linked to H101 and L103 respectively, and their placement was influenced by engineering criteria for the design of a fuel efficient vehicle. The main observable differences between these silhouettes was the position of P6x which varied as the minimum PEF values increased. Silhouettes that had increased minimum PEF values increased the value of P6x to ensure the vehicle had a curved look. The increase in P6x also increased the vehicle length which in turn reduced the fuel economy.

We should also note that, although several significant digits are used the model computations to ascertain numerical optimality, in practice perhaps only two significant digits may exist. So these results have practical value only in that they idnciate trends, not actual "optimal" numbers.

4.8 Limitations

The analysis presented in this chapter was based on a well-defined model with a number of assumptions that had to be made in order to proceed with the analysis. This presents a number of limitations that must be noted. The dimensions for $H101$ and $L103$ provided a first approximation for the geometric basis for the inclusion of PEF in models. These dimensions could readily be mapped to 2 of the control points in the silhouette geometry, those being P4y and P6x respectively. The placement of the other 8 control points were strictly based on PEF. This limited the models' ability to optimize the placement of the other 8 control points as they also relate to the engineering criteria considered in the model. Additional mathematic expressions that relate the 8 control points to relevant engineering criteria in the model should be considered in future studies. This would ensure that the silhouettes generated met both PEF and engineering criteria for all control points.

As noted above, the numerical results achieved from the model were not very significant. The results of the parametric study indicate that there there is a tradeoff between fuel economy and PEF as shown in Figure 4.6. However, the tradeoffs were numerically insignificant and such values would not warrant an actual design change.

The silhouettes did not not fully conform to the assumptions made in the model. One such area relates to the cargo volume computations. The cargo volume computation assumed that the shape of the cargo area was that of a box and does not take into consideration the curviness of backend of the vehicle. The results of the computed cargo volumes for the silhouettes would most likely be reduced if the curviness of the back was factored into the calculation. In addition, the proportions shown in the silhouette are not analogous to those exhibited in existing internal combustion engine vehicles. The positioning of key features on the vehicle such as the cowl point, the front over-hang, and the windshield are not in compliance with manufacturing standards. The shapes created would be more suitable for futuristic vehicle designs, such as the "skateboard" technology based on hydrogen fuel cells where the powertrain no longer limits the shape of a vehicle design (see *Wikipedia* (2010) for examples of images).

The original model developed by Frischknecht has the capability of studying how resulting designs can affect the profit of a firm. It is therefore plausible that the optimization results achieved could change once profit is taken into consideration. Future studies should examine the impact of PEF on the profitability of the firm. One way to examine this is by correlating the performance of fuel efficient-PEF vehicle designs with the performance desired by consumers as shown in revealed preference data. Based on the work done in Frischknecht's dissertation as well as by *Ewing and Sarigöllü* (2000), we conjecture that the designs generated in this study may negatively impact the profit of the firm due to some of the performance inadequacies. The work done by *Ewing and Sarigöllü* (2000) demonstrated that consumers were not willing to tradeoff standard performance criteria which includes acceleration. The accelerations listed in Table 4.6 perform below values that are competitive for crossover vehicles where about 8 seconds is acceptable for 0-60 mph [*Frischknecht* (2009). A follow-up parametric study is presented in Appendix D.

CHAPTER V

Conclusions

5.1 Summary

This dissertation developed a methodology for quantifying subjective attributes and integrating them into a product optimization framework. The methodology uses techniques from the behavioral sciences and engineering, and is demonstrated by quantifying a subjective attribute we called perceived environmental friendliness (PEF) and integrating it into an optimization framework that designs a fuel efficient vehicle.

The physical characteristics and visual aesthetics that influence perceptions on green were identified using the first series of steps in the methodology presented in Chapter 3: 1) development of visual stimuli using a design of experiments, 2) development of a survey instrument based on hypotheses, 3) analyzing the data using descriptive and inferential statistics, 4) using the data to generate new designs and 5) validating those designs with a survey instrument. The results of the first study indicated the specific silhouettes that received the highest ratings for PEF. ANOVA and two-sample t-tests identified the specific factors and the levels that influenced individual judgments. These factors were then used to generate "ideal" designs or to maximize PEF. A validation study verified that the specific factors selected were effective for generating designs that met the subjective criteria being measured. Using the most significant factors, a model for PEF was developed using regression analysis.

The model for PEF was then included in an optimization framework that examined the tradeoff between PEF and fuel economy which was the topic of Chapter 4. The optimization study expressed PEF as a function of geometry variables in the model. The results showed that, under certain conditions, there was a tradeoff between PEF and fuel economy: as PEF increases, the fuel economy decreases. The overall vehicle length was the design variable that had the most influence on this behavior. The optimization model permitted a second method for generating new silhouettes that were designed simultaneously for maximized PEF and fuel economy.

The methods developed in this dissertation demonstrate the integration of consumer preference, visceral judgments and engineering criteria to develop an optimally designed product that is both functional and meets consumer's subjective needs. The use of optimality here is done under the usual caveat that it is defined relative only to the model used, the objectives, constraints, and variables contained in the model. Therefore, any optimal results must be interpreted in that context. There are many more design considerations that must be accounted for before a design is finalized for eventual production. These techniques developed here can be applied to other visceral characteristics that consumers use in choosing consumer products, including tactile, olfactory, and auditory judgments.

5.2 Contributions

This research makes four main contributions. The first is the development of a methodology that quantifies subjective attributes that are not well understood a priori. Previous research had demonstrated the quantification of subjective attributes using methods such as conjoint analysis to capture consumer preference. The work presented in this dissertation is comparable to the work done by Orsborn but with some differences [*Orsborn et al.* (2009)]. Like Orsborn et al., the present work develops a method to quantify a subjective preference and incorporate it in an optimization environment. Visual stimuli are used and subjects are presented with vehicle silhouette profiles. Some immediate differences with Orsborn's work are the goals of the subjective preference being measured, the means for obtaining it, and the use of the subjective measure once obtained. In the aforementioned work, the goal was to quantify and maximize the aesthetic preference of SUV silhouettes based on vehicles from the 2003 model year. A utility function was developed that captured consumer preference as a function of seven product characteristics that were considered; a unique utility function was developed for each individual subject (30 total participants). An optimization study was then run with the objective being to maximize consumer preference as a function of these product characteristics. A new design was created and then validated in a follow up study with the same individual for which the utility function was developed. In this work, the goal was to quantify and maximize PEF and relate it to consumer preference. In contrast, in the present study the stimuli created were original designs generated using design of experiments in order to explore a design space outside of existing vehicles. A regression model was used to model PEF based on the 10 significant factors identified through the statistical analysis. This was based on aggregate data from almost 200 participants, largely from outside the university and the engineering college. New designs were generated and validated using a separate subject pool of individuals who did not participate in the original study. The two approaches also differ in how the maximized subjective functions are used. In this dissertation work, the model for PEF is integrated into a broader engineering framework that examines the impact that the inclusion of subjective measures such as PEF may have on the design of a fuel efficient vehicle. In other words, it allows for styling cues to be optimized concurrently with objective engineering criteria, and it helps to assess how a design may have to change to accommodate subjective preferences. Demonstrating how PEF can be integrated in a broader optimization framework is one of the major contributions of this dissertation.

A second contribution is the quantification of PEF. To our knowledge, no prior work has done this, including in the context of automobile design. Previous work examined consumer preference for paper towels with recycled paper content [*MacDonald et al.* (2007a,b)] and consumer preferences for alternative fuel vehicles [*Ewing and Sarigöllü* (2000)]. The work done by MacDonald et al. demonstrated other psychological phenomena in the context of environmental conscious decision making such as the identification of crux and sentinel attributes and preference inconsistencies. However, this work was not directed to identifying green styling cues in automotive design. The work by Ewing and Sarigöllü identified the specific attributes of fuel efficient vehicles that appeal to consumers. Although it provided some insight on the value consumers place on performance specifications, the work did not provide insight on green styling cues that could be considered in a broader design situation. Other research had addressed the quantification of preference and emotional or feeling qualities of a product [*Lai et al.* (2005); *Nagamachi* (2002); *Achiche and Ahmed* (2008, 2009)] that is amenable to PEF measures. However, these research efforts did not integrate engineering criteria in their models and were not able to provide information about consumer choice.

