Proceedings of the ASME 2007 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference
IDETC/CIE 2007
September 4-7, 2007, Las Vegas, Nevada, USA

DETC2007/DAC-34883

DRAFT: DESIGN OPTIMIZATION OF A LAPTOP COMPUTER USING AGGREGATE AND MIXED LOGIT DEMAND MODELS WITH CONSUMER SURVEY DATA

Ching-Shin Shiau
Research Assistant

Ian H. Tseng
Research Assistant

Andrew W. Heutchy
Graduate Student

Jeremy Michalek
Assistant Professor

Department of Mechanical Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
Corresponding author email: jmichalek@cmu.edu

ABSTRACT

Laptop computers are designed in a variety of shapes and sizes in order to satisfy diverse consumer preferences. Each design is optimized to attract consumers with a particular set of preferences for design tradeoffs. Gaining a better understanding of these tradeoffs and preferences is beneficial to both laptop designers and to consumers. This paper introduces an engineering model for laptop computer design and a demand model derived from a main-effects choice-based conjoint survey. Several demand model specifications are compared, including linear-in-parameters and discrete part-worth specifications for aggregate multinomial logit and mixed logit models. An integrated optimization scheme combines the engineering model with each demand model form for profit maximization. The solutions of different optimal laptop designs and market share predictions resulting from the unique characteristics of each demand model specification are examined and compared.

Keywords: Laptop Computer; Conjoint Analysis; Demand Modeling; Multinomial Logit; Mixed Logit; Design Optimization

1. INTRODUCTION

The laptop computer has become a mainstream product in the personal computer market because of its portability and convenience. A major portion of the laptop consumer market is made up of college and graduate students. This group presents a unique sector of the laptop market due to their financial constraints and need for portability. This need generally demands reduction of size and weight, while maintaining the functionality of screen and keyboard size. Additionally, battery life plays a significant role in how students select their laptops. The objective of this study is to present a methodological demonstration of product design optimization under several alternative models of consumer choice using the laptop as an example. A survey was conducted to collect information on customer preferences from a class of graduate students at Carnegie Mellon University. The survey data were then analyzed through three discrete choice models. An optimization model to combine the engineering constraints and market demand for maximizing the profit is applied to seek the optimal design.

This paper builds on recent research in engineering design that has begun to offer approaches to integrating quantitative models of engineering performance and market performance in product design. Hazelrigg [1] first proposed a decision-based design (DBD) framework to integrate firm-level considerations into engineering design for the maximization of firm utility. This DBD framework has resulted in an array of research in preference modeling for engineering design [2]. In particular, several authors have made use of established quantitative techniques common to market research: Li and Azarm [3,4] developed a product selection approach using ratings-based conjoint analysis survey-derived utility functions to explicitly measure consumer preferences and account for them in design optimization. Wassenaar and Chen [5,6] used discrete choice analysis with revealed preference data to predict expected profit as a function of product attributes and demographic information. Michalek *et al*. [7,8] applied the analytical target cascading (ATC) decomposition methodology to coordinate models of engineering and market performance, including a mixed logit specification to model heterogeneity of preferences in the market and design a line of products. Here we adopt the choice-based conjoint survey design approach used by Michalek *et al*. [7] because the choice-based survey task is most similar to the tasks that consumers make in realistic shopping scenarios, and we optimize the design for profitability while examining the effects of utility form and heterogeneity specification on design solutions.

This paper proceeds in Section 2 by introducing the laptop engineering model, including the survey of current laptop specifications, battery life function and cost modeling. The consumer conjoint survey and applications of three demand model forms are then introduced in Section 3. In Section 4, an integration model to join the engineering model and marketing demand model is used to maximize profit. The final section presents the conjoint analysis results with different demand model forms and analyzes the optimal solutions of the integrated model.

2. ENGINEERING MODEL

The engineering model details for the laptop design study are explained in the following sections, including definitions of design variables, design parameters and constraint functions.

2.1 Design variables

The five design variables in the engineering model of this laptop design study are listed in Table 1, and the graphical representations of these variables are illustrated in Figure 1. They are LCD size (diagonal length), body width, body depth, body thickness, and battery volume ratio. The body dimensions are measured when the laptop is folded. The battery volume ratio is the ratio of battery volume divided by total body volume. The ratio determines how much of the space inside the laptop is dedicated to the battery. The last variable is price of the laptop. The lower and upper bounds of each design variable are also provided in Table 1 based on laptop specifications observed in the market. We assume the upper bound of price is $2000 as a maximum purchase budget for general college students.

2.2 Design Parameters

Design parameters of the engineering model are presented in Table 2. These parameters are chosen based on several assumptions. First, the LCD aspect ratio a is assumed to be 16:10 widescreen because it has become a mainstream specification in the laptop market [10]. A weight-to-volume ratio r_V of the laptop body without the battery and a battery weight-to-volume ratio r_B are both assumed as constants, which are calculated from the specifications of Toshiba Satellite laptop products [11]. For simplicity, Lithium-ion is the only battery technology considered in this study, as these represent the majority of current battery packages. As a result, a heavier battery provides higher current capacity with longer battery life, but at the expense of an increase in total weight and volume.

Table 1: Design variables in the engineering model

Design variable	Description	Unit	Lower bound	Upper bound
x_1	LCD size (diagonal)	inch	10	17
x_2	Body width	inch	5	20
x_3	Body depth	inch	5	20
x_4	Body thickness	inch	0.75	2.0
x_5	Battery volume ratio	--	0.05	0.20
p	Price / 100	$100	0	20

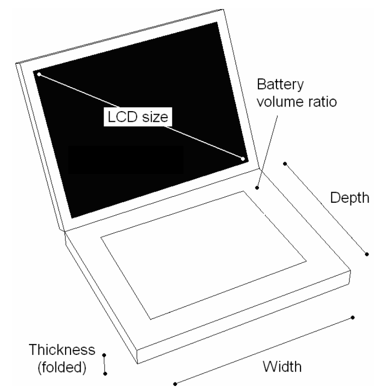

Figure 1: Design variables in the laptop model

The remaining parameters provide constraints [1] in the model, including the minimum margin width of the LCD screen m_{LCD}, the minimum body volume (not including the battery) v_{min}, the maximum allowable total weight w_{max}, which should be a reasonable upper limit for a portable computer, and the minimum battery life t_{min}. These parameters were determined based on the latest laptop specifications surveyed [11-14].

