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# AN APPROACH TO DECISION-BASED DESIGN

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## ABSTRACT

In this paper, we present the importance of using a single-criterion approach to Decision-Based Design (DBD) by examining the flaws and limitations of multicriteria approaches. We propose in this paper an approach to DBD as an enhancement to Hazelrigg's DBD framework that utilizes the economic benefit to the producer as the single criterion in alternative selection. The technique of Discrete Choice Analysis (DCA) is introduced for constructing a product demand model, which is crucial for the evaluations of both profit and production cost. An academic universal motor design problem illustrates the proposed DBD approach. It appears that DBD, when applied correctly, is capable of unambiguously selecting the preferred alternative in a rigorous manner. Open research issues related to implementing the DBD approach are raised. The focus of our study is on demonstrating the approach rather than the design results *per se*.

Key words: Decision-Based Design, single criterion approach, product demand, Discrete Choice Analysis

## 1 INTRODUCTION

In the engineering research community, there is a growing recognition that decisions are the fundamental construct in engineering design (Chen et al. 2000). The decision-based design perspective (Hazelrigg, 1998) models design as a decision-making process that seeks to maximize the value of a designed artifact. The DBD framework is structured to successfully perform in design environments characterized by ambiguity, uncertainty and risk. Although recent years have seen many DBD related research developments (Thurston, 1999; Gu et al, 2000; Li and Azarm, 2000; Tang and Krishnamurty 2000; Callaghan and Lewis, 2000; Scott and Antonsson, 1999; Messac 1996; Wang and Jin, 2000; Kim et al, 2000; Roser and Kazmer, 2000; Marston et al, 2000; Allen, 2000; Shah and Wright, 2000; Wood, 2000), there is still lack of consensus on how the DBD approach should be implemented for engineering design. One of the distinctive debating issues is how the value (utility[1]) of a design should be formulated under a DBD framework. The common challenge lies in the issue of how to properly construct the design utility under uncertainty to reflect the interests of the producer while considering the preferences of the end-users.

We propose in this paper an approach to DBD as an enhancement to Hazelrigg's DBD framework (Hazelrigg 1998) that utilizes the economic benefit to the producer as the single criterion in alternative selection. The economic benefit to the producer could be the only criterion that addresses both the needs of the producer and those of the customers when developing a commercial product. The contribution of our research lies in the development of a systematic procedure for implementing DBD and the introduction of the technique of Discrete Choice Analysis (Ben-Akiva and Lerman, 1985) for constructing a product demand model, which is crucial for the evaluation of economic benefit.

Our paper is organized as follows. In Section 2, the technological base of our research is provided. We first introduce DBD as a new perspective in design research. The necessity of a single-criterion approach for unambiguous decision-making is demonstrated by examining the limitations of the multicriteria alternative selection procedures. The background of DCA and its advantages is also provided in Section 2. Our proposed approach to single-criterion DBD is presented in Section 3. An academic example problem on motor

[1] We will use the word "utility" in this paper as it stands for the selection criterion in the presence of uncertainty, while the word "value" is often interpreted as a selection criterion without uncertainty.

 

design is provided in Section 4. In Section 5, the Closure, we discuss the advantages of our proposed approach and some of the open research issues related to its implementation.

## 2 OUR TECHNOLOGICAL BASE

### 2.1 DBD – A Normative Approach to Engineering Design

Many common engineering design methods focus only on aspects of the design process as their names suggest, i.e. design for cost, design for manufacture etc, therefore leading to sub-optimal results when considering the total economic benefit. Decision-Based Design (DBD) is a normative approach that prescribes a methodology to make unambiguous design alternative selections under uncertainty and risk wherein the design is optimized in terms of the expected utility (Hazelrigg, 1998). The product's total life cycle is considered in meeting the needs from both the consumers and the producer.

When seen as a decision-making process, the product development can be reduced to *alternative generation*, followed by an *alternative selection* stage. Many (design) alternative selection methods are in use, such as Majority Vote, Quality Function Deployment (Clausing, 1994), Pugh Matrix (Otto and Wood, 2000), Weighted Sum, Taguchi signal-to-noise ratio function (Phadke, 1989), and Suh's design axioms (Suh 1990). However, these methods produce different results when applied to the same problem as they impose preferences on designers in different ways. There is a need for a method to aggregate the multiple attributes such that the alternatives can be compared in a consistent manner. In the following section, we discuss the limitations of existing multicriteria approaches and bring out the need for a single-criterion approach.