A third contribution is the development of two methods that can be used to generate new PEF designs based on user data. The first method uses the results of the survey to identify the significant factors that influence PEF judgments. Discrete variations of each of the significant control points provided a unique silhouette that maximizes PEF and was later verified using a follow up survey. Previous work demonstrated how to generate new designs based on consumer's aesthetic preferences by optimizing a utility function [*Orsborn et al.* (2009); *Swamy et al.* (2007)]. Other work showed how subjective feeling quality data can be used to do a redesign on vehicle silhouettes [*Lai et al.* (2005)]. The work here demonstrated how new designs can be generated using methods from behavioral science. The second method developed in this dissertation generates designs based on the results of solving an engineering optimization model that includes PEF. The PEF attribute is used as a constraint in what is essentially a bi-objective optimization problem. The objective to be maximized is fuel economy and the constraints include a bound of PEF along with engineering performance ones. Since PEF is a function of the control points, optimal values returned for each of the control points provide an optimal silhouette. This method for generation new silhouettes provides a way to concurrently design for maximum PEF and fuel economy.

5.3 Future Work

The methodology presented can be applied to products outside of the automotive industry. The techniques presented are is also suitable for quantifying any subjective attributes where there is limited information about the specific factors or cues that elicit individual judgments. There are number of enhancements that would improve the presented work.

5.3.1 Model Enhancements

The results of Chapter 3 left some open questions. Future work should examine the role that proportionality might have had on the judgments made by the subjects. Some of the proportions resembled sports utility vehicles and a minivan, rather than a cross-over vehicle as intended. These shapes are more readily associated with not being environmentally friendly and made some aspects of the results obvious. Subjects were told to assume that all vehicles belong to the same vehicle class (i.e., are cross-over vehicles) but there is no guarantee that they actually kept this in mind during the study. Next steps should take care to develop stimuli that have a higher degree of accuracy in representing the vehicle class or product category being examined.

In Chapter 3, the top two PEF vehicles were also seen as the top two most preferable. An open question is understanding the true motivations for some of the vehicle choices that subjects rated to be high on the PEF scale as well as in preference. It was conjectured that familiarity played a role in the judgments based on work by Crozier and Kelly where people tend to gravitate to the familiar [*Crozier* (1994); *Kelly* (2008)]. There also may have been some other visceral assessments influencing the judgment such as the "cuteness" of a particular vehicle. Another question is whether or not social-desirability bias influenced the choices where subjects preferred the vehicles that appeared to be the most environmentally friendly. One way to examine these questions is by conducting a study with these silhouettes and asking subjects to choose the most preferable vehicle before being primed about environmental conscious thinking. This would allow subjects to make their choices free of any external influences on their personal preferences.

Another improvement to the methodology would be the development of a model for PEF that can capture non-monotonic relations between the factors and ratings such as PEF or preferences of the significant factors. The current study used two levels for each of the fifteen factors. The decision was to have the first study include a broad range of control points to identify the critical ones for PEF and to keep the number of questions that subjects answer to a minimum using a Taguchi design. Future studies can limit the number of factors and increase the number of levels to three or even four so that non-monotonic relations can be captured, if it exists.

The model for PEF was included in the optimization framework through the length and height dimensions of a vehicle. This allowed for the inclusion of two, out of ten, control points in the analysis. Future work would involve the development of mathematic relations that could relate additional control points to other geometric dimensions or engineering criteria of the vehicle involved in measures of fuel economy, such as proportionality. A very relevant engineering criterion that the control points could be related to is the coefficient of drag measure. Drag measurements are best suited for three dimensional models. Future work could take three dimensional CAD models of the silhouettes and computing the coefficient of drag using computational fluid dynamics (CFD) software. Another approach could be to develop small scale prototypes of the CAD models using rapid prototyping and computing the drag coefficients using an experimental wind tunnel. These computed measures could then be used to improve the optimization model to capture specific drag coefficients as a function of the control points. Future work could also be to use the 3-D models in a follow up survey and assess the differences in preference and judgments on PEF that may be observed.

The optimization framework used is capable of studying profit as an objective function to develop optimal designs that are profitable for a firm and meet consumer demand. This functionality was not used in the present work but could provide different optimality results and is worth exploring further.

5.3.2 New Investigations

The quantification of subjective attributes can be expanded to include additional methods for understanding factors that influence decisions, such as eye-tracking studies. Through eye-tracking studies, one can can do more in-depth studies on consumer judgments and observe how visual attention changes after being primed with certain information. This would provide some indication on the movement of the eyes but might not readily track covert visual attention [*Duchowski* (2007)].

APPENDICES

APPENDIX A

PEF Regression Model

The results from the data analysis identified 10 main factors that were statistically significant in influencing judgments about PEF. Figure A.1 is the complete data table of each of the 16 vehicles and the means computed for PEF. The specific values for each of the control points is also listed for each vehicle.

A regression analysis of the form was run using Microsoft Excel 2007:

$$PEF = \beta_{02} + \sum_{i=2}^{7} (\beta_{ix} P_{ix} + \beta_{iy} P_{iy}) \tag{A.1}$$

where $i = 2, 4, 5, 6, 7$ correspond to the control points and β_{02} is the intercept. The results of the analysis are shown in Table A.1.

Vehicle #	Acutal Means	P2x	P2y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	Predicted Means	Error
1	**3.99**	**-1.6**	**1.6**	**2**	**3.4**	**8.5**	**3.2**	**10.1**	**2**	**10**	**0.3**	**4.34**	**0.35**
2	**4.56**	**-1.6**	**1.6**	**2**	**3.4**	**8.5**	**3.2**	**10.5**	**2.5**	**10.5**	**0.4**	**4.04**	**-0.53**
3	**3.20**	**-1.4**	**1.9**	**2**	**3.4**	**8.5**	**4**	**10.1**	**2**	**10.5**	**0.4**	**3.42**	**0.21**
4	**3.53**	**-1.4**	**1.9**	**2**	**3.4**	**8.5**	**4**	**10.5**	**2.5**	**10**	**0.3**	**3.50**	**-0.03**
5	**2.82**	**-1.6**	**1.9**	**2**	**3.7**	**10**	**3.2**	**10.1**	**2.5**	**10**	**0.4**	**3.02**	**0.20**
6	**2.98**	**-1.6**	**1.9**	**2**	**3.7**	**10**	**3.2**	**10.5**	**2**	**10.5**	**0.3**	**2.96**	**-0.02**
7	**2.60**	**-1.4**	**1.6**	**2**	**3.7**	**10**	**4**	**10.1**	**2.5**	**10.5**	**0.3**	**2.68**	**0.08**
8	**3.32**	**-1.4**	**1.6**	**2**	**3.7**	**10**	**4**	**10.5**	**2**	**10**	**0.4**	**3.06**	**-0.26**
9	**4.08**	**-1.4**	**1.6**	**3**	**3.4**	**10**	**3.2**	**10.5**	**2**	**10.5**	**0.3**	**4.29**	**0.20**
10	**4.37**	**-1.4**	**1.6**	**3**	**3.4**	**10**	**3.2**	**10.1**	**2.5**	**10**	**0.4**	**4.34**	**-0.02**
11	**3.40**	**-1.6**	**1.9**	**3**	**3.4**	**10**	**4**	**10.5**	**2**	**10**	**0.4**	**3.48**	**0.08**
12	**3.35**	**-1.6**	**1.9**	**3**	**3.4**	**10**	**4**	**10.1**	**2.5**	**10.5**	**0.3**	**3.09**	**-0.26**
13	**3.94**	**-1.4**	**1.9**	**3**	**3.7**	**8.5**	**3.2**	**10.5**	**2.5**	**10.5**	**0.4**	**4.29**	**0.35**
14	**5.12**	**-1.4**	**1.9**	**3**	**3.7**	**8.5**	**3.2**	**10.1**	**2**	**10**	**0.3**	**4.59**	**-0.53**
15	**3.85**	**-1.6**	**1.6**	**3**	**3.7**	**8.5**	**4**	**10.5**	**2.5**	**10**	**0.3**	**4.06**	**0.21**
16	**4.02**	**-1.6**	**1.6**	**3**	**3.7**	**8.5**	**4**	**10.1**	**2**	**10.5**	**0.4**	**3.98**	**-0.03**
17	4.60	-1.6	1.7	3.7	3.7	9.5	2.8	10.2	1.5	10.2	0.2	4.99	0.39
18	4.59	-1.4	1.9	2	3.4	8.5	3.2	10.1	2	10	0.3	4.18	-0.41
19	5.04	-1.4	1.6	3	3.4	8.5	3.2	10.1	2	10	0.3	5.13	0.09
20	4.50	-1.4	1.9	3	3.4	8.5	3.2	10.1	2	10	0.3	4.82	0.32

Figure A.1: Regression tables for the 20 vehicles; bold rows were used in the actual regression

Control Point	Coefficient	Value
	$intcpt$	18.53631801
$P2x$	β_1	0.742725625
$P2y$	β_2	-1.019072917
$P4x$	β_3	0.640592125
$P4y$	β_4	-0.76652625
$P5x$	β_5	-0.44144525
$P5y$	β_6	-0.719213594
$P6x$	β_7	0.065708437
$P6y$	β_8	-0.27742225
$P7x$	β_9	-0.41492225
$P7y$	β_{10}	0.14402375

Table A.1: Regression results

APPENDIX B

Survey Instrument

The survey used in this research was developed using Sawtooth Software [*Sawtooth Software* (2009)]. There was a total of 5 main parts to the survey. Sample pages from the survey will be presented in each of the sections below.

