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DEMAND ANALYSIS FOR DECISION-BASED DESIGN OF AUTOMATIVE ENGINE

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ABSTRACT

Our research is motivated by the need for a rigorous engineering design framework and the need for developing demand analysis approach that is critical for assessing the profit a product can bring. A Decision-Based Design framework is presented as a rigorous design approach and the method of Discrete Choice Analysis (DCA) is applied to create the demand model that facilitates engineering decision making in vehicle design with emphasis on engine design. Through interdisciplinary collaborations, we illustrate how the gap between market research and engineering analysis can be bridged in product design.

Key words: decision-based design, demand modeling, discrete choice analysis, vehicle design, engine design

1 INTRODUCTION OF TECHNICAL BACKGROUND

Our research is motivated by the need for developing a rigorous engineering design framework (Hazelrigg, 1999) and the need for developing an approach to demand modeling that is critical for assessing the profit[1] a product can bring. Many existing engineering design methods, such as Taguchi's robust design (Phadke, 1989) and Design for Six-Sigma (Fowlkes and Creveling, 1995), constitute preference systems in which it is assumed that meeting customer satisfaction is the primary goal of design decision making. Such methods seldom consider the cost associated with adding or improving a quality feature. Decision-based design (DBD) is emerging as a new approach to engineering design that recognizes the substantial role that decisions play in design and in other engineering activities. The approach is developed to perform in design environments characterized by ambiguity, uncertainty and risk. It seeks to maximize the value of a designed artifact while considering the interests of both the producer and the end-users (Hazelrigg, 1999; Wassenaar and Chen, 2001).

The flowchart of the DBD framework that links engineering design with business decision making and that we proposed as an enhancement to the framework proposed by Hazelrigg (1999) in our previous work (Wassenaar and Chen, 2001) is shown in Fig. 1. We proposed to use the Discrete Choice Analysis (DCA) (Ben-Akiva and Lerman, 1985) as a demand modeling approach to establish the relationship between the key customer attributes $\boldsymbol{A}$, the socioeconomic and demographic background $\boldsymbol{S}$ of the market population, time t, and the demand Q. We discern two different types of attributes in our approach, namely the engineering attributes $\boldsymbol{E}$ and the key customer attributes $\boldsymbol{A}$. The engineering attributes $\boldsymbol{E}$ are product properties that are of interest to a design engineer, represented as functions of design options $\boldsymbol{X}$ through engineering analysis. The key customer attributes $\boldsymbol{A}$ are product features (next to brand, price, and warranty) that a customer typically considers when purchasing the product. In a demand model $\boldsymbol{A}$ needs to be represented using engineering languages (see more details in Section 2). The arrows in the flowchart indicate the existence of relationships between the different entities (parameters) in DBD.

Different from other market analysis techniques such as conjoint analysis, a key concept of DCA is the use of random utility (probabilistic choice theory) to address unobserved taste variations, unobserved attributes, and model deficiencies. A quantitative process based on *multinomial analysis* is used to generate the demand model. Random utility entails the assumption that the individual's true utility U consists of a deterministic part W and a random disturbance ε (see Eq. 1). The deterministic part of the utility can be parameterized as a function of observable independent variables (key customer attributes $\boldsymbol{A}$, socioeconomic and demographic attributes $\boldsymbol{S}$, and price P) and unknown coefficients β, which can be estimated

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[1] Profit is a result of accounting practices, which need not be related to engineering design such as depreciation. Therefore, with profit is meant net revenue, i.e., the difference between revenue and expenditure. The net revenue can be discounted to present value.

by observing the choices respondents make (real or stated) and thus represent the respondent's taste, see Eq. 2. The β-coefficients and utility functions are indicated with the subscript *n,* representing the n^{th} respondent, the index *i* refers to the *i*-th choice alternative. There is no functional form imposed on the utility function *W,* i.e., *W* can be additive, multiplicative, quadratic, etc.