Table 2: Design parameters in the engineering model

Parameter	Description	Value	Unit
a	LCD aspect ratio	1.60	--
r_V	Body weight-to-volume ratio (not including battery)	0.033	lb/inch^3
r_B	Battery weight-to-volume ratio	0.052	lb/inch^3
m_{LCD}	Minimum margin of LCD	0.5	inch
v_{min}	Minimum volume not including battery	100	inch^3
w_{max}	Maximum total weight	10	lb
t_{min}	Minimum battery life	1	hour

2.3 Battery Life

The battery life function was created based on the laptop battery data collected from the major laptop manufacturer websites [11-14]. As shown in Figure 2, the data points reveal an approximately linear relation between battery weight and

[1] These "modeling constraints" are intended to restrain the solution within "reasonable" bounds. An active modeling constraint at the solution would imply that more market data is needed to measure the lack of desirability of variable values outside the specified ranges.

energy storage. The equation obtained from least-squares regression is given by:

$$\begin{aligned} e_B &= 160 w_B - 5.69 \\ &= 160 v_B r_B - 5.69 \\ &= 160(x_2 x_3 x_4 x_5) r_B - 5.69 \end{aligned} \quad (1)$$

where e_B is the storage capacity of the lithium-ion battery (unit: Watt-hour), w_b is the weight of battery (unit: kg) and v_b is the volume of battery (unit: m^3). The power consumption of a laptop computer varies from 8 to 30 Watts [15]. An average power consumption P_{avg} 19 Watts is used for our study, which means a battery with capacity of 19 Watt-hours can support laptop operation for one hour. The equation is written as:

$$\begin{aligned} t_b &= e_b / P_{avg} \\ &= (160 x_2 x_3 x_4 x_5 r_B - 5.69) / P_{avg} \end{aligned} \quad (2)$$

where t_b is the battery life in hours.

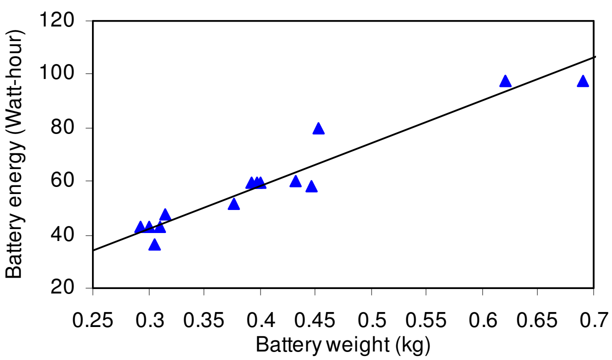

Figure 2: Linear regression of the battery energy data

2.4 Cost and Price Model

The detailed cost structure of a laptop computer is complicated and confidential to the laptop makers. Almost all of today's laptop computers are designed and produced by original design manufacturer (ODM) companies and resold to consumers by major brand owners. The ODM price is the wholesale price at which the brand owner purchases the computers from the ODM suppliers. It comprises of material cost, assembly cost, manufacturing value added (MVA), overhead, ODM profit margin and international shipping cost. Then the brand owner decides the retail price, which is basically a function of ODM cost, overhead, warranty cost and the brand owner's profit margin. Due to the highly competitive nature of the personal computer market, the profit margins of laptop manufacturing and selling are notoriously razor-thin for both brand owners and ODM manufacturers [16].

For the cost modeling of this study, we have to make several assumptions based on the available information. First, the costs of certain components are assumed constant based on a survey of computer component-selling websites [17]. Since the prices of computer parts are highly dynamic, the numbers we use in this model only represent a stationary time point. A dynamic model to realize the cost variation is possible, but the complexity raises issues beyond the scope of this study. The items in Table 3 are assumed unchanged during the design, which results in constant cost terms.

The second part in the cost model is design-variable dependent. They are the costs of the LCD panel, the Lithium-ion battery package and the motherboard. The LCD panel cost data for a range of sizes are and shown in Figure 3 [18]. Theoretically the larger LCD panel size should result in a higher cost, however, the prices are strongly market-demand-driven and it can be seen that there is no significant price difference between 14.1-inch and 15.4-inch panels. The cost data points are fit by a 3rd-order polynomial such that the LCD panel cost equation is given by:

$$c_{LCD} = 1.79 x_1^3 - 78.3 x_1^2 + 1140 x_1 - 5160 \quad (3)$$

Table 3: Constant component costs

Cost component description	Cost
CPU T5500 1.66GHz	206
DRAM DDR2 512MB	46
Hard drive 80GB	65
Keyboard	40
CD-ROM/DVD burner	60
Wireless module IEEE 802.11abg	35
Power adaptor [16]	18
Other components [16]	65
Subtotal of constant costs	535

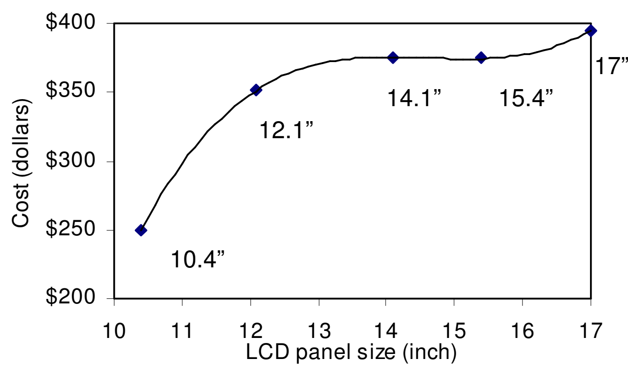

Figure 3: Cost of LCD screen panel

The cost function of the Lithium-ion battery is created using data collected from three Toshiba laptop batteries with different Lithium-ion cells [11]. As shown in Figure 4, the capacity-price function is obtained using linear least-squares regression:

$$\begin{aligned} c_B &= 1.13 e_B + 66.9 \\ &= 181(x_2 x_3 x_4 x_5) r_B + 60.4 \end{aligned} \quad (4)$$

where e_B is the storage capacity of Lithium-ion battery and c_B is the cost of battery.