Welcome Page

The text contained on the welcome page was as follows:

Welcome and thank you for volunteering to participate in a vehicle design study! This study will help a product design team understand how consumers evaluate vehicles based on minimal information about shape.

The study should take approximately 20 minutes of your time.

The survey consists of 4 parts. Part I of the survey involves making judgments about individual vehicles then a larger group of vehicles. Part II involves looking at these vehicles individually and judging how much they look like vehicles you typically see on the street. Part III asks for your opinion on several statements. Part IV involves specific judgments about the vehicle shape.

Your participation is voluntary. You can decide to stop at any time.

All your survey responses will be kept confidential.

If you have any questions, concerns or comments, please feel free to contact us at support@surveysavvy.com

Figure B.1: Welcome page of the survey

Background Info

After completing the demographics information, subjects were presented with background information on the study as shown below. This working definition of environmental friendliness that is used in this study is first presented on this page.

> In the pages to follow, you will be asked to judge vehicles that were randomly selected from a pool of 700 images. Even though the vehicles may appear to be very similar to each other they are in fact different vehicles. Please answer each question as honestly as possible and to the best of your ability. We value your participation and your comments.
>
> The first part involves questions about your perceptions of environmental friendliness based on the shape of the vehicle. The definition for environmental friendliness is defined below and it will be available throughout the survey.
>
> We realize that the information provided about each vehicle is minimal. We are studying people's immediate gut level reactions to seeing the shape of the vehicle.
>
> The next page will have a practice question similar to what you'll see in the survey.
>
> **Environmental friendliness** is a term used to describe products, ideas, or concepts that have minimal to no impact on the environment (i.e. air, water, land and natural resources). Examples of negative impacts on the environment include water pollution, the removal of resources from nature that once removed cannot be replaced, and the release of air pollutants that reduces the ozone layer which protects us from the harmful rays emitted from the sun.

Part I: PEF and Preference Questions

Part I contained questions about PEF and preference. The introductory section was written as follows:

> The picture to the right is an example of the vehicles you will see throughout the study. We intentionally present minimal information about the vehicle because we are studying impressions that people have about the general shape of a vehicle.

Just respond with your initial impressions about how well the overall shape characterizes environmental friendliness. Again, your input is really valuable to us!

For all the vehicles shown, assume that all:

- have excellent fuel economy
- have clean emissions
- have an equal number of doors
- carry the same number of passengers
- are equally priced
- belong to the same vehicle class (i.e. cross-over vehicles)

A link to this list and any definitions you need will be available throughout the survey.

Are you ready? Then let's go!!

Here, the participants are first introduced with the list of assumptions they need to consider as they do the questions about PEF. For the remainder of the section with PEF, those questions and the definition for environmental friendliness were made available by clicking a link to a pop-up window that contained this information.

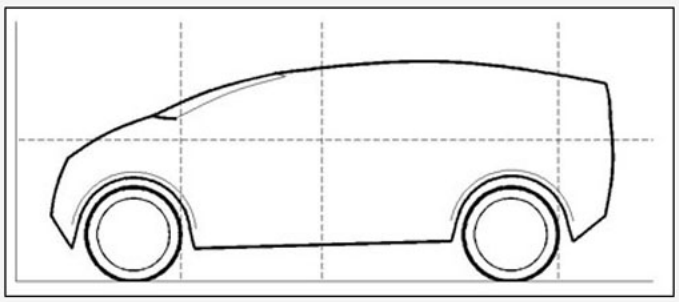
Part Ia: PEF questions

Each of the 17 vehicles were presented as shown in Figure B.2 to the subjects. For the first study, a total of 17 questions were provided; the validation study presented a total of 20 questions: the original 17 and the 3 selected for the validation study (See Chapter 3).

Part Ib: Preference questions

The questions about preference were presented as shown in Figure B.3. Each question presented six vehicles at a time for the first experiment; the validation study showed five vehicles at a time.

Based on the visual content, please rate how well this vehicle conveys environmental friendliness.



	Does not convey environmental friendliness at all	2	3	Neutral	5	6	Definitely conveys environmental friendliness
	○	○	○	○	○	○	○

Click here for environmental friendly definition.
Click here for a reminder of the assumptions being made about these vehicles.

Next

Figure B.2: Sample PEF question

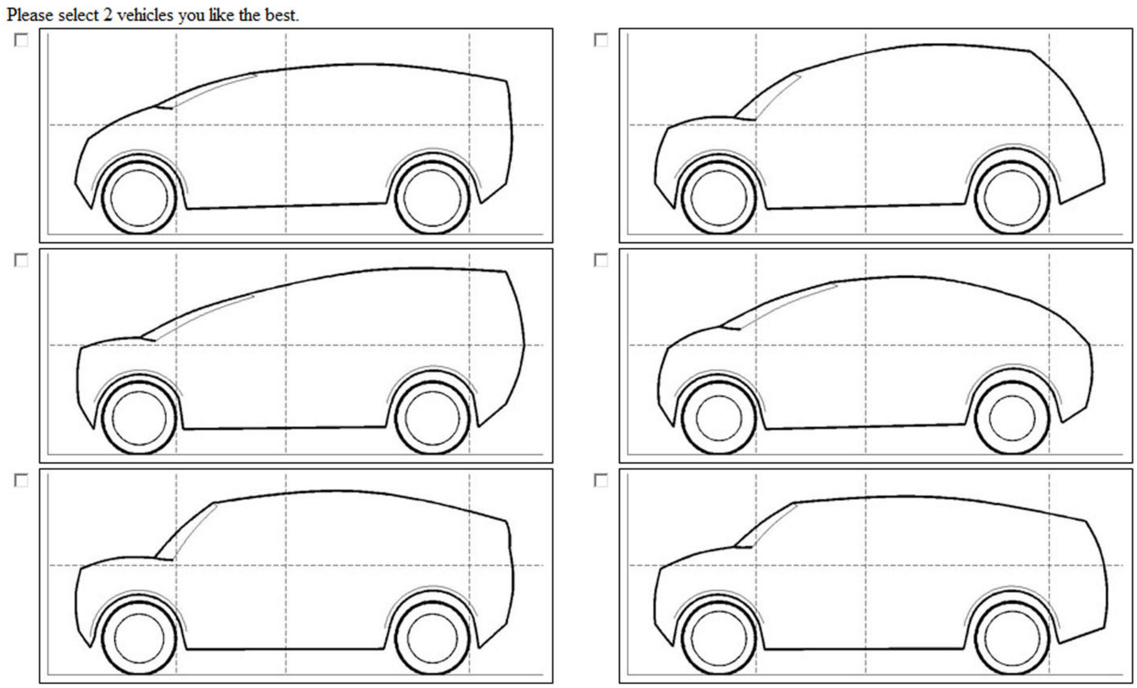


Figure B.3: Sample preference question

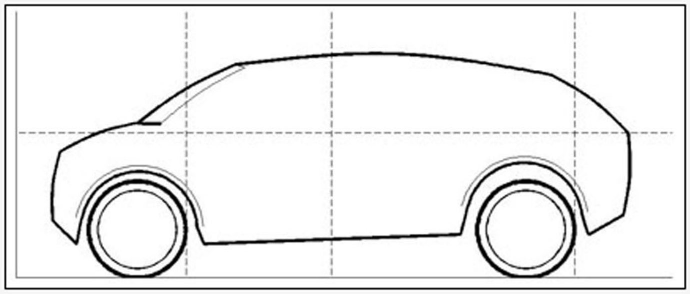
Part II: Familiarity questions

Subjects were introduced to the section about familiarity as shown as follows:

> In your daily life, there are a number of sources where you are exposed to various vehicle designs. These sources include ads on television and in magazines but may also include times when you see vehicles while walking on a sidewalk or entering a parking lot.
>
> The following questions ask about the designs you saw in Part I. We want you to rate each design on a scale of 1 to 7 where 1 = Very similar to previous vehicles and 7 = Not similar to previous vehicles at all.