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

$$W_{in} = f(A_i, P_i, S_n; \beta_n) \tag{2}$$

The probability that alternative 1 is chosen from a choice set containing two alternatives (binary choice) is then defined as the probability that the utility of alternative 1 exceeds the utility of alternative 2 or alternatively on the *probability that the difference between the disturbances does not exceed the difference of the deterministic parts of the utility*, i.e.

$$\begin{aligned} \Pr(1)\big|[1,2] &= \Pr(W_{1n} + \varepsilon_{1n} \geq W_{2n} + \varepsilon_{2n}) \\ &= \Pr(\varepsilon_{2n} - \varepsilon_{1n} \leq W_{1n} - W_{2n}) \end{aligned} \tag{3}$$

Methods such as logit (Ben-Akiva and Lerman, 1985; Hensher and Johnson, 1981) or probit (Daganzo, 1979; Hensher and Johnson, 1981) can be used to form a choice model that predicts the choice probabilities. The choice probability of the multinomial logit model is shown in Eq. 4, where $\Pr_n(1)$ is the probability that respondent *n* chooses alternative *i*.

$$\Pr_n(i) = \frac{e^{W_{in}}}{\sum_{l=1}^{J} e^{W_{ln}}} \tag{4}$$

Estimation techniques such as the maximum likelihood method can be used to determine the β-coefficients such that the predictions of the model matches the observed choices as closely as possible. *The total demand for a particular design i is the summation of the predicted choice probabilities across the choice alternatives for the entire market population* (Ben-Akiva and Lerman, 1985).

The disaggregate demand models built from DCA use data of individuals instead of group averages, which enables the variation of characteristics of individuals to be captured more accurately and avoids paradox associated with group decision-making.

In this paper, the use of DCA for developing product demand models is demonstrated using a real (passenger) vehicle engine design case study. We further show how the demand model can facilitate engineering decision makings under the Decision-Based Design framework.

2 IMPLEMENTING DISCRETE CHOICE ANALYSIS FOR VECHLE DEMAND MODELING

In this section, we show an implementation of the three major phases of the discrete choice approach to constructing a vehicle demand model with emphasis on evaluating engine design changes in a DBD engineering design model. Demand analysis plays an important role in vehicle design since it has a significant impact on a company's profit due to the high value and large production volume of design changes and feature upgrades. Vehicle demand can be modeled as a function of the vehicle's pricing, engine performance, ride and handling characteristics, exterior styling, interior design, climate control, etc. The demand model developed in this case study emphasizes the impact of engine design changes on vehicle demand thus facilitating the evaluation of engine design and making proper tradeoffs between the performance and cost. This example is developed in collaboration with the Analytical Powertrain & Engine Engineering division of Ford Motor Company and the Power Information Network group (PIN) at J.D. Power & Associates. The statistical software package STATA is used to estimate the multinomial choice model coefficients based on the maximum likelihood criterion. Twelve vehicles (7 models, 12 trims) are considered in the