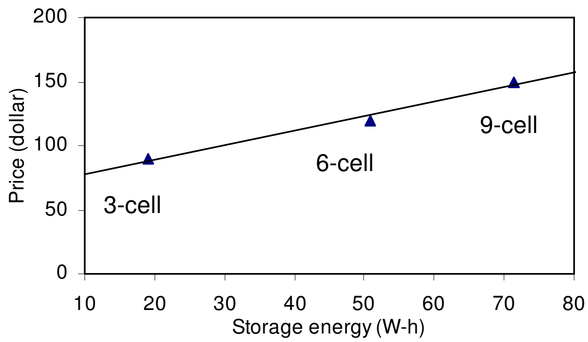

Figure 4: Relation between battery capacity and price

The last cost component is the motherboard cost. Theoretically, when the motherboard size (volume) is reduced, the cost increases significantly because of the difficulties in electrical circuit design, thermal management and more expensive components to be used for saving space. However, there is no readily available information since the motherboard design is highly specific, and it is difficult to describe the cost as a general function of board size. Therefore, we use the field replacement unit (FRU) cost of the IBM Thinkpad motherboard to generate a linear motherboard cost function of laptop volume, not including battery volume.

$$\begin{aligned} c_{MB} &= -2.79 v_{NB} + 565 \\ &= -2.79 x_2 x_3 x_4 (1 - x_5) + 565 \end{aligned} \tag{5}$$

where c_{MB} is the estimated cost of motherboard and v_{NB} is the laptop body volume without battery. Finally the total material cost function can be written as:

$$c_{TM} = c_{CT} + c_{LCD} + c_{MB} + c_B \tag{6}$$

where c_{TM} is the total material cost and c_{CT} the subtotal cost for the constant components in Table 3. Since the numbers are obtained from consumer component purchasing websites, these cost data are expected to be higher than the actual purchase costs of the laptop manufacturer due to quantity discounts [19]. Further, the component prices we see here already include international shipping cost, ODM profit and overhead. The total cost is:

$$c_T = c_{TM} s_q + c_{ASM} \tag{7}$$

where s_q is a constant rate of quantity discount, c_{ASM} is the ODM assembly cost. The ODM assembly cost, including labor and electricity, is assumed constant at 15 dollars [16].

2.5 Constraint Functions

The engineering model contains six constraints. The first constraint limits the minimum volume allowed for a laptop design. This is necessary since the components of each laptop require a certain amount of physical space. The second and third constraints restrict the LCD width and height, including margins, such that they cannot be larger than the body width and height. The fourth constraint represents the shortest acceptable battery life. It avoids the battery life shorter than an unrealistic time. The fifth constraint is the predetermined maximum allowable total weight determined using the ergonomic goals, where an over-weight laptop design is considered infeasible. The total weight is the sum of body weight and battery weight. The equations of the five constraints are listed below. These constraints allow a wide range of design variations while limiting the design space to a practical domain.

$$v_{min} - (x_2 x_3 x_4)(1 - x_5) \le 0 \tag{8}$$

$$x_1 \left(1 + a^2\right)^{-1/2} a + 2m_{LCD} - x_2 \le 0 \tag{9}$$

$$x_1 \left(1 + a^2\right)^{-1/2} + 2m_{LCD} - x_3 \le 0 \tag{10}$$

$$t_{min} - (160 x_2 x_3 x_4 x_5 r_B - 5.69) / P_{avg} \le 0 \tag{11}$$

$$r_V (x_2 x_3 x_4)(1 - x_5) + r_B (x_2 x_3 x_4) x_5 - w_{max} \le 0 \tag{12}$$

3. DEMAND MODEL

The following sections discuss the different forms of discrete choice models used in the study, as shown in Table 4. We study two different levels of consumer preference heterogeneity specification: aggregate logit (standard logit) and mixed logit (random-coefficient logit). The attribute coefficients of the aggregate logit are deterministic values, which conceptually represent the choice behavior presented by an average consumer. On the other hand, the mixed logit describes coefficients as distributed across the population, and numerical simulation methods are used to evaluate the mixed logit probability.

Logit model forms can be further classified by the assumed form of the utility function. In this paper we examine two forms: linear-in-parameters and discrete part-worth. The linear-in-parameters logit model assumes that utility increases (or decreases) at a constant rate as an attribute value is increased, so that the utility change from a 10-inch to 12-inch LCD screen is the same as the utility change from a 15-inch to 17-inch screen. The part-worth utility described by discrete levels of product attributes relaxes this restriction by determining the utility at specific discrete levels and then interpolating to find intermediate values. The details of these models will be explained in the following sections.

Table 4: Section index for the demand model forms

Demand model form	Linear-in-parameters	Discrete part-worth
Aggregate logit	Section 3.2.1	Section 3.2.2
Mixed logit	Section 3.3.1	Section 3.3.2

3.1 Conjoint Survey and Analysis

Conjoint analysis is a popular technique in marketing research and product management. Marketing researchers use conjoint analysis to understand consumers' preference. Instead of asking consumers to specify their rankings of specific product attributes, conjoint analysis generates hypothetical product alternatives in a survey. In choice-based conjoint, consumers select their favorite from a set of alternatives in each question. The collected data are post-processed and analyzed with discrete choice models. In the designer's view, the data from the choice model provides useful information when making design decisions. Without considering consumers' preferences, the product may have high engineering performance but low market performance.

In the conjoint analysis of laptop demand, there are five major attributes selected, LCD size, laptop thickness, battery life, weight and price. Each attribute has five levels to represent the product variations, as shown in Table 5. Instead of conducting a full-factorial survey design, which would have 50 questions and 150 product profiles, a fractional factorial analysis with reduced 25 questions and clear main effects is generated using SAS macros for experimental design [20-21]. Other than the standard design efficiency optimizer in SAS, there are alternative approaches implementing Bayesian methods to design conjoint choice experiments [22-24]. The resulting survey contains three alternatives in each question, plus a no-choice option (i.e. the outside good). A sample question from the conjoint questionnaire is provided in Figure 5.