They were then presented with 17 questions as shown in Figure B.4.

Please rate how much this design shape looks like a vehicle you may encounter in your daily life.



	Very similar to previous vehicles	2	3	Neutral	5	6	Not similar to previous vehicles at all
	○	○	○	○	○	○	○

Figure B.4: Sample familiarity question

Part III: Environmental Consciousness questions

A total of 30 questions that measure environmental consciousness based on the work by *Thompson and Barton* (1994) were presented to subjects on at a time. Figure B.5 provides one example of the thirty that were shown. The questions were presented in random order. The introduction was presented as follows:

> Before we move into the last part of the survey, we'd like to assess your opinion on several statements. Please answer the questions as honestly as possible. Please indicate your agreement with the following statements on a scale from 1 (strongly agree) to 7 (strongly disagree).

Environmental threats such as deforestation and ozone depletion have been exaggerated.

	Strongly Agree	2	3	Neutral	5	6	Strongly Disagree
	○	○	○	○	○	○	○

Figure B.5: Sample environmental consciousness question

Part IV: IBN rating questions

Subjects were asked to rate the degree to which they thought shapes were inspired by nature. Figure B.6 shows how the section was introduced and Figure B.7 provides an example of how the question was presented.

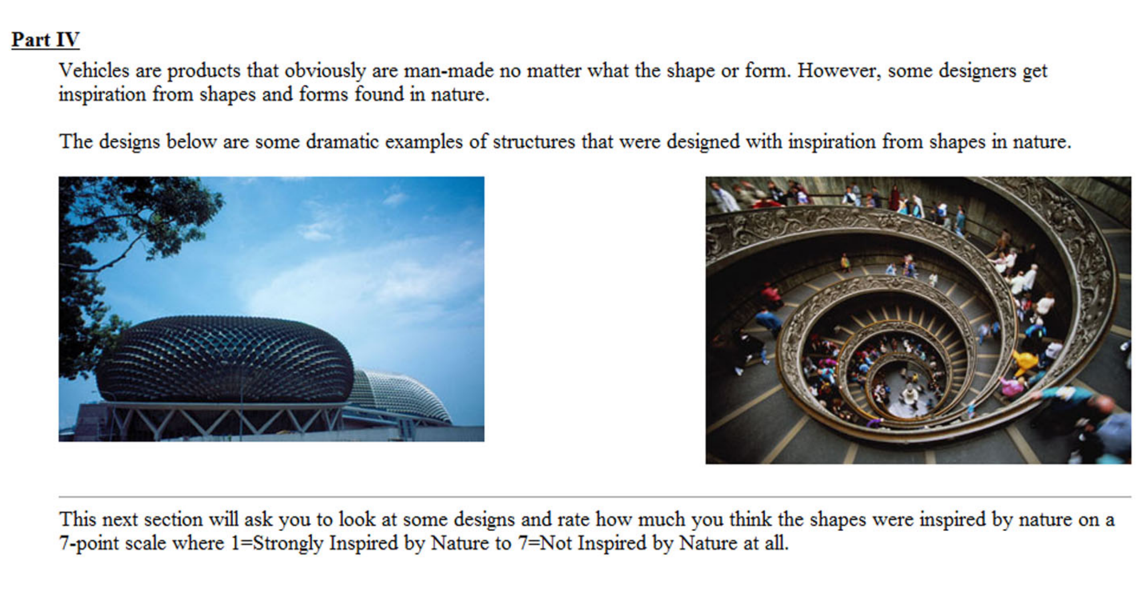


Figure B.6: Introduction to the section on shapes being inspired by nature

Part V: IBN sorting task

Subjects that were in-person did a sorting task using 17 cards (see Chapter 3). However, the online subjects did the task similar to the preference questions. Figure B.8 provides an example of how the sorting task was done online.

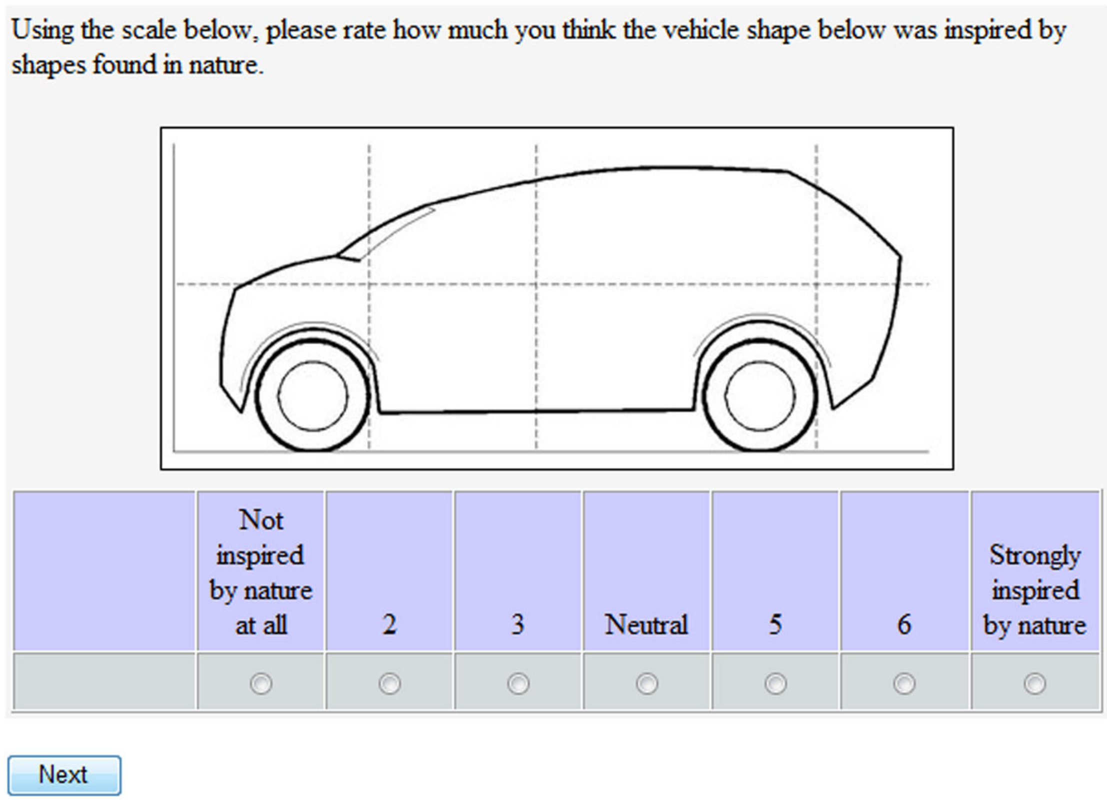


Figure B.7: Sample inspired by nature question

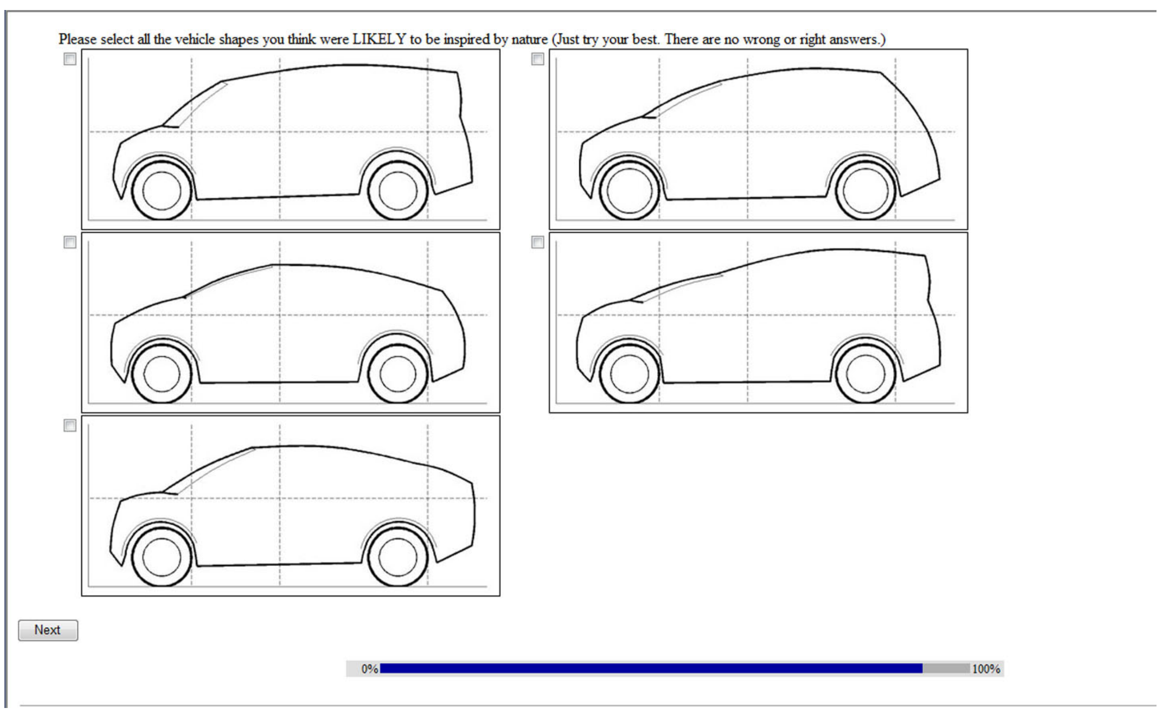


Figure B.8: Online version of the sorting task

APPENDIX C

Model Development Details

The models in Chapter 4 were adapted from the models in Frischknecht's PhD thesis [*Frischknecht* (2009)] which were based on a combination of simulations done in *Cruise* and developed MATLAB-based models. This section provides more of the background behind some of the analyses and computations done in Chapter 4. It also provides more details about the geometry.