### 2.2 Problems with Multicriteria Approaches

In this paper, we will only briefly comment on the limitations of any procedures that involve normalization, weighting, multiattribute ranking, and a multiattribute utility function. These procedures are involved in existing multicriteria approaches in one way or another.

The problem with **multiattribute ranking** methods occurs when more than two attributes are considered. The votes (or alternatively, weights) are based upon the rank order of the alternatives. As shown by Saari (2000), the selected alternative may result from the underlying voting method rather than the quality of the alternative itself. According to Coombs's condition (Arrow, 1986), the chance of paradox is over 97% when six alternatives are ranked using multiple attributes. When 10 alternatives with multiple attributes are considered, the chance of paradox is virtually 100%. Along the same line, Arrow's impossibility theorem (Arrow, 1986) shows that group-voting, analogue to multicriteria methods, leads to intransitive outcomes. It indicates that neither the preference of a group of decision-makers nor of a set of criteria can be captured by multiattribute rankings.

**Normalization** is often used to address the dimension problem. However when two or more attributes are considered, normalization itself may cause problems. The normalized value depends on the relative position of the attribute value within the range of values. The lack of a rigorous method to determine the normalizing range leads to paradox. The attribute importance, not accounted for by normalization, is considered by the **weighted sum method** (WS) by assigning weights to attributes. WS however, may lead to subjective choice, i.e. the attribute weights are based upon the decision-maker's intuition, knowledge, and personal experience. The weights are subject to fluctuation and likely differ when assessed at a different time. An attribute's weight often becomes biased when the attribute is correlated to a product's success (Arrow, 1986). WS assumes linear attribute tradeoff which is only true for limited variation of attribute values.

The **multiattribute utility function** (Keeny and Raifa, 1976) has been adopted to overcome the limitations associated with WS and multiattribute rankings. However, multiattribute utility requires mutual utility independence of each attribute. This condition is seldom checked and sometimes leads to unnatural attributes. In presence of **uncertainty** however, the preference of an alternative also depends on the level of uncertainty and the decision-maker's risk attitude. The utility independence is then questionable. Logically, high uncertainty (i.e. risk) of one attribute would have to be compensated by a reduced uncertainty of the other attribute, such that the *total amount of risk* remains more or less the same. Another concern is whether it is logical to combine the different single attribute utility functions into a single multiattribute utility function. Only *cardinal* utility functions can be combined into a single utility function. Finally, forming the multiattribute utility function involves normalization, its shortcomings have been pointed out earlier.

From the discussion in Subsection 2.2, we conclude that when three or more alternatives with multiple attributes are involved, normalizing procedures, weighting methods, ranking methods, and multiattribute utility functions cannot guarantee unambiguous alternative selection. This conclusion is astounding because all existing multicriteria approaches possess these limitations in one way or another. In fact, the selection of attributes themselves may be biased and incomplete. In addition, there are mathematical limitations associated with some of these approaches. For example, the WS method cannot capture the complete set of Pareto solutions (Chen et al. 1999). Further, the votes and weights may be impaired due to personal and political interests, that is, votes and weights do not necessarily coincide with the corporate interests. *These problems are absent if one and only one attribute is used for selecting the preferred design.*

### 2.3 Desired Features of the Single-Criterion

When using a single-criterion approach to Decision-Based Design, the selected criterion should reflect many different issues involved in product design, such as product features, manufacturing issues, and physical restrictions imposed by engineering disciplines. *Therefore a first condition is that the single criterion should reflect the interests of both the* *consumers and the producer. A second condition for the single criterion is that it needs to capture all uncertainties in the life cycle development of a product.* The only criterion that satisfies both conditions when designing a commercial product is the economic benefit of the producer. The economic benefit does not only reflect the producer interest in making profit, it captures customers interest as well since the profit depends on a product's market demand.