Table 5: Attributes in the conjoint analysis

Attribute/ Level	1	2	3	4	5	Unit
LCD size z_1	10.4	12.1	14.1	15.4	17	inch
Thickness z_2	0.75	1	1.25	1.5	1.75	inch
Battery life z_3	1	2	4	6	8	hour
Weight z_4	2.5	4.5	6	8	10	lb
Price/100 z_5	7.5	10	12.5	15	20	dollar

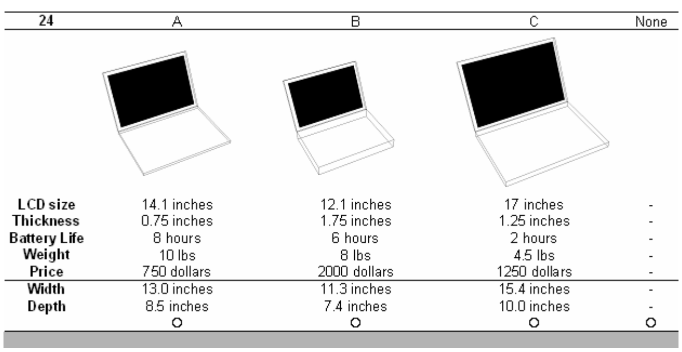

Figure 5: A question sample in the conjoint survey questionnaire

3.2 Standard Logit Model

The multinomial logit model is the most commonly used discrete choice model [25]. Based on the theory of random utility models, when a consumer i chooses a product j, the utility function can be written as:

$$U_{ij} = v_{ij} + \varepsilon_{ij} \tag{13}$$

where v_{ij} is the observed utility and ε_{ij} is the unobserved term for product j, which is represented as a random variable. For the logit model, it is assumed that the unobserved random term follows the independent and identically-distributed (iid) extreme value distribution, which is known to generate results indistinguishable from assuming normal distributions in most applications while providing the benefit of a closed-form expression of choice probability. The resulting well-known logit choice probability formulation is given by:

$$Pr_j = \frac{\mathbf{exp}(v_j)}{\sum_k \mathbf{exp}(v_k)} \tag{14}$$

where the Pr_j is the probability of product j chosen by an average consumer among all k products (i.e.: the probability that the utility of product j is greater than the utility of all alternatives) [25].

3.2.1 Linear-in-Parameters Logit Model

A widely-used form for the standard logit model is to assume that the observed utility term v_j has a linear relation with determined parameter vector $\boldsymbol{\beta}$ and attribute vector $\mathbf{z}_j$. The size of the vector is determined by the number of observed attributes in the demand model. Based on this assumption, the logit choice probability can be expressed as:

$$Pr_j = \frac{\mathbf{exp}(\boldsymbol{\beta}^T \mathbf{z}_j)}{\sum_k \mathbf{exp}(\boldsymbol{\beta}^T \mathbf{z}_k)} \tag{15}$$

where k is the number of all alternatives in one choice situation faced by an average consumer. The standard logit model also assumes all consumers share the same attribute coefficients (i.e.: there is no modeled taste variation across consumers). This aggregate model form presents a statistically average preference in product selection.

3.2.2 Discrete Part-Worth Logit Model

Though the linear-in-parameters form provides a simple formulation with computational benefits, it ignores the possibility of nonlinearities in the utility function. Use of latent utility functions and nonparametric methods to include nonlinearities is undesirable because of excessive computational cost, which is not suitable for numerical optimization. It is possible to discretize the attribute domains to obtain a main-effects model and used natural cubic splines to interpolate the utility values at intermediate attribute levels [7]. The advantages of this method are that the potential nonlinearity in the observed utility is taken into account, and the mapping process of product discrete attributes is not complicated[2]. Based on this method, the utility function of a specific alternative j for an average consumer can be expressed as:

[2] The part-worth model continues to assume that interactions are negligible; however, specific interactions can be included by introducing new attributes that represent combinations of the original attributes [23].

$$v_j = \sum_{\zeta}\left(\sum_{\omega}\beta_{\zeta\omega}\delta_{j\zeta\omega}\right) \quad (16)$$

where ω is the discrete attribute level, $\beta_{\zeta\omega}$ is the part-worth coefficient at level ω, and δ is attribute level indicator function: $\delta_{j\zeta\omega}$ is equal to one if product j has attribute ζ at level ω, otherwise zero [26]. Therefore, $\delta_{\zeta\omega}$ can be considered as a function of attribute z_j. The logit choice probability for this case is given by:

$$Pr_j = \frac{\mathbf{exp}\left(\sum_{\zeta}\left(\sum_{\omega}\beta_{\zeta\omega}\delta_{j\zeta\omega}\right)\right)}{\sum_k \mathbf{exp}\left(\sum_{\zeta}\left(\sum_{\omega}\beta_{\zeta\omega}\delta_{k\zeta\omega}\right)\right)} \quad (17)$$

3.3 Mixed Logit Model

The mixed logit model is an extension of the standard multinomial logit model. It accounts for consumer preference heterogeneity in choice modeling. Instead of limiting the β coefficients as deterministic for an average consumer, the mixed logit model poses β as a distribution across the consumer population. This form explicitly models heterogeneity and removes some limitations of the standard logit model such as the well-known independence of irrelevant alternatives (IIA) property [25]. The mixed logit probability can be written as an integral:

$$Pr_{ij} = \int \frac{\mathbf{exp}(v_{ij})}{\sum_k \mathbf{exp}(v_{ik})} f(\boldsymbol{\beta}_i)d\boldsymbol{\beta}_i \quad (18)$$

where $\boldsymbol{\beta}_i$ is preference coefficient vector for consumer i and $f(\boldsymbol{\beta}_i)$ is the (joint) probability density function of $\boldsymbol{\beta}_i$ distribution across individuals.

3.3.1 Linear-in-Parameters Mixed Logit Model

Assuming the utility is linear in attributes, the mixed logit probability in the linear-in-parameters form is given by:

$$Pr_{ij} = \int \frac{\mathbf{exp}(\boldsymbol{\beta}_i^T \mathbf{z}_{ij})}{\sum_k \mathbf{exp}(\boldsymbol{\beta}_i^T \mathbf{z}_{ik})} f(\boldsymbol{\beta}_i)d\boldsymbol{\beta}_i \quad (19)$$

The integral is approximated by numerical simulation with a finite set of draws from $f(\boldsymbol{\beta}_i)$. The simulated mixed logit probability $\hat{P}r_{ij}$ derived from Eq. (19) is:

$$\hat{P}r_{ij} = \frac{1}{R}\sum_{r=1}^{R} \frac{\mathbf{exp}(\boldsymbol{\beta}_i^{rT} \mathbf{z}_{ij})}{\sum_k \mathbf{exp}(\boldsymbol{\beta}_i^{rT} \mathbf{z}_{ik})} \quad (20)$$

where R is the total number of random draws in the simulation, and $\boldsymbol{\beta}_i^r$ is the vector of random coefficient for consumer i at the r-th random draw. It can be seen that the β coefficient is a stochastic value described by its distribution parameters, which represents heterogeneity and taste variations across consumers. The β coefficient can be described by any probability distribution, although normal and lognormal distributions are most frequently used in discrete choice models [25]. The most critical difference between the lognormal form and the normal form is that the lognormal distribution is bounded greater than zero. This feature of the lognormal distribution is utilized if the coefficient is known to be of a particular sign [27]. For example, people always prefer lower prices, so the preference coefficient of the price attribute should be negative. The lognormal distribution, unlike the normal, does not assume that there is small number of individuals in the tail of the distribution that have a parameter of the opposite sign.