Vehicle characteristics

Main Design Variables

In Chapter 4, there were seven main vehicle characteristics that were considered. The first three were performance variables including engine bore, x_{EB}, final drive, x_{FD}, and engine bore to stroke ratio, x_{EBS}. The engine bore, bore-to-stroke ratio and other parameters are used to compute the aspects of the engine size such as the engine length and engine depth.

The Society of Automotive Engineers handbook J1100 provides standard dimensions for automotive design [*SAE International* (2005)]. Several dimensions were considered in the model, three of which were used in the fuel economy model. Figures C.1-C.2 shows schematics from the SAE handbook which shows all the critical length dimensions. The four geometry design variables included in the model were: vehicle length, x_{L103}; width, x_{W105}; height, x_{H101}; and wheelbase, x_{L101}.

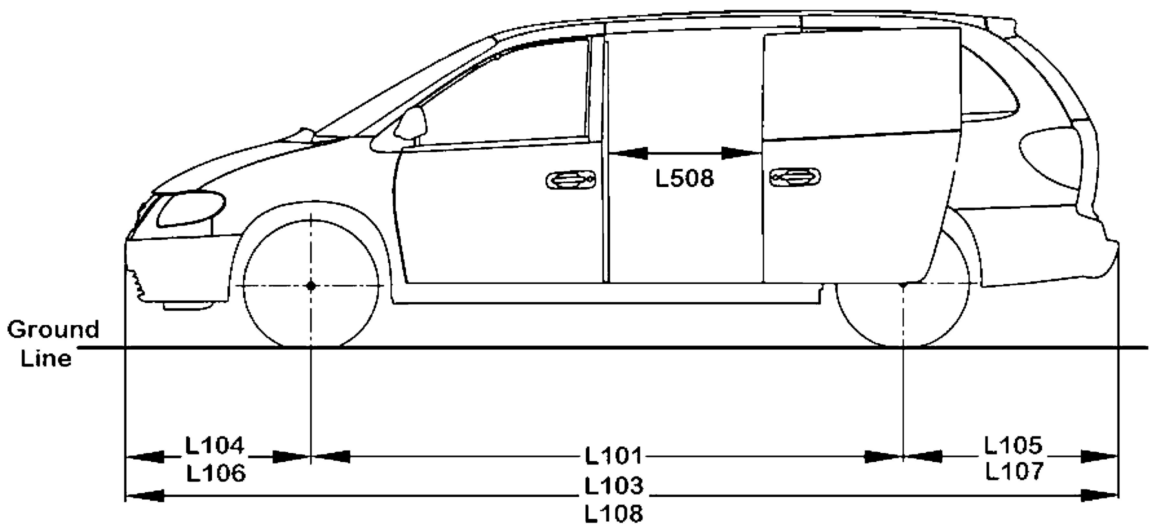


Figure C.1: SAE J1100 length dimensions

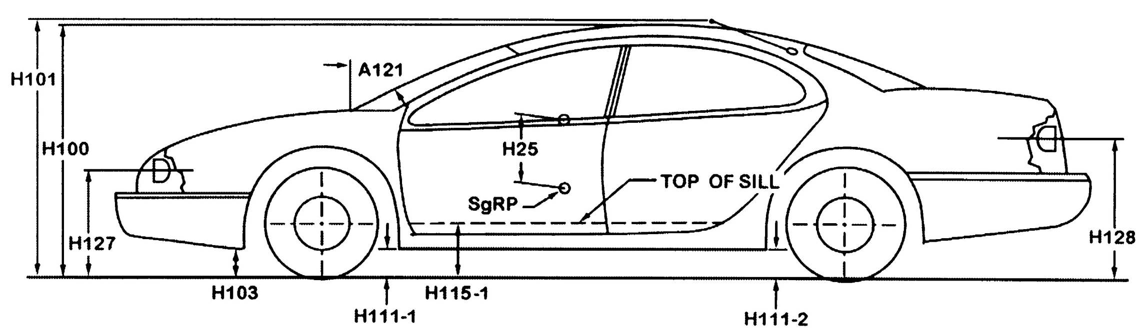


Figure C.2: SAE J1100 height dimensions

Model Parameters

The complete list of parameters and their description is shown in Table C.1.

Veh. Char.	Design Var.	Units	Description
EngBore	✓	[mm]	engine bore
EngBoretoStroke	✓	[-]	bore to stroke ratio
FinalDrive	✓	[-]	final drive ratio
L103	✓	[mm]	exterior length
W105	✓	[mm]	exterior width
H101	✓	[mm]	exterior height
L101	-	[mm]	wheelbase
EngNofCyl	-	[-]	number of engine cylinders
GearRatio	-	[-]	gear ratios (1-6)
VehGTankVol	-	[l]	gas tank volume
L104	-	[mm]	dist. f. bumper to f. axle
H103-1	-	[mm]	dist. f. bumper to f. axle
H103-2	-	[mm]	dist. f. bumper to f. axle
H156	-	[mm]	dist. f. bumper to f. axle
*VehLegRoom*1	-	[mm]	driver legroom
*VehLegRoom*2	-	[mm]	2nd row legroom
VehHeelPointX	-	[mm]	longitudinal location of driver heel point
MidRailThick	-	[mm]	mid-rail thickness
MidRailWidth	-	[mm]	mid-rail width
VehTurnRad	-	[mm]	minimum turn radius
WheelDiam	-	[mm]	wheel diameter
H108	-	[mm]	tire static rolling radius
C_D	-	[-]	vehicle drag coefficient
VehSeatCap	-	[-]	max seating capacity
PassWeight	-	[lbm]	average weight of vehicle occupant

Table C.1: Partial list of vehicle parameters, taken from *Frischknecht* (2009)

Details about the Fuel Economy Model

The fuel economy models developed by Frischknecht [*Frischknecht* (2009)] was based on surrogate models obtained from the *Cruise* simulation software using design of experiments. Polynomials were found for both the city and highway drive cycles and the gradeability simulation to compute the variable "Grad65Tow". The powertrain used in the models were naturally aspired spark-ignition engines. The polynomials were fit to compute the fuel econonomy and the gradeability. The polynomial elements are shown in the matrix shown below.

$$N = \begin{bmatrix} 1 \\ C_D \\ EB \\ FD \\ H101 \\ L103 \\ W105 \\ EBS \\ EB^2 \\ FD^2 \\ L103^2 \\ EBS^2 \\ EB * FD \\ EB * EBS \\ FD * L103 \\ FD * W105 \\ L103 * W105 \\ FD^3 \end{bmatrix}$$

For the model, these values were scaled between [0,1] based on the upper and lower bounds for each element. A matrix of the polynomial coefficients were used to quantify fuel consumption in the city, highway, and the measure of gradeability. The C_{NASI} matrix describes the coefficients that were used in the model.

$$\mathbf{C}_{NASI} = \begin{bmatrix} 8.944 & 5.453 & -2.410 \\ 0.1281 & 0.2881 & -0.2008 \\ 1.371 & 0.7173 & 2.046 \\ 0.0730 & 0.4728 & 3.707 \\ 0.1120 & 0.2498 & -0.1897 \\ -0.0256 & 0.0 & 0.0530 \\ 0.1621 & 0.2968 & -0.1428 \\ -0.5295 & -0.2377 & -1.465 \\ 0.1070 & 0.0 & 0.2098 \\ 0.2054 & 0.1011 & 4.7509 \\ 0.0879 & 0.0544 & 0.0 \\ 0.0603 & 0.0 & 0.1735 \\ 0.090 & 0.0 & 0.6704 \\ -0.126 & 0.0 & -0.3412 \\ 0.0 & 0.0 & -0.3506 \\ 0.0 & 0.0 & -0.2292 \\ 0.1316 & 0.0913 & 0.0 \\ 0.0 & 0.0 & -1.791 \end{bmatrix}$$

Values for fuel consumption during the city drive cycle, $CycUSCity$, highway drive cycle, $CycUSHwy$, and Grad65Tow were found using Equation (C.1).

$$\mathbf{C}'_{NASI}\mathbf{N} = \begin{bmatrix} CycUSCity \\ CycUSHwy \\ Grad65Tow \end{bmatrix} \tag{C.1}$$

CycUSCity and CycUSHwy were then used to compute the equations for fuel economy in the city and highway respectively and is shown in Equations (C.2) and (C.3).