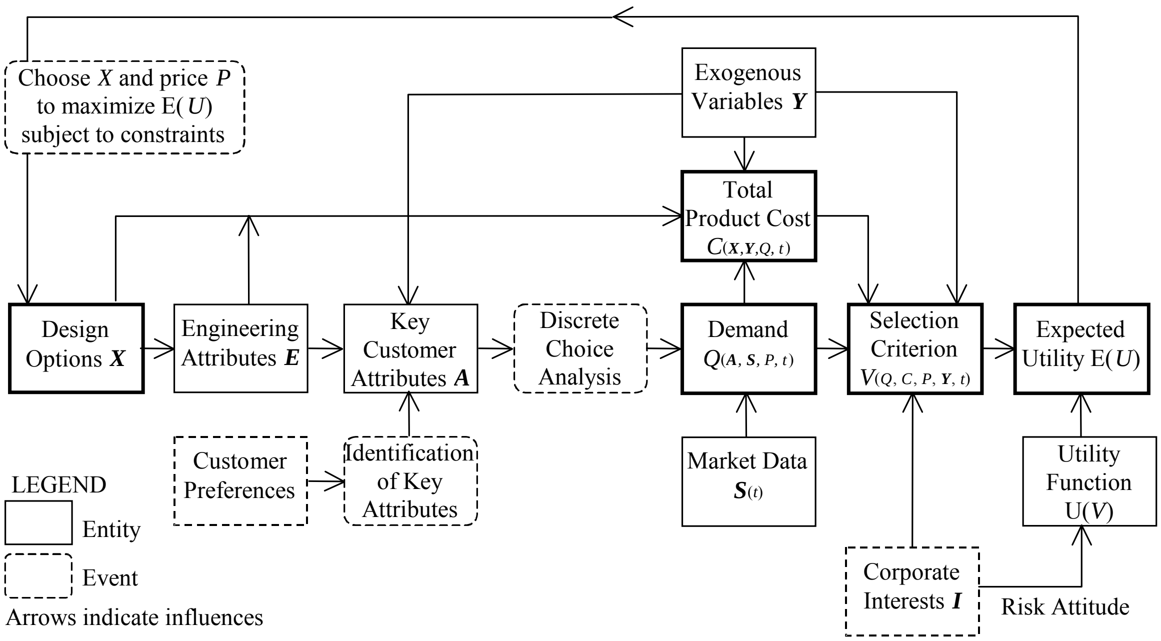

Figure 1. Decision-Based Design flowchart (Wassenaar and Chen, 2001)

demand model representing the midsize car segment, which includes vehicles like Ford Taurus, Toyota Camry, and Honda Accord. Data in tables is normalized to protect proprietary rights of manufacturers.

Our implementation is subject to the following assumptions. A simplifying assumption is that customers *only* consider vehicles from the midsize car segment and in specific the 12 vehicle trims considered when purchasing a vehicle, in reality this may not be true. The demand model developed is a static model, as such demand changes over time are not considered. It takes approximately 48 months to redesign an engine, that is, a vehicle demand model used for engine design should be capable of predicting vehicle demand 4 years into the future. We assume however that engine design changes are immediately introduced in the market. We also assume that the designs of the other vehicles do not change, i.e., the demand model does not account for market introductions of restyled vehicle models, which can have a large impact on market demand. Next the three phases of implementing discrete choice analysis are presented.

The case study is used to examine how market surveys can be extended to address specific design interests (e.g., feature upgrade, addition, etc.). The demand analysis model can be used to answer important questions such as: *what* are the effects of product content/feature upgrade on market share/profitability? *what* are the effects of product quality improvement on market share/profitability? and *what* is the pricing leverage with improved product features or quality? Once the demand analysis and engineering modeling have been carried out, choosing the best design option along with marketing strategies and product price can be formulated as a utility optimization problem, maximizing the expected utility E(U), subject to various uncertainties associated with demand modeling, cost modeling, and exogenous and engineering parameters.

Vehicle Demand Modeling - Attributes and Choice Set Identification

Based on J.D. Power's VQS survey we identify five top-level customer desires related to vehicle choice at the vehicle system level, these are: price/cost, engine/transmission performance, comfort & convenience, ride/handling performance, and roominess. For reasons of simplicity we do not consider customer desires related to sound system, seats, and style. Specific customer desires can be identified for each top-level vehicle system customer desire. Take engine/transmission performance as an example, the specific customer desires include performance during rapid acceleration, passing power at highway speeds, fuel economy, range between fuel stops (which highly impacts the *perceived* fuel economy), sound while idling, and sound at full throttle acceleration. To facilitate the demand evaluation of product design it is necessary to identify appropriate customer attributes that can capture the customer's intend reflected in the customer desires. Interaction between engineering experts at Ford Motor Company and market research specialists from J.D. Power helped identify the key customer attributes corresponding to the customer desires. Linking the key customer attributes with engineering attributes, and then design options is also an important activity of designers, however, it is not covered in our case study as our study only focuses on demand and does not reach beyond the key customer attribute level.

In total we consider 21 key customer attributes related to the general vehicle design (e.g., price, vehicle length, legroom), 10 key customer attributes related to engine design at the system level (e.g., horsepower, fuel economy) , 5 socio-economic attributes of customers (e.g., age, income), and 2 dummy variables. The dummy variables can be used to separate the slopes (i.e., separate β coefficients) of key customer attributes when there is a strong correlation between vehicle origin (domestic or Asian) or engine configuration (inline 4 cylinder or V6) with the recorded customer choice, which may lead to problems (e.g., illogical coefficient estimates) when fitting the logit choice model.

Vehicle Demand Modeling – Data Collection

The demand model is created using *revealed choice data* at the respondent level provided by J.D. Power. The data consists of 2552 observed individual vehicle purchases of the US year 2000 vehicle market of the seven vehicles considered in the case study including respondents' background. The values of customer attributes related to the general vehicle descriptions such as weight, fuel economy, legroom, etc of the 12 discrete choices are obtained from Ward's Automotive. The values of some other customer attributes such as, ride, handling, noise, and vibration are provided by Ford Motor Company. Based on the data collected, the correlation of a number of explanatory variables is obtained; a *partial* of the correlation matrix is presented in Table 1.