3.3.2 Discrete Part-Worth Mixed Logit Model

The discrete part-worth form can be implemented into the mixed logit model to include heterogeneity across consumers as well as nonlinearity in different attribute levels. However, in such a model, it is unreasonable to ignore correlations in the random coefficients, and the complexity of the resulting model prohibits practical use of traditional statistical approaches to model fitting, such as maximum likelihood estimation used in the prior three models. It is possible to estimate such a model using Bayesian Markov chain Monte Carlo (MCMC) methods to simulate the β coefficients as drawn from a joint normal distribution, which includes the nonlinearity in the observed utility term as well as correlations between attributes [28]. Nevertheless, due to the significant increase in complexity, we do not explore the model in this study.

4. INTEGRATED OPTIMIZATION MODEL

Based on the engineering model and the demand model, an integrated optimization scheme is created for maximizing the profit of a new product design, and the full formulation is:

Maximize: Profit $\prod = q(p - c_T)$ w.r.t. $x_1,\ldots,x_5$ (21)

where $q = S \cdot Pr(\boldsymbol{\beta}, \mathbf{z}(\mathbf{x}, p))$

$c_T = c_{TM}s_q + c_{ASM}$

Subject to:

$$g_1(\mathbf{x}) = v_{min} - (x_2x_3x_4)(1-x_5) \le 0$$

$$g_2(\mathbf{x}) = x_1\left(1+a^2\right)^{-1/2}a + 2m_{LCD} - x_2 \le 0$$

$$g_3(\mathbf{x}) = x_1\left(1+a^2\right)^{-1/2} + 2m_{LCD} - x_3 \le 0$$

$$g_4(\mathbf{x}) = t_{min} - (160x_2x_3x_4x_5r_B - 5.69)/P_{avg} \le 0$$

$$g_5(\mathbf{x}) = r_V(x_2x_3x_4)(1-x_5) + r_B(x_2x_3x_4)x_5 - w_{max} \le 0$$

where S is the market size, Pr is the new product market share, which is calculated from Eq. (15), (17) or (20) upon the specific logit demand model form. The product of market size and share is the demand quantity[3]. A 2006 consumer report from an

[3] Choice predictions from a conjoint survey can be considered a predictor of demand if the survey respondents are representative of the market, if survey

Internet computer retailer shows that the average price of a student laptop is $1,446 [29]. The total market size (in dollars) of U.S. student laptop for academic year 2006 is $2.3 billion [30]. Upon these two figures, the demand quantity for the market segment of U.S. college student laptops is calculated as 1.6 million.

The profit is generated by the difference between price and total cost. Since the article assumes all products have the same profit margin in this highly competitive market, the task is identical to maximization of market share. The integrated optimization model is illustrated in Figure 6.

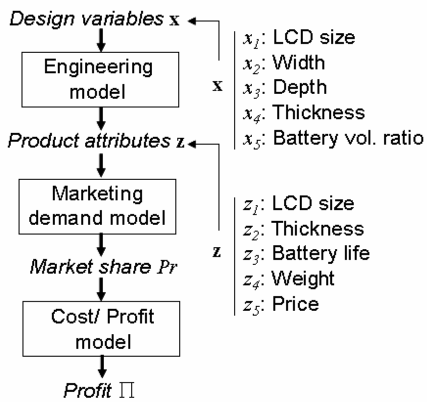

Figure 6: Process flow diagram of the integrated model

4.1 Competitors in the Market

In the marketing demand model, we assume an oligopolistic market having ten existing laptop designs with attributes shown in Table 6. These competitor data were collected from the specifications of current laptop computers. Since the computer market in the real world is highly dynamic and specifications change rapidly, the information we consider here is only sufficient for our simplified analysis at a stationary time point.

5. RESULTS AND DISCUSSIONS

5.1 Demand model coefficients

Based on the conjoint survey data of 18 respondents in a graduate-level design class, the attribute preference coefficients β of the three choice models were determined using maximum likelihood estimation (MLE). The coefficients of standard logit linear-in-parameters model are shown in Table 7. It can be seen that, on average, respondents prefer larger LCD size, smaller thickness, longer battery life, lighter weight and lower price.

The part-worth coefficients of the discretized logit model are presented in Table 8. The discrete points are interpolated using natural cubic splines for estimating the utility of intermediate values of product attributes, shown in Figure 7.

responses match choice behavior in the marketplace and if non-modeled aspects, such distribution, advertising, etc. are assumed constant across all alternatives.

The part-worth curves reveal more practical information than the linear coefficients of the standard logit model. For example, from the LCD size utility curve, we see that preference generally increases as the LCD size increases, but decreases if the screen becomes too large. The response of battery life is similar to LCD size. The longest battery life of 8 hours may not be necessary for general users, which causes a flattening of the utility curve. The weight and price give clear indications that light weight and low price are appreciated by consumers, and the thickness curve shows a small amount of noise, probably due to the small sample size or possibly from non-negligible interaction terms that were conflated in the main effects model. Further research would be needed to determine the cause; however, because the parameter appears to have the smallest influence on utility, and because the noise is relatively small, the model will suffice for the purposes of the study.

Table 6: Competitor product attributes

Competing product	LCD size z_1	Thickness z_2	Battery Life z_3	Weight z_4	Price z_5
	inch	inch	hour	lb	dollar
U2	12.1	1.34	5.2	4.10	1200
X6	12.1	1.40	7.8	3.50	1400
M1	14.1	1.50	2.8	5.24	800
M5	14.1	1.29	5.2	5.20	1200
R6	14.1	1.58	5.2	6.10	650
A1	15.4	1.31	3.5	6.00	1070
T7	15.4	1.22	5.8	5.10	1200
N5	15.4	1.35	3.0	6.27	700
P1	17.0	1.70	3.4	7.10	1000
N8	17.0	1.42	2.8	7.60	1300

Table 7: Attribute coefficients of standard logit model

Attribute		Linear coefficient (std. error)
LCD size	z_1	0.231 (0.025)
Thickness	z_2	-0.967 (0.171)
Battery life	z_3	0.273 (0.030)
Weight	z_4	-0.315 (0.031)
Price/100	z_5	-0.140 (0.020)