In turn, the combined fuel economy was computed as shown in Equation (C.4). The result for the Grad65Tow was used in the constraint equation, g1.

$$MPGCycUSCity = \frac{1}{\frac{1.609344 CycUSCity}{100 \times 3.786235}} \tag{C.2}$$

$$MPGCycUSHwy = \frac{1}{\frac{1.609344 CycUSHwy}{100 \times 3.786235}} \tag{C.3}$$

$$CombinedFuelEconomy = \frac{1}{\frac{0.55}{MPGCycUSCity} + \frac{0.45}{MPGCycUSHwy}} \tag{C.4}$$

Engineering Constraint Descriptions

The list of constraints presented in Chapter 4 were used in the MATLAB simulations. Table C shows the complete list.

Constraint		Description
g_1	:	Min towing grade @ 65 mph
g_2	:	Min angle of departure
g_3	:	Min ramp breakover angle
g_4	:	Min cargo volume
g_5	:	Max cargo volume
g_6	:	Max rollover score
g_7	:	Min % weight on front wheels
g_8	:	Min payload capacity
g_9	:	Min front crash crush space
g_{10}	:	Max estimated deceleration
g_{11}	:	Max powertrain width
g_{12}	:	Max wheelbase
g_{13}	:	Min top speed
g_{14}	:	Min available passenger sitting height

The MATLAB code used a number of constraints that were not directly involved with modeling discussed in this dissertation but were necessary for the code to work. Some of these constraints were relaxed for the current work. That list is shown below:

$$
\begin{aligned}
g_{15} &= MinBoretoStroke - EngBoretoStroke && \text{(C.5)}\\
g_{16} &= EngBoretoStroke - MaxBoretoStroke && \text{(C.6)}\\
g_{17} &= MinEngDisp - EngDisp && \text{(C.7)}\\
g_{18} &= EngDisp - MaxEngDisp && \text{(C.8)}\\
g_{19} &= MinFinalDrive - FinalDrive && \text{(C.9)}\\
g_{20} &= FinalDrive - MaxFinalDrive && \text{(C.10)}\\
g_{21} &= GearBoxRatio(1) - Max1stGear && \text{(C.11)}\\
g_{22} &= Min6thGear - GearBoxRatio(6) && \text{(C.12)}\\
g_{23} &= MinGear1to2 - (GearBRatio(1) - GearBRatio(2)) && \text{(C.13)}\\
g_{24} &= MinGear2to3 - (GearBRatio(2) - GearBRatio(3)) && \text{(C.14)}\\
g_{25} &= MinGear3to4 - (GearBRatio(3) - GearBRatio(4)) && \text{(C.15)}\\
g_{26} &= MinGear4to5 - (GearBRatio(4) - GearBRatio(5)) && \text{(C.16)}\\
g_{27} &= MinGear5to6 - (GearBRatio(5) - GearBRatio(6)) && \text{(C.17)}\\
g_{28} &= MinHwyRange - VehHwyRange && \text{(C.18)}\\
g_{29} &= MinCityRange - VehCityRange && \text{(C.19)}\\
g_{30} &= (TireDynRollRad + 10 * 25.4) - L104 && \text{(C.20)}\\
g_{31} &= MinAofApr - A106 && \text{(C.21)}\\
g_{32} &= MinFrontClear - H103d1d3 && \text{(C.22)}\\
g_{33} &= MinRearClear - H103d2d3 && \text{(C.23)}\\
g_{34} &= MinDriverLegRoom - VehLegRoom1 && \text{(C.24)}\\
g_{35} &= VehLegRoom1 - MaxDriverLegRoom && \text{(C.25)}\\
g_{36} &= Min2ndRLegRoom - VehLegRoom2 && \text{(C.26)}\\
g_{37} &= VehLegRoom2 - Max2ndRLegRoom && \text{(C.27)}\\
g_{38} &= (W101 + 7 * 25.4) - W105 && \text{(C.28)}\\
g_{39} &= Acc3050Tow - Max30to50 && \text{(C.29)}\\
g_{40} &= Acc060 - Max0to60 && \text{(C.30)}\\
g_{41} &= (L104 + TireDynRollRad + 10 * 25.4) && \\
&\quad -VehHeelPointX && \text{(C.31)}\\
g_{42} &= 62.5 - MidRailWidth/MidRailThick && \text{(C.32)}\\
g_{43} &= MidRailWidth - 3.75 * 25.4 && \text{(C.33)}\\
g_{44} &= 1.5 * 25.4 - MidRailWidth && \text{(C.34)}\\
g_{45} &= MPGConstraint - CombinedMPG && \text{(C.35)}\\
&\quad \text{if } Powetrain = HEV &&
\end{aligned}
$$

where

Constraint		Description
g_{15}	:	Min bore to stroke ratio
g_{16}	:	Max bore to stroke ratio
g_{17}	:	Min engine displacement
g_{18}	:	Max engine displacement
g_{19}	;	Min final drive ratio
g_{20}	:	Max final drive ratio
g_{21}	:	Max 1st gear ratio
g_{22}	:	Min 6th gear ratio
g_{23}	:	Min difference 1st gear ratio to 2nd gear ratio
g_{24}	:	Min difference 2nd gear ratio to 3rd gear ratio
g_{25}	:	Min difference 3rd gear ratio to 4th gear ratio
g_{26}	:	Min difference 4th gear ratio to 5th gear ratio
g_{27}	:	Min difference 5th gear ratio to 6th gear ratio
g_{28}	:	Min vehicle range on highway
g_{29}	:	Min vehicle range in city
g_{30}	:	Min front wheel clearance
g_{31}	:	Min angle of approach
g_{32}	:	Min front ground clearance
g_{33}	:	Min rear ground clearance
g_{34}	:	Min driver leg room
g_{35}	:	Max driver leg room
g_{36}	:	Min 2nd row leg room
g_{37}	:	Max 2nd row legroom
g_{38}	:	Max wheel track width
g_{39}	:	Max 30 to 50 mph acceleration time @tow
g_{40}	:	Max 0 to 60 mph acceleration time
g_{41}	:	Min clearance between heelpoint and tire
g_{42}	:	Min midrail width to thickness ratio
g_{43}	:	Max midrail width
g_{44}	:	Min midrail width
g_{45}	:	Min miles per gallon

Summary of MATLAB Functions

MATLAB software was used to run the simulations. Figure C.3 shows a summary of how the design variables were used in the simulations. The first column lists three types of inputs: variables, computed quantities, and the outputs of previously computed quantities.

Inputs			Function Name/Purpose	Outputs
Variables	Parameters	Sub Function/Output		
H101, L101, L103, W105, EB, EBS, FD, VehCoeffDrag			CityHwyGrad Function	CycCity, CycHwy, Grad65Tow*
		CycCity, CycHwy	Combined MPG Function	Combined MPG, City MPG, Hwy MPG
City MPG, Hwy MPG, Gas volume			Range	City Range, Hwy Range
L101, EB	EngVee		Powertrain Function	Engine Length, Tire Flop
VehCoeffDrag, H101, L101, W105, EB, EBS			Acc0to60 Function	Max Speed, Acc0to60
L103, W105, EB, EBS, FD			Acc30to50 Function	Acc30to50 Tow
EB, EBS	Eng No of cylinders		Engine Size Function	EngStroke, EngDisp, EngDepth
EB	Eng No of cylinders	EngStroke	Engine Scaling Function	Engine Fuel Consumption, Eng Max Speed
	EngVee	EngDisp	Engine Mass Function	EngExMass
H101, L103, W105		EngExMass	Curbweight Function	VehMass
L101, L104, H101, L103		VehMass	VehCG Function	VehHeighCG, VehTopofTire
W101		VehHeighCG	Rollover Function	RolloverScore, SSF
		VehMass, EngDepth	Front Crash Function	Crush Space, AccelTestFront,...
	VehRows, VehSeat Cap	VehMass	GrossWeight Function	Gross Weight Rating
H101, L103	W101	VehTopofTire	CargoVolume	CVID2

*Grad65Tow is used in a constraint

Figure C.3: Summary of MATLAB functions

APPENDIX D

Monotonicity Analysis

Monotonicity Analysis was developed to analyze optimization problems prior to numerical computation [*Papalambros* (1979)]. Designers were newly acquainted with the use of numerical optimization methods to solve design optimization problems. However, because these numerical techniques were not created for designing, finding a solution became a challenge. Properties of engineering problems such as nonlinearity, nonconvexivity, and multiple optima contributed to these problems [*Papalambros and Wilde* (1979)]. Monotonicity Analysis provides a means for identifying constraint activity, reducing the problem to search for fewer variables in a limited feasible region and also provides insight to the designer, thus negating the need for extensive experience [*Papalambros and Wilde* (1979)].