It is very important to construct proper models for demand and total product cost to enable utilization of the economic benefit as the single selection criterion in a DBD framework. Note that the total product cost also depends on the demand. *Our survey shows that little work exists in the field of engineering design on constructing the product demand*. Gu et al. (2000) develop a collaborative approach, in which DBD is decomposed in business and engineering decision-making processes to more accurately model the existing relationship between business and engineering in multidisciplinary design. Li and Azarm (2000) present an iterative two stage approach, multiobjective optimization, followed by alternative evaluation. It is our interest in this work to develop a systematic procedure for implementing DBD and to introduce the technique of Discrete Choice Analysis (DCA) for constructing a product demand model.

### 2.4 Discrete Choice Analysis

DCA is a statistical technique, which identifies patterns in choices customers make between competing products. DCA allows examining the market share impact of product features, price, service, and promotion on different classes of consumers (Ben-Akiva and Lerman, 1985). The origin of its application lies in transportation engineering, wherein DCA is employed in analyzing the user's response (traveler, shipper) to changes of service, infrastructure, price, etc. DCA builds upon design of experiments, formal data collection procedures, and the method of MultiNomial Logit (MNL) to predict the probability that an alternative is selected over other choices. In this work, the probability of being selected is extended to predict the probable market share of a design option. A key concept of DCA is the use of random utility (probabilistic choice theory) to address unobserved taste variations, unobserved attributes, and model deficiencies. The use of statistical techniques in DCA can be supported by the analogy of observing many flips of a coin. When many choices of respondents are observed it is possible to deduce the probability of purchasing a certain product based on the product's features, price, and the profile of the consumers. An advantage of DCA over other research techniques, such as Conjoint Analysis (CA) (Green and Wind, 1975; Green and Srinivasan, 1990), is that survey alternatives need neither to be characterized by the same attributes, nor at the same levels. Additionally, unlike CA, DCA rarely suffers from the degree of freedom problem. With DCA, the respondent's task is simply to choose which product to buy. This is what consumers do best, thus avoiding the unnatural task of ordering alternatives with CA. The features of DCA are further detailed in Section 3.2.

## 3 AN APPROACH TO DECISION-BASED DESIGN

### 3.1 The DBD Framework

The flowchart of our proposed DBD product selection process is shown in Figure 1. The discussion is limited to the enhancements with respect to the DBD framework proposed by Hazelrigg (1998). Two different types of attributes are differentiated in our approach, namely the engineering attributes $\boldsymbol{E}$ and the customer key attributes $\boldsymbol{A}$. The engineering attributes $\boldsymbol{E}$ are product properties that are of interest to a design engineer, represented as functions of design variables $\boldsymbol{X}$. The engineering attributes may impose restrictions on design options , e.g. due to material stress limits. The considerations of these restrictions (design constraints) enable reduction of the design space, improving the efficiency of the optimization process without risk of omitting potential successful design alternatives. The customer key attributes $\boldsymbol{A}$ are the product features (next to brand, price, and warranty) a customer typically assesses when purchasing the product. The arrows in the flowchart indicate the existence of relationships between the different entities (parameters) in DBD.

One of the contributions of this paper lies in introducing DCA as a systematic approach to establish the relationship between the design options $\boldsymbol{X}$, the socioeconomic and demographic background $\boldsymbol{S}$ of the market population, time $t$, and the demand $Q$. Another major contribution is the differentiation of corporate interests, which encompass more than maximizing profit. It may be preferable to consider multiple corporate interests such as market share, employment, etc. In Section 2 however we concluded that a single criterion approach is required for unambiguous decision-making. This apparent paradox is avoided by selecting one corporate interest as the single criterion $V$, while other corporate interests $\boldsymbol{I}$ act as requirements (constraints), e.g. a specified minimum market share. The single criterion could be profit related, though a decision-maker may choose to capture market share no matter the cost, in which case the market share is the selection criterion. In another situation, like spacecraft design, reliability could be the single criterion while a maximum expense could be specified under $\boldsymbol{I}$. The selection criterion is associated with economic benefit in this paper. The selection criterion $V$ is expressed as a function of the demand $Q$, price $P$, total product cost $C$, encompassing the design's entire lifecycle. The time $t$ is considered when discounting $V$ to the net present value.

While Hazelrigg's framework is void of constraints, we recognize constraints/requirements are fundamental in decision-making and useful in limiting the design options and hence in reducing optimization burden. However constraints that limit a design engineer in generating design alternatives or that exclude potentially valuable design alternatives should be avoided.