Table 8: Part-worth coefficients of logit model

Attribute		Part-worth coefficient				
		1	2	3	4	5
LCD size	z_1	-1.076	-0.509	0.231	0.583	0.381
Thickness	z_2	0.519	-0.075	-0.249	0.091	-0.676
Battery life	z_3	-1.438	-0.687	0.335	0.778	0.622
Weight	z_4	1.179	-0.455	0.069	-0.471	-1.621
Price/100	z_5	0.659	0.314	0.279	-0.018	-1.624

The β distribution types have to be determined first when evaluating the attribute coefficients of the mixed logit model. In general, the attributes may be correlated with one another, which forces covariance to be considered. In this paper, the distribution of β for each of the five attributes are assumed to be independent. Examining the LCD size attribute, consumers generally prefer larger LCD screens, but some might prefer smaller screens for better portability. Therefore the preference coefficient of LCD size attribute is given an independent normal distribution, which covers the positive and negative signs. For the other four preference coefficients, we expect that all consumers prefer thinner thickness, longer battery life, lighter weight and lower price. As a result, the distributions of these coefficients are specified as independent lognormal.

Table 9 shows the distribution parameters of the mixed logit random coefficients after performing maximum likelihood estimation with 1000 random draws. The positive mean and relatively small standard deviation of normal distribution for the LCD size coefficient show that the vast majority of consumers prefer larger LCD sizes. For the other four attributes described by lognormal distributions, the means and standard deviations in Table 9 represent the natural logarithm of their coefficients. For example, the logarithmic mean of the negative thickness preference coefficient is -0.216. The mean value of original thickness coefficient in the normal space is -0.806 by exponentiation. The logarithmic standard deviation needs conversion as well when calculating the utility for these attributes.

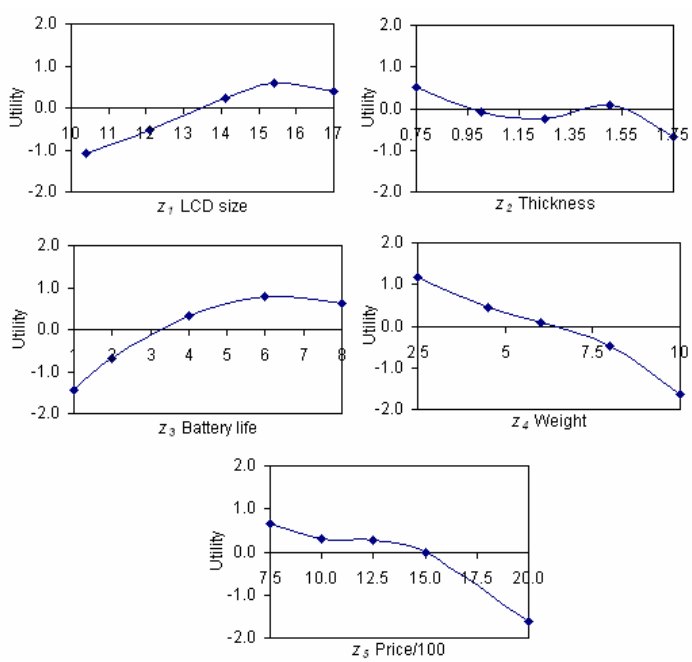

Figure 7: Part-worth coefficients fit with splines

Table 9: Attribute coefficients of mixed logit model

Attribute		Dist type	Mixed logit coefficient Mean (SE)	Std. dev. (SE)
LCD size	z_1	N	0.302 (0.039)	0.104 (0.020)
(-) Thickness	z_2	LN	-0.216 (0.335)	0.813 (0.219)
Battery life	z_3	LN	-1.166 (0.144)	0.361 (0.121)
(-) Weight	z_4	LN	-1.116 (0.186)	0.816 (0.147)
(-) Price/100	z_5	LN	-1.801 (0.204)	0.641 (0.223)

Distribution type: N: normal, LN: Lognormal

5.2 Solutions of Integrated Model

The sequential quadratic programming (SQP) algorithm of the Matlab Optimization Toolbox [31] is used to solve the nonlinear programming problem (NLP) in the integrated model. The results of optimal laptop design are shown in Table 10. The mixed logit prediction is based on the simulation of 1000 random draws. The optimal solution of the part-worth logit model presents a LCD size different from the other two. This is because the part-worth spline of the LCD size coefficient has the highest utility at 15.4 inches. In contrast, the positive attribute coefficient in the linear-in-parameters logit and mixed logit models both predict the largest LCD size to have the highest utility. As for the mixed logit model in linear-in-parameters form, the positive mean 0.302 and standard deviation 0.104 of the normal distribution result in 1.8% probability to have a negative coefficient. Therefore the optimal solution with the mixed logit model has a 17 inch LCD screen.

These optimal design solutions have several active lower and upper bounds, including maximum LCD size, maximum depth and minimum battery volume ratio. The purpose of these constraints is to confine the final design in a practical range. For example, a 19-inch LCD size is common for desktop LCD monitor but not usual for laptop design although it is physically feasible. LCD manufacturers do not offer 19-inch laptop LCD panel in their standard product line such that the customized module results high cost which is beyond our cost model range. Moreover, the LCD size greater than 17 inches is not included in our survey. Based on the reasons, the upper bound of 17-inch LCD size presents not only a modeling constraint but also a partially physical constraint. All three solutions reached the thickness lower bound 0.75 inches, a constraint determined by technical consideration because a thickness smaller than this value encounters manufacturing difficulty. The three solutions have the optimal prices less than the assumed maximum purchase budget $2,000.

The battery volume ratios of three reach the upper bound in order to have the longest battery life. When the battery volume ratio is bounded, the only way to increase battery life is to increase the total laptop volume, but a larger volume with heavier weight contradicts the consumer's light weight preference. This situation forces the algorithm to search for an optimal solution for width and depth with minimum weight. The solution in the first column of Table 10 for the linear-in-parameters logit model has the fifth constraint and depth upper bound active, which are maximum weight 10 lbs and maximum depth 20 inches, a modeling constraint to prevent overweight and oversize laptop in ergonomic consideration. This indicates that the model predicts respondent willingness to choose laptops with longer battery life and heavier weight than were included in the pilot survey. The linear-in-parameters mixed logit solution has the first constraint active, and all solutions have the minimum thickness constraint and the maximum battery volume ratio active, indicating that component packaging constraints prevent construction of more desirable laptops.