This method still remains a valuable tool that provides insight into optimization models and provides designers with intuition about the behavior of models prior to numerical computations and interpretation of the results after.

Monotonicity Principles

There are two monotonicity principles [*Papalambros and Wilde* (2000)]:

MP1: In a well-constrained minimization problem every increasing(decreasing) variable is bounded below(above) by at least one nonincreasing(nondecreasing) active constraint (p.100).

MP2: In a well-constrained minimization problem every nonobjective variable is bounded both below by at least one nonincreasing semiactive constraint and above by at least one non-decreasing semi-active constraint (p.115).

Monotonicity Table and Analysis

Table D.1 shows the monotonicities of the objective function and constraints. The expressions below help to summarize the behavior occurring in the table:

$MPG : f(H101^+, L103^+, W105^+, EB^+, EBS^-, FD^+) \leq 0$

$g1 : f(H101^-, L103^-, W105^+, EB^-, EBS^-, FD^-) \leq 0$

$g4 : f(H101^-, L103^+) \leq 0$

$g6 : f(H101^+, L103^-) \leq 0$

$g12 : f(L101^+, L104^+, L103^-) \leq 0$

$g14 : f(H101^-, L103^+) \leq 0$

$g39 : f(EB^+, EBS^-, FD^+) \leq 0$

$g45 : f(H101^?, L103^?, W105^?, EB^?, EBS^?, FD^?) \leq 0$

$g47 : f(2x^-, 2y^+, 4x^-, 4y^+, 5x^+, 5y^+, 6x^-, 6y^+, 7x^+, 7y^-) \leq 0$

The constraint activity derived from monotonicity analysis can be summarized as follows:

- g1 is always active. This is the max gradeability which estimates the percent grade achievable at 65 mph while towing a trailer.

- g4, is conditionally active with respect to L103. Constraint g4 is the minimum cargo volume index. This constraint is active when L103 is closer to it's

	P2x	P2y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	W105	EB	EBS	FD
-MPG				+			+				+	+	-	+
$g_{47} : 4.5 - PEF \leq 0$	-	+	-	+	+	+	-	+	+	-				
g_{UBofEB}												+		
g_{LBofEB}												-		
g_{UB_EBS}													+	
g_{LB_EBS}													-	
g_{UB_2x}	+													
g_{LB_2x}	-													
g_{UB_2y}		+												
g_{LB_2y}		-												
g_{UB_4x}			+											
g_{LB_4x}			-											
g_{UB_4y}				+										
g_{LB_4y}				-										
g_{UB_5x}					+									
g_{LB_5x}					-									
g_{UB_5y}						+								
g_{LB_5y}						-								
g_{UB_6x}							+							
g_{LB_6x}							-							
g_{UB_6y}								+						
g_{LB_6y}								-						
g_{UB_7x}									+					
g_{LB_7x}									-					
g_{UB_7y}										+				
g_{LB7y}										-				
g_1:GradTow65				-			-				+	-	-	-
g_4:MinCVID				-			+							
g_5:MaxCVID				+										
g_6:Rollover				+			-							
g_{11}:MinTrackwidth											-			
g_{12}:L101+L104-L103							-							
g_{14}:MinH101				-			+							
g_{39}:Acc3050												+	-	+
g_{45}:MinTopSpeed				?			?				?	?	?	?

Table D.1: Monotonicity table

lower bound. However, when L103 increases towards it's upper bound as PEF increases, this constraint becomes inactive. The physical meaning of this is that when when the optimal vehicle length is relatively short, this reduces the cargo room available. However, when the vehicle gets longer, there is more volume available for cargo and so it exceeds the minimum requirement and the constraint no longer is active.

- g6 is always active. This is the constraint for the rollover score
- g12, is inactive. This is the constraint for the minimum value for L103.
- g14, is active, with respect to H101.
- g39, is inactive. This is the constraint for the minimum time to accelerate from 30 to 50 mph while towing.
- g45, is inactive.
- g47, is conditionally active with respect to L103.

The activity of constraint g45 can not be readily determined since its computations are based on neural network simulations. However, what is known is that this constraint is active in the Frischknecht model (i.e., the "MPG-only original") but becomes inactive in the revised fuel economy model (i.e.,"MPG-only revised"). We conjecture that the variables that may influence the activity of g45 are the engine bore and engine bore-to-stroke ratio because their lower and upper bounds, respectively, become and remain active in the revised model.

The PEF constraint contains eight design variables that do not appear in the objective. By MP2, these variables are relevant and are bounded above and below by at an active constraint. PEF is a linear function and so the eight variables will hit their bounds in the optimization problem. By substituting the active upper and lower bound values, the PEF monotonicity relation can be reduced to:

$$g47 : f(4y^+, 6x^-) \leq 0$$

and since these control points are functions of geometry, the constraint effectively can be expressed as:

$$g47 : f(H101^+, L103^-) \leq 0$$

An optimum value is identified and essentially it behaves as a constant. Of the seven design variables, H101 contributes the least to the computation of fuel economy. In the polynomial function used, H101 contributes one term and has very little impact on the computation for the fuel economy. It only contributes one term to the polynomial expression that computes the combined fuel economy. Therefore, it does not vary much throughout the analysis. Therefore, the PEF constraint can be further reduced to:

$$g47 : f(L103^-) \leq 0$$

Upon inspection, it can be seen that g47 is conditionally active with respect to $L103^-$. Increases in P6x increases PEF determined by values of P6x that forces it towards its lower bound.

Parametric Study Details

PEF Parametric Study

A parametric study was done on the minimum value for PEF while still considering all the control points. The results are shown in Figure D.1. The study was done in MATLAB by varying the minimum value of the PEF constraint from 3.5 to 4.734 as shown in the first column labeled "Min PEF". The resulting fuel economy is shown in the second column labeled "MPG". Columns 2x - 7y are the values of the control points for each iteration. In some instances, the control points do not hit their bounds and the optimizer finds values that will satisfy the minimum PEF requirement as shown in the column labeled “PEF Constraint”. Changes in the minimum cargo volume are shown in the column “CVID”. Constraint activity is shown for both lower bounds (LB), upper bounds (UB) and nonlinear constraints. Active constraints are marked with an “x” and those that are not active are marked as “inactive”.

A number of things can be observed immediately. The constraints g1, g6, and g14 are always active. The PEF constraint, g47 and the minimum cargo volume index, g4 are both conditionally active as previously discussed. In Chapter 4, it was discussed that the range of minimum PEF between 3.5 and 4.7 is where g4 was dominant and always active. However, it can be seen that PEF is active in this range for 3 instances. PEF becomes active for instances where the optimizer finds a combination of values that produces the exact minimum PEF as set in the criteria “Min PEF” column. Those are the only instances where PEF becomes active.

Redoing the parametric study based on $g47 : f(L103^{-}) \leq 0$ would produce the results shown in the range of minimum PEF from 4.71 -4.734. The constraint activity would change as a result leaving only the bounds on the engine bore and engine bore-to-stroke ratio active and the four active nonlinear constraints.

Acc0to60 Parametric Study

A parametric study was conducted to examine the impact of adjusting the minimum time to accelerate from 0 to 60 mph. It can be seen that there is a direct tradeoff between fuel economy and acceleration time (see Figure D.2) where the fuel economy increases as the time to accelerate increases.

Details of these results can be found in Figure D.3. MATLAB simulations were run holding all things fixed and varying the max time to accelerate from 8-10 seconds in increments of 0.2 seconds. The reduced form of PEF ($g47 : f(L103^{-}) \leq 0$) was used here at its largest minimum value. The first column lists the time increments.