The variables gender and USA/import of Table I are binary variables: female = 1, and import = 1, otherwise 0. The correlations indicate among others that females apparently buy smaller cars, and that older consumers tend to prefer American built cars, and imports are generally sold with smaller rebates. The correlation between customer background and key customer attributes appears to be very weak. Highly correlated variables are prone to being collinear, which is undesirable. Further, high correlation between the dependent variable (in this case the vehicle choice) and independent explanatory variables implies that few variables are sufficient to predict vehicle choice, excluding many variables (customer attributes) required for engineering design decision-making. Obviously, high correlation does not necessarily indicate a causal (i.e., econometric) relationship required for accurate demand predictions. Note that USA/import is a dummy variable. The next phase is to create the demand model using the collected revealed choice data, and the vehicle description (key customer attributes).

TABLE 1. PARTIAL CORRELATION MATRIX

	gender	age	income	usa/import
gender	1			
age	-0.192	1		
income	-0.074	-0.176	1	
USA/import	0.150	-0.220	0.087	1
msrp_price	0.006	-0.041	0.141	0.183
rebate	-0.101	0.256	-0.141	-0.869
apr	-0.072	0.173	-0.017	-0.425
resale index	0.178	-0.215	0.031	0.869
vdi	-0.117	0.036	0.024	-0.746
iqs	-0.162	0.187	-0.059	-0.928
hp/mass	-0.011	-0.104	0.180	0.212
torque/mass	-0.051	-0.005	0.148	0.013
le torq./mass	-0.087	0.036	0.120	-0.255
fuel econ.	0.127	-0.047	-0.102	0.444
fuel range	0.138	-0.063	-0.045	0.680
wheel base	-0.106	0.076	0.050	-0.667
veh. width	-0.119	0.157	-0.066	-0.918
veh. lengt	-0.149	0.154	-0.038	-0.907
overhang	-0.137	0.185	-0.097	-0.854
front-headrm	-0.013	-0.103	0.145	0.290
frong-legrm	0.072	-0.094	0.116	0.762
rear-headrm	-0.162	0.132	0.053	-0.695
rear-legrm	-0.140	0.157	0.013	-0.731
trunk space	-0.132	0.139	0.004	-0.844

Vehicle Demand Modeling – Multinomial Logit Model

Customer purchase data (revealed choice) by itself is not sufficient to construct the demand model. A database (input data) needs to be formed containing for each individual: the individual's background, the description of the alternatives that individual choose from (i.e., the choice set), and what alternative that individual actually chooses from that choice set. This implies that the demand modeling specialist recreates the choice set considered by the customer when faced with the purchase decision as *perceived* by the specialist. An example of the choice set (which could be used to elicit stated choice in a discrete choice survey) containing the vehicles considered in this case study is presented in Table 2.

TABLE 2 CASE STUDY CHOICE SET

example of choice set								totals		
vehicle id	engine type	displace ment	horse power	fuel econ.	msrp price	cust. choice		vehicle id	choice rate	% market share
1	I4	0.80	0.76	1.15	0.87	0		1	251	9.84
2	V6	1.08	1.02	0.98	1.15	0		2	190	7.45
3	I4	0.73	0.73	1.12	0.89	0		3	335	13.13
4	V6	1.04	1.02	0.98	1.05	0		4	220	8.62
5	V6	0.94	1.06	1.02	1.03	0		5	231	9.05
6	V6	0.94	1.06	1.00	0.89	0		6	192	7.52
7	V6	1.08	1.28	1.00	1.07	0		7	199	7.80
8	V6	1.08	0.93	1.00	0.96	0		8	167	6.54
9	V6	1.21	1.10	0.96	1.07	0		9	67	2.63
10	V6	1.19	1.01	0.98	1.11	0		10	435	17.05
11	V6	0.83	1.01	0.94	0.89	0		11	213	8.35
12	V6	1.08	1.01	0.90	1.02	1		12	52	2.04