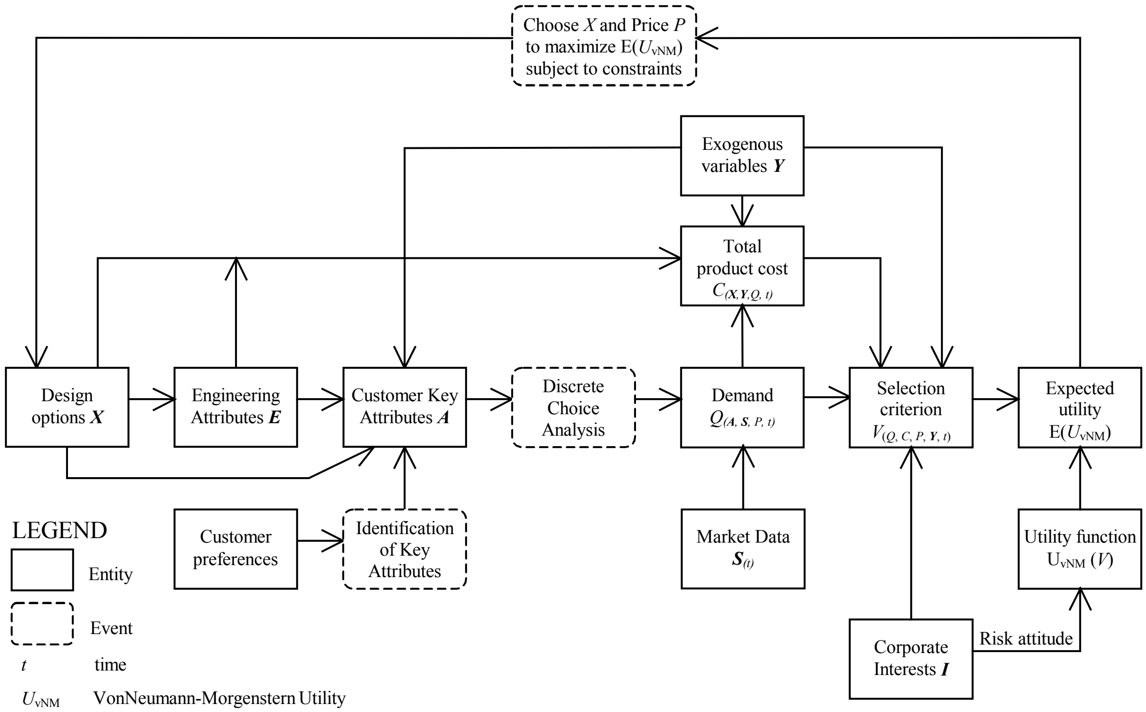


**Figure 1. Decision-Based Design flowchart**

Under the DBD framework, distributions of uncertain factors such as the exogenous variables $\boldsymbol{Y}$ and cost $C$ are estimated. Thurston and Liu (1991) showed that an estimated probability distribution is preferable to a point estimate. A probability distribution enables consideration of the decision-maker's risk attitude in the evaluation of the product design by means of a utility function of the net present value of the selection criterion. The probability distributions of the corporate interests could be addressed with confidence levels to determine whether a particular interest is satisfied or not.

The optimal product design is determined by choosing both the design options $\boldsymbol{X}$ and the price $P$, such that the expected utility $E(U_{vNM})$ of the selection criterion is maximized while satisfying the constraints. This optimization flow is illustrated with the loop in the DBD flowchart. Our single loop optimization approach is different from using two separate loops for optimizing design options $\boldsymbol{X}$ and the price $P$ in Hazelrigg's DBD framework.

### 3.2 Constructing the Demand Model

Discrete Choice Analysis (DCA) (Daganzo, 1979; Hensher, 1981; Ben-Akiva and Lerman, 1985) is introduced to model demand $Q$ as the function of customer key attributes $\boldsymbol{A}$, price $P$, and socioeconomic and demographic attributes $\boldsymbol{S}$. A DCA is carried out in the following major phases:

I Identify customer key attributes $\boldsymbol{A}$ and the range of price $P$;
II Collect quantitative choice data of proposed designs versus competing products;
III Record customers' socioeconomic and demographic background $\boldsymbol{S}$;
IV Create a model for demand estimation based on the probability of choice.