The predicted market shares of the new laptop design with the competing products are presented in Figure 8. It can be seen that the predictions made by the three demand model forms differ. Compared to the discrete part-worth logit model, both the linear-in-parameters logit and mixed logit have similar market share predictions. The logit model in discrete part-worth form has distinct market share predictions from the other two, especially on the laptop X6 and R6. Laptop X6 represents an ultra-portable design that has the lightest weight, a small LCD screen, the longest battery life, and the highest price on the market. Apparently the part-worth coefficients model's capture of the lack of need for an extremely long battery life affects predictions for this model. Laptop R6 has the thickest thickness and the lowest price and average specifications for the other three attributes. For this case, the part-worth coefficients catch the utility fluctuation around a thickness of 1.5 inches while the linear-in-parameters models predict low utility. The highest market share in Figure 8 is the laptop R6 estimated by the discrete part-worth logit model. Comparing R6 to the new product, which owns the second high market under the same demand form, the new laptop offers similar LCD screen size, battery life and weight, but much thinner thickness and higher price. Apparently the low price of $650 for the laptop R6 dominates the predicted market in this case. Finally, the mixed logit predicts the lowest profit since it accounts for consumer heterogeneity and the inability to please all consumers with a single design.

The solution in Table 10 represents design of a new laptop under the assumption that competitors will remain static in design and pricing. In an oligopoly, producers will change their laptop designs and pricing strategies to gain maximum profit, and so the study represents only the first stage in a series of movements toward a market equilibrium [32]. A limitation of this model is that the laptop brand is not taken into account in demand estimation. Certain consumers are willing to pay more money to purchase a laptop computer from preferred or reputable brands, despite less desirable specifications. The small number of competitors in this simulated market is another limitation. In the real laptop computer market, there are several market segments and more than one hundred competing products. Finally, the uncertainty in our demand prediction is expected: Because the study relies on data from a small sample of graduate students and assumes that this sample is representative of the whole student laptop market segment, we might expect that it would be possible to design a specialized product for the survey respondent group that would match their preferences better than the set of competitor laptop designs in Figure 8, which were presumably optimized for a broader group of consumers. Collection of data from a larger group of representative consumers would improve predictions for the broader laptop market.

Table 10: Optimal solutions of the integrated model

Variable		Unit	Logit linear	Logit part-worth	Mixed logit linear
LCD size	$x_1 (z_1)$	inch	17*	15.9	17*
Width	x_2	inch	18.2	18.3	16.6
Depth	x_3	inch	20.0*	10.7	10.0
Thickness	$x_4 (z_2)$	inch	0.75*	0.75*	0.75*
Bat. vol. ratio	x_5	--	0.2*	0.2*	0.2*
Bat. life	z_3	hour	10.4	5.5	4.5
Weight	z_4	lb	10.00	5.38	4.25
Price	z_5	Dollar	1821	1612	1699
Cost	c_T	Dollar	1013	1145	1186
Mkt. share	Pr	%	11.4%	15.7%	11.5%
Profit	Π	dollar	148M	117M	94.6M
Active constraint		--	5th	none	1st

*Variable at an upper or lower bound.

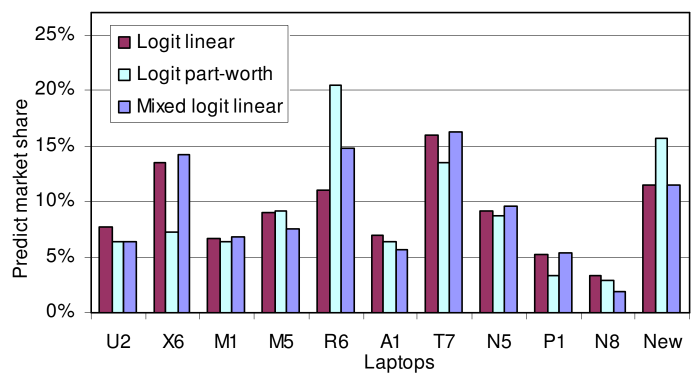

Figure 8: Predicted market share of laptops in the market

6. CONCLUSIONS

This project carried out a computer laptop design study for technical and market performance by deriving an engineering design model for laptop computers and constructing alternative logit and mixed logit demand models using data from a main-effects conjoint survey. Responses from the target consumer group were analyzed, and results show that respondents generally prefer larger LCD screens, longer battery life, lighter weight and lower price, and they are less sensitive to increased thickness than they are to increased weight. In such a case, the linear coefficients of a standard logit model are not able to represent nonlinearities and heterogeneity in consumer preferences. Instead, the discrete part-worth logit model with spline-fit coefficients and the mixed logit model provide alternatives for demand modeling: The discrete part-worth model captures nonlinearities, and the mixed logit model captures consumer heterogeneity. The final solutions show that the part-worth logit model is able to present more detailed utility responses than the linear-in-parameters model. On the other hand, the mixed logit model provides marketing predictions with stochastic behavior based on the coefficient distribution parameters and captures the heterogeneity of consumer preferences in the market.

ACKNOWLEDGEMENTS

This research was supported in part by a grant from the National Science Foundation program for Material Use, Science, Engineering and Society: Award #0628084 and in part by NSF grant DMI-0627894.

NOMENCLATURE

a	=	LCD aspect ratio
b	=	Purchase budget
c_B	=	Cost of battery
c_{MB}	=	Cost of motherboard
c_{ASM}	=	Assembly cost
c_{TM}	=	Total material cost
c_T	=	Total cost
e_B	=	Battery storage capacity
i	=	Consumer index
j	=	Product alternative index
k	=	Product alternative index
t_B	=	Battery life
t_{min}	=	Minimum battery life
m_{LCD}	=	Minimum margin of LCD
m_p	=	Profit margin
Pr	=	Demand probability (market share)
$\hat{P}r$	=	Simulated probability
p	=	Product price
P_{avg}	=	Average power consumption
q	=	Demand quantity
r	=	r-th random draw
R	=	Total number of random draws
r_V	=	Weight-volume ratio (not including battery)
r_B	=	Average battery weight-volume ratio
S	=	Market size
s_q	=	Quantity discount rate
u	=	Utility
v_B	=	Volume of battery
v_{NB}	=	Laptop volume without battery
v_{min}	=	Minimum volume not including battery
x	=	Design variable
$\mathbf{x}$	=	Design variable vector
w_B	=	Weight of battery
w_{max}	=	Maximum total weight
z	=	Product attribute
$\mathbf{z}$	=	Product attribute vector
$\boldsymbol{\beta}$	=	Attribute preference coefficient vector
δ	=	Attribute level indicator function
ζ	=	Product attribute index
ω	=	Discrete attribute level
Π	=	Profit