The choice set presented in Table 2 shows the 12 vehicle choices with *partial* (normalized) description of the explanatory variables used in the customer utility function of the logit choice model. For each respondent there are 12 rows of data in the database, one for each choice alternative, each row containing the customer background, the key customer attributes that describe the vehicle, and the respondent's observed choice (real purchase). The customer choice is treated as a binary variable and in this particular case the customer selected car 12. The second table shows the total number of cars purchased of each car model (choice rate) and the market shares as identified in the revealed data. In total the database contains 30624 observations (2552 respondents * 12 vehicles). In this case study we use STATA (www.stata.com) to estimate the choice model. STATA employs a substitute for multinomial logit: grouped logit. Grouped logit considers multinomial choice (i.e., one vehicle picked from the choice set) as a grouped set of binary choices (pick/not-pick). One and only one binary choice of a group is allowed positive (i.e., a pick).

A linear (including interactions) customer utility function shape is considered for the utility function used in the logit choice model (Eq. 2). All customers share the same utility function coefficients, i.e., market segmentation is not considered. STATA fits the logit choice model (Eq. 4) to the data set using the maximum likelihood method. It is necessary to evaluate several different interactions of explanatory variables. We tested over 200 customer utility functions with different combinations of linear and interaction items. Eventually a model using 38 explanatory variable items is selected based on the Bayesian Information Criterion score (BIC). Results of the top six most promising models are shown in Table 3, the BIC score indicates that model 6 should be preferred. The MS_R2 is the R2 error measure of the observed market shares vs. predicted market shares. The 11 explanatory variables of model 1 are all key customer attributes, customer background is not considered in the choice model of model 1. This implies that vehicle choice is independent from customer background, which is highly improbable. Even though model 1 fits the data set quite well as Table 3 shows, it may be expected that its predictions are poor given the lack of connectivity with the customer background. Table 3 shows that the observed market shares and the market shares as predicted by model 6 match quite well. The customer utility function of model 6 includes customer background, key customer attributes, and selected interactions between key customer attributes and customer background (e.g., horsepower/income). Except interactions, it should be noted that no higher than second order items are considered in the models tested so far.

TABLE 3. MODEL COMPARISON AND MARKET SHARES PREDICTED BY MODEL 6

model id	lik.hood.	Expl.Var.	MS_R2	BIC
model 1	-362457.6	11	1	725028.78
model 2	-350915.1	43	0.995346	702274.37
model 3	-355220.2	31	0.989278	710760.56
model 4	-350890.6	40	0.994903	702194.28
model 5	-350789	40	0.994941	701991.22
model 6	-350630.6	38	0.994941	701653.78

veh.id	observed	predict
1	0.0984	0.1002
2	0.0745	0.0771
3	0.1313	0.1304
4	0.0862	0.0851
5	0.0905	0.0846
6	0.0752	0.0718
7	0.0780	0.0771
8	0.0654	0.0669
9	0.0263	0.0266
10	0.1705	0.1760
11	0.0835	0.0840
12	0.0204	0.0202

Cross Validation of Demand Models

Achieving a good model fit indicated by error measures such as the log-likelihood and R-square value indicates that the model will predict well on the data used to fit the model, however, it does not guarantee accurate predictions of the demand model at new model inputs. The approach we take for validating the obtained vehicle demand model is through the technique of cross-validation (Breiman and Spector, 1992) which does not require the collection of additional data. Cross-validation entails dividing the data into k subsets of approximately equal size (k-fold cross validation). The choice model is then fitted k times using k-1 subsets of data. Each time the fitted choice model is used to predict the choice of the remaining data set to calculate the measure of error (e.g., log likelihood score). The average of the obtained error measurements is the error of measure of the model. A lower k value is chosen for large data sets, in general a 10-fold (k=10) or 5-fold cross-validation is recommended. The model can be validated using 5-fold cross validation given the large data set. The dataset consisting of 2552 individuals is divided into 5 subsets of approximately equal size using random sampling. The model is fitted to the combined data of 4 out of the 5 datasets. The fitted model is then used to predict the choice for the remaining choice set and the R2 value for the market shares, which is used as error measure, is calculated. This procedure is repeated 5-fold, every time using a different data set from the 5 data sets for prediction and error measure calculation. The R2 value of the demand model fitted on the full data set is 0.99. The R2 value decreased to 0.92 averaged the 5 cross validation tests, which is still an acceptable value. The cross validation helps us build more confidence in using the proposed DCA approach to demand modeling and demand prediction. It also shows that the accuracy of the demand model is satisfactory.