Min PEF	MPG	2x	2y	4x	4y	5x	5y	6x	6y	7x	7y	PEF Constraint	CVID	Active bounds		Nonlinear constraint activity				
														LB	UB	g1	g4	g6	g14	g47
3.50	23.61	-1.56	1.79	2.79	3.92	8.65	3.27	10.09	2.41	10.42	0.40	3.8982	29	EB	EBS	x	x	x	x	inactive
3.60	23.61	-1.55	1.75	2.99	3.92	8.69	3.29	10.09	2.39	10.39	0.40	4.0541	29	EB	EBS	x	x	x	x	inactive
3.70	23.61	-1.55	1.75	2.72	3.92	8.77	3.36	10.09	2.38	10.39	0.40	3.8105	29	EB	EBS	x	x	x	x	inactive
3.80	23.61	-1.55	1.74	2.72	3.92	8.78	3.37	10.09	2.38	10.39	0.40	3.8050	29	EB	EBS	x	x	x	x	inactive
3.90	23.61	-1.55	1.73	2.90	3.92	8.77	3.36	10.09	2.37	10.38	0.40	3.9462	29	EB	EBS	x	x	x	x	inactive
4.00	23.61	-1.54	1.72	2.98	3.92	8.79	3.36	10.09	2.37	10.37	0.40	4.0023	29	EB	EBS	x	x	x	x	inactive
4.10	23.61	-1.53	1.68	2.98	3.92	8.76	3.35	10.09	2.33	10.34	0.40	4.1028	29	EB	EBS	x	x	x	x	inactive
4.20	23.61	-1.49	1.63	2.90	3.92	8.75	3.34	10.09	2.25	10.26	0.40	4.2000	29	EB	EBS	x	x	x	x	x
4.30	23.61	-1.46	1.60	2.88	3.92	8.76	3.33	10.09	2.17	10.18	0.40	4.3000	29	EB, 2y	EBS	x	x	x	x	x
4.40	23.61	-1.40	1.60	2.80	3.92	8.70	3.32	10.09	2.00	10.10	0.40	4.4002	29	EB	EBS	x	x	x	x	inactive
4.50	23.61	-1.44	1.60	2.76	3.92	8.52	3.20	10.09	2.03	10.10	0.40	4.5000	29	EB,7x	EBS	x	x	x	x	x
4.60	23.61	-1.40	1.60	2.87	3.92	8.50	3.21	10.09	2.00	10.10	0.40	4.6151	29	EB,2y	EBS	x	x	x	x	inactive
4.70	23.61	-1.40	1.60	3.00	3.92	8.50	3.20	10.09	2.00	10.10	0.40	4.7042	29	EB,5x,5y	EBS,4x	x	x	x	x	inactive
4.71	**23.59**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.12**	2.00	10.10	0.40	**4.7100**	**29.5**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x
4.72	**23.49**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.27**	2.00	10.10	0.40	**4.7200**	**32.1**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x
4.73	**23.38**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.43**	2.00	10.10	0.40	**4.7300**	**34.7**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x
4.731	**23.36**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.44**	2.00	10.10	0.40	**4.7310**	**35.0**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x
4.732	**23.35**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.46**	2.00	10.10	0.40	**4.7320**	**35.2**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x
4.733	**23.34**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.47**	2.00	10.10	0.40	**4.7330**	**35.5**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x
4.734	**23.33**	-1.40	1.60	3.00	3.92	8.50	3.20	**10.49**	2.00	10.10	0.40	**4.7340**	**35.8**	EB,2y,5x,5y,6y,7x	EBS,2x,4x,7y	x	inactive	x	x	x

Figure D.1: Details of PEF parametric study

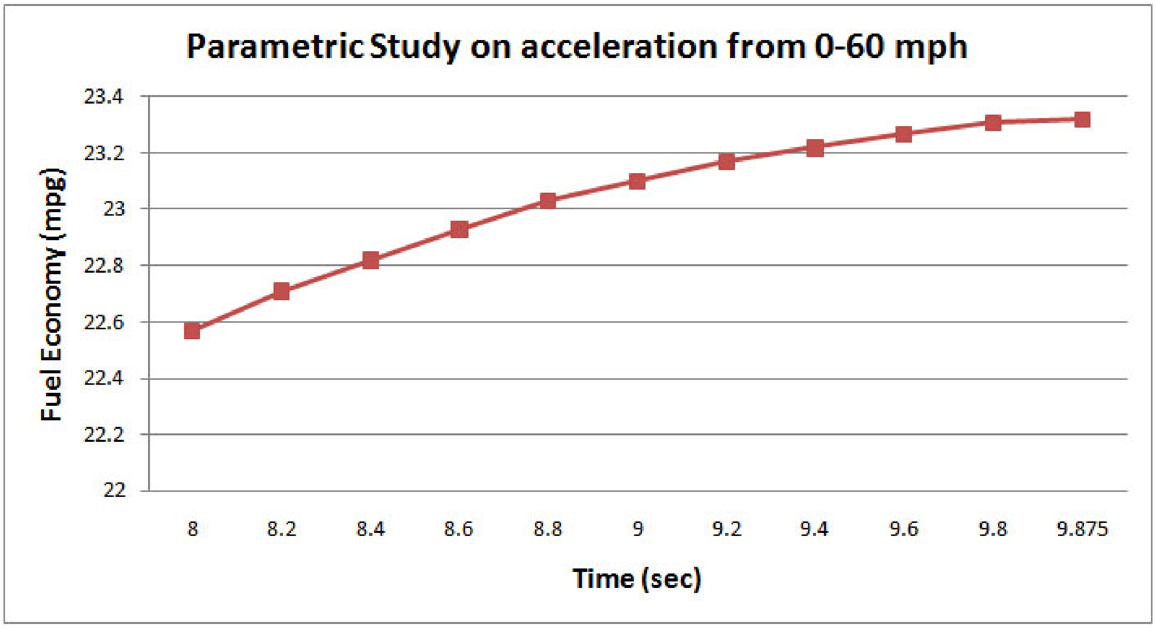


Figure D.2: Parametric Study of Time to accelerate from 0-60 mph

Ten seconds is not shown because the max attainable time was 9.875 seconds. The second column contains the results of the fuel economy. The column labeled “EB” is for the engine bore; “EBS” is the engine bore-to-stroke ratio; “FD” is the final drive ratio, and “W105” is for the vehicle width. Performance measures are also included: the maximum acceleration time from 30 - 50 mph at tow (“Acc3050Tow”) and the maximum speed.

Three constraints were active in the study: the lower bound on the engine bore, minimum H101 (g14), PEF (g47), and the maximum rollover score (g6). Between the range 8.0-8.6 seconds, the constraint for the minimum gradeability (g1) is inactive. Starting at 8.6 seconds, g1 becomes active. The constraint for the maximum acceleration from 0-60 mph remains active for each iteration except for the last which is not able to attain the maximum value, and therefore it becomes inactive.

Time (sec)	MPG	EB	EBS	FD	W105	Grad65Tow	Acc3050Tow	Maxspeed	CVID	Active bounds		Nonlinear constraint activity				
										LB	UB	g1	g14	g6	g40	g47
8	22.57	86	1.02	3.40	1885.26	5.74	5.530	120.7	35.876	EB		inactive	x	x	x	x
8.2	22.71	86	1.03	3.35	1885.32	5.49	5.659	123.4	35.878	EB		inactive	x	x	x	x
8.4	22.82	86	1.04	3.31	1885.37	5.27	5.779	125.4	35.879	EB		inactive	x	x	x	x
8.6	22.93	86	1.05	3.27	1885.42	5.06	5.891	126.9	35.880	EB		inactive	x	x	x	x
8.8	23.03	86	1.07	3.31	1885.53	5.00	5.916	127.5	35.883	EB		x	x	x	x	x
9	23.10	86	1.09	3.37	1885.67	5.00	5.906	127.8	35.887	EB		x	x	x	x	x
9.2	23.17	86	1.11	3.43	1885.79	5.00	5.896	128.0	35.890	EB		x	x	x	x	x
9.4	23.22	86	1.13	3.49	1885.90	5.00	5.885	128.1	35.893	EB		x	x	x	x	x
9.6	23.27	86	1.15	3.56	1886.01	5.00	5.872	128.3	35.896	EB		x	x	x	x	x
9.8	23.31	86	1.17	3.62	1886.13	5.00	5.855	128.4	35.899	EB		x	x	x	x	x
9.875	23.32	86	1.18	3.65	1886.17	5.00	5.847	128.4	35.900	EB	EBS	x	x	x	inactive	x

Figure D.3: Details of Acc0to60 parametric study

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