REFERENCES

1. Hazelrigg, G. A., 1998, "A Framework for Decision-Based Design," ASME J. Mech. Des., **120**(4), pp. 1-13.
2. Lewis, K, Chen, W., and Schmidt, L., 2006, *Decisions Making in Engineering Design*, ASME Press, New York.
3. Li, H., and Azarm, S., 2000, "Product Design Selection Under Uncertainty and With Competition Advantage," ASME J. Mech. Des., **122**(4), pp. 411-418.
4. Li, H., and Azarm, S., 2002, "An Approach for Product Line Design Selection Under Uncertainty and Competition," ASME J. Mech. Des., **124**(3), pp. 385-392.
5. Wassenaar, H. J. and Chen, W., 2003, "An Approach to Decision Based Design with Discrete Choice Analysis for Demand Modeling," ASME J. Mech. Des., **125**(3), pp. 490-497.
6. Wassenaar, H. J., Chen, W., Cheng, J. and Sudjianto, A., 2005, "Enhancing Discrete Choice Demand Modeling for Decision-Based Design," ASME J. Mech. Des., **127**(4), pp. 514-523.
7. Michalek, J. J., Feinberg, M. F., and Papalambros, P. Y., 2005, "Linking Marketing and Engineering Product Design Decisions via Analytical Target Cascading," J Prod. Innov. Manag., **22**(1), pp. 42-62.
8. Michalek, J. J., Ceryan, O., Papalambros, P. Y., and Koren, Y., 2006, "Balancing Marketing and Manufacturing Objectives in Product Line Design," ASME J. Mech. Des., **128**(6), pp. 1196-1204.
9. Fruchter, G. E., Fligler, A., and Winter, R. S., 2006, "Optimal Product Line Design: Genetic Algorithm Approach to Mitigate Cannibalization," J. Optim. Theor. Appl., **131**(2), pp. 227-244.
10. Laptop Buyer's Guide, <http://laptopmag.com/Tools/Guide/Notebooks/mainstream.asp>, accessed Jan 24, 2007.
11. Toshiba Laptop and Notebook Computers, <http://www.toshibadirect.com/>, accessed on Jan 2, 2007.
12. Lenovo Thinkpad Laptop Website, <http://www.lenovo.com/us/en/>, accessed on Jan 2, 2007.
13. HP Notebooks & Tablet PCs Website, <http://welcome.hp.com/country/us/en/prodserv/notebooks_tabletpcs.html>, accessed on Jan 2, 2007.
14. Sony Office Site, <http://www.SonyStyle.com/>, accessed on Jan 2, 2007.
15. Mahesri, A., and Vardhan, V., 2004, "Power Consumption Breakdown on a Modern Laptop, Workshop on Power Aware Computing Systems," 37th International Symposium on Microarchitecture, Portland, OR, Dec. 8, 2004.
16. Yang, Y., 2006, "The Taiwanese Notebook Computer Production Network in China: Implication for Upgrading of the Chinese Electronics Industry," PCIC report, Irvine,

CA, <http://www.pcic.merage.uci.edu/papers/2006/ TaiwaneseNotebook.pdf >, accessed on Jan. 2, 2007.
17. Pricewatch, <http://www.pricewatch.com/>, accessed on Jan. 2, 2007.
18. ScreenTek, <http://www.screentekinc.com/>, accessed on Jan. 2, 2007.
19. Nelson, R.A., Tanguay, T.L., and Patterson, C.D., 1994, “A Quality-Adjusted Price Index for Personal Computers,” J. Bus. Econ. Statist., **12**(1), pp. 23-31.
20. Wu, C. F., and Hamada, M., 2000, *Experiments: Planning, Analysis, and Parameter Design Optimization*, John Wiley & Sons, New York, NY.
21. Kuhfeld, W. F., 2005, “Conjoint Analysis,” SAS technical report, <http://support.sas.com/techsup/technote/ts722h.pdf >, accessed on Jan. 2, 2007.
22. Arora, N., and Huber, J., “’Improving parameter estimates and model prediction by aggregate customization in choice experiments,” Journal of Consumer Research, 2001, 28(2), pp. 273-283.
23. Sándor, Z., and Wedel, M., “Heterogeneous conjoint choice designs,” Journal of Marketing Research, 2005, 42(2), pp. 210-218.
24. Kessels, R., Goos, P., and Vandebroek, M., “A comparison of criteria to design efficient choice experiments,” Journal of Marketing Research, 2006, 43(3), pp. 409-419.
25. Train, K., 2003, *Discrete Choice Methods with Simulation*, Cambridge University Press, New York.
26. Louviere, J.J., Hensher, D.A., and Swait, J.D., 2000, *Stated choice methods: analysis and applications*, Cambridge University Press, New York, NY.
27. Brownstone, D., and Train, K., 1998, “Forecasting new product penetration with flexible substitution patterns,” Journal of Econometrics, **89**(1-2), pp. 109-129.
28. Michalek, J., Feinberg, F., Ebbes, P., Adigüzel, F., and Papalambros, P., 2006, “Optimal Coordinated Positioning and Design of Product Lines for Markets with Heterogeneous Preferences,” Working Paper, Carnegie Mellon University.
29. PriceGrabber.com, Inc., Consumer Behavior Report: Back-to-School College Spending Trends, Sep. 2006, <https://mr.pricegrabber.com/ september_2006_back_to_ school_college_spending_trends.pdf>, accessed on May 1, 2007.
30. Datamonitor, “College & University Student Spending on Laptops in the US and Western Europe (Databook),” Oct. 2006, <http://www.cbronline.com/article_researchwire.asp ?guid =783E62A0-DEF4-42C5-BE99-36E6C4DD10F4>, accessed on May 1, 2007.
31. The MathWorks, Inc., Matlab Optimization Toolbox User's Guide, <http://www.mathworks.com/access/helpdesk/help/ pdf_doc/optim/optim_tb.pdf>, accessed on Jan. 24, 2007.
32. Shiau, C.-S., and Michalek, J.J., 2007, A game-theoretic approach to finding market equilibria for automotive design under environmental regulation, ASME 2007 International Design Engineering Technical Conferences, Las Vegas, NV.