3 DEMAND PREDICTION AND INTEGRATION WITH DBD

Market Share Prediction and "What If Scenarios"

The choice model developed in the previous section can be used to predict the market shares for the midsize vehicles considered. A matching sample of the target market population (e.g., obtained using random sampling) is used to estimate the coefficients of the demand model. Matching in the sense that the distribution of age, income, and gender, which are explanatory variables our model, of the sample and the target market are comparable. Using the model the 12 choice probabilities (one for each vehicle of the choice set) are determined for each sampled individual using that individual's background and the descriptions of the 12 vehicles of the choice set. The choice probabilities of the vehicles are aggregated and averaged across all individuals to obtain the predicted market shares. Prediction of the impact of customer attribute changes (which reflect engineering design changes) on the vehicle market shares is possible by updating the vehicle descriptions and recalculating the choice probabilities predicted for each individual. In our study, our special interest is to study the impact on market shares when design changes are made to the engine (attributes) of a particular vehicle in the choice set. As an example we consider the following "*what if* scenario" consisting of three successive vehicle updates. The impact on the market shares are presented in Table 4. Let's assume our manufacturer produces two trims of one vehicle model for the midsize car segment, a basic version and a more powerful luxury version. In Table 4 these are identified as vehicle 11 and vehicle 12. Suppose our manufacturer decides to improve the fuel efficiency of the base model, vehicle 11, with 10%, the impact on the market shares is shown in Table 4 under the heading "scenario 1". It appears that increasing the fuel efficiency of vehicle 11 increases its market share from 8.35 to 9.25% but it also shows that vehicle 12's market share is negatively affected. This negative impact of feature upgrades of a product on other members of the same manufacturer is known in marketing literature as "cannibalism". It implies that *the product being designed should not be considered in isolation*. The predicted market shares listed under Scenario 1 also show the impact of the fuel efficiency increase on the market shares of competing vehicles in the midsize vehicle market. It appears the market share of vehicle 5 is the most affected, decreasing with 0.24 points to 8.81%. Scenario 2 shows the impact on the market shares if the producer of vehicle 5 decides to introduce a rebate of $500 to boost its market share in response to the upgrade of vehicle 11. Finally Scenario 3 shows the impact of increasing vehicles 12 engine power with 5%.

TABLE 4 RESULTS OF "*WHAT IF* SCENARIOS"

Veh. Id.	Market shares (%) base	scenario 1.	scenario 2.	scenario 3.
1	9.84	9.81	9.41	9.38
2	7.45	7.47	7.18	7.15
3	13.13	12.91	12.42	12.37
4	8.62	8.53	8.21	8.18
5	**9.05**	**8.81**	**12.15**	**12.08**
6	7.52	7.37	7.12	7.08
7	7.80	7.63	7.38	7.34
8	6.54	6.45	6.20	6.17
9	2.63	2.71	2.62	2.60
10	17.05	17.09	16.49	16.41
11	**8.35**	**9.25**	**8.92**	**8.87**
12	**2.04**	**1.95**	**1.89**	**2.36**

This illustrative example shows how a demand model that captures the relationship between key customer attributes and market demand can be used to explore "what if" scenarios or to set targets for key customer attributes that maximize market demand. Obviously the feasibility or if you will desirability of design changes depends on the impact on profit, which necessitates consideration of the cost of such changes. This is considered in the next section.

Decision-Based Design Case Study

We integrate the vehicle demand model developed in the previous section with a cost model into a DBD optimization model, which we then use to evaluate 5 different engine design configurations. To simplify matters, our implementation of the DBD engineering design model does not reach beyond the key customer attribute level. This implies that the vehicle demand model developed in this case study can be used to determine the targets of attributes for the engine design but not to optimize the engine design itself at the design option level. The vehicle demand model can be used to set design targets for the engine of vehicle 11 by assuming a simplified relationship between engine key customer attributes and cost. The cost model we use considers the impact on cost of performance improvements related to power, torque, and low-end torque, with respect to the base line engine design. Low-end torque is the maximum torque an engine produces at approximately 2000 rpm and is important for accelerating to pass a vehicle when driving at highway speed.

Two different engine design configurations are considered for use in vehicle 11. One engine design offers increased power, torque, and low-end torque with 3% relative to the existing engine used in vehicle 11, and another engine design that only increases the power with 3% relative to the base model. Four different alternatives are created by considering the two engine designs at base price and at a 5% increased price. A fifth choice alternative is added by also considering using an existing engine for vehicle 11 of a different model, which is less powerful but enables a reduction in price of 10% when compared with the base model. The 5 alternative designs are presented in Table 5.

TABLE 5 DESIGN ALTERNATIVES FOR DECISION-BASED DESIGN CASE STUDY. (% Change)

Att. name	**Design Alternative (Vehicle 11)** 1	2	3	4	5
price	5	0	5	0	-5
hp	3	3	3	3	0
torque	3	3	0	0	-10
low-end torque	3	3	0	0	-10

The market for 12 midsize vehicles is estimated at 1,000,000 vehicles annually. Uncertainty is introduced by assuming a normal distribution of the market size with standard deviation of 50,000 vehicles. As when considering the "what if scenario" our manufacturer produces two vehicles for the midsize car segment, vehicle 11, and vehicle 12. To facilitate the consideration of the impact of engine changes of vehicle 11 on vehicle 12 and on the manufacturer's profit we assume that vehicle 12 contributes $1,100 per vehicle to the profit. The manufacturer's expected utility is obtained by assuming a risk averse risk attitude, which is obtained by taking the log of the profit. The market share impact (% change) for the 12 vehicles and the manufacturer's profit (in millions of dollars) and expected utility for the five design alternatives (vehicle 11) are presented in Table 6. When considering maximizing the expected utility it appears that design alternative 4, consisting of a 3% torque increase while leaving the price unchanged, should be preferred.

4 CONCLUSION

In this paper, a Decision-Based Design framework is presented as a rigorous design approach and the method of Discrete Choice Analysis (DCA) is applied to create the demand model that facilitates engineering decision making. *The advantages of the proposed demand analysis procedure can be summarized as:* (1) The method does not involve any ranking, weighting, or normalization, thus avoiding the paradox associated with many multicriteria approaches. (2) Probabilistic choice addresses the uncertainties associated with unobserved taste variations, unobserved attributes, and model deficiencies. (3) Competing products are considered, enabling analysis of market impact and competitive actions through "*what if*" scenarios. (4) Choices do not necessarily share the same set of attributes or attribute levels, expanding market testing possibilities and leaving more freedom to the marketing engineer. (5) The customer survey embedded in DCA resembles real purchasing behavior more closely, reducing respondent errors and enabling the analysis of more attributes. The proposed approaches are demonstrated using a real (passenger) vehicle engine design problem as a case study in collaboration with the market research firm J.D. Power & Associates and Ford Motor Company. The obtained demand model is shown to be satisfactory through cross validation. We illustrate through our case study the usefulness of using demand models in predicting the change of market share subject to various options of feature change/upgrade. We also illustrate the integration of demand model with cost model in making rational product design decisions subject to designer's preference and risk attitude under uncertainty.

TABLE 6 MARKET SHARE IMPACT (% CHANGE), PROFIT ($ MILLION) AND EXPECTED UTILITY

Veh. Id.	**Design Alternative** 1	2	3	4	5
1	-0.4	-0.6	0.1	-0.1	0.2
2	-0.8	-0.9	-0.3	-0.5	-0.1
3	-1.1	-1.3	-0.6	-0.9	-0.5
4	-1.0	-1.1	-0.5	-0.7	-0.3
5	-0.3	-0.5	0.1	-0.1	0.4
6	-0.6	-0.7	-0.1	-0.4	0.1
7	-1.5	-1.7	-1.1	-1.3	-0.8
8	-1.8	-1.9	-1.3	-1.5	-1.0
9	2.9	2.7	3.4	3.1	3.7
10	-1.0	-1.1	-0.5	-0.7	-0.3
11	**9.7**	**11.4**	**4.4**	**7.0**	**2.0**
12	-3.8	-3.9	-3.4	-3.6	-3.0
ExpProfit	77.77	77.0	87.6	89.1	31.01
ExpUtil	90.84	90.78	91.43	91.52	86.24

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