In Phase II survey alternatives can be generated with a factorial design, using the customer key attributes and price as factors. Each survey alternative *together with competing products* form a choice set from which a respondent chooses one or more products he or she most probably will purchase and indicates the quantity (how many). Each respondent usually completes an (near) orthogonal subset of the large number of possible choice sets. In Phase III, the socioeconomic and demographic background of each respondent is recorded as the respondent's choice may be influenced by his or her personal situation. The demand can be correlated to selected market segments via the socioeconomic data. Phase IV is a quantitative process to generate the demand model. Based on the collected survey data, model forming techniques such as MultiNomial Logit (MNL) could be used to create a model to forecast the demand for a new design. Phase IV is detailed next.

**Multinomial Analysis** It is assumed that the respondents select the alternative with the highest utility among those available. The utility can be parameterized as a function of observable independent variables (customer key attributes $\boldsymbol{A}$, socioeconomic and demographic attributes $\boldsymbol{S}$, and price $P$) and unknown coefficients $\boldsymbol{\beta}$, which represent the respondent's taste, see Equation 3.1. The $\beta$-coefficients are estimated from the choice data of the market survey. The accuracy of the demand estimates can be increased by identifying unique β-coefficients and utility functions $W$ per market segment, or class of consumers to capture systematic preference variations. The market can be classified according to socioeconomic background. Classes of consumers or market segment populations can be characterized by distributions of socioeconomic attributes. Ultimately, random β-coefficients can be employed to represent the taste variations present within a (market segment) population. The β-coefficients and utility functions are indicated with the subscript $n$, representing the $n^{th}$ market segment or consumer class, the index $i$ refers to the $i$-th alternative in Equation 3.1. There is no functional form imposed on the form of the utility function $W$, i.e. $W$ can be additive, multiplicative, quadratic, etc.

$$W_{in} = f(\beta_n, \boldsymbol{Z}_i), \quad \boldsymbol{Z}_i = (A_1, \ldots, A_j, S_1, \ldots, S_k, P) \tag{3.1}$$

An individual's choice may correspond to an infinite number of attributes (Arrow, 1963). Therefore due to unobserved taste variations, unobserved attributes, and measurement errors it is impossible to correctly predict the utility and thus the discrete choices of all individuals with certainty. The concept of random utility is adopted by assuming that the individual's true utility $U$ consists of a deterministic part $W$ and a random disturbance ε (called the disturbance), see Equation 3.2. The disturbance may be assumed normal according to the central limit theorem.

$$U_{in} = W_{in} + \varepsilon_{in} \tag{3.2}$$

The probability that a given alternative is chosen is then defined as the probability that it has the greatest utility among the available alternatives (Ben-Akiva and Lerman, 1985). The probability that alternative 1 is chosen from a choice set containing two alternatives (binary choice) depends on 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.

$$\begin{aligned}\Pr(1)\big|[1,2] &= \Pr(W_{1n} + \varepsilon_{1n} \geq W_{2n} + \varepsilon_{2n} \\ &= \Pr(\varepsilon_{2n} - \varepsilon_{1n} \leq W_{1n} - W_{2n})\end{aligned} \tag{3.3}$$

MNL approximates the normal distribution with a logistical distribution, which can be evaluated in a closed format. Equation 3.4 shows the choice probability of the binary logit model.

$$\begin{aligned}\Pr_n(1)\big|[1,2] = \Pr_n(U_{1n} \geq U_{2n}) &= \frac{1}{1 + e^{-\mu(W_{1n} - W_{2n})}} \\ &= \frac{e^{\mu W_{1n}}}{e^{\mu W_{1n}} + e^{\mu W_{2n}}}\end{aligned} \tag{3.4}$$

$\Pr_n(1)$ is the probability that respondent $n$ chooses alternative 1 over alternative 2. The scale parameters μ are considered equal as the result of the Independent and Identically Distributed (IID) assumption, which implies that the variances of the disturbances are assumed equal and independent. Details of deriving Equation 3.4 and the IID assumption can be found in (Ben-Akiva and Lerman, 1985). The binary logistical cumulative distribution function of the difference of the (deterministic) utilities $W_{1n} - W_{2n}$ is depicted in Figure 2. Note that the predicted choice probability does not reach unity, nor zero. The binomial logit model is extended to the multinomial logit model in Equation 3.5. $C_m$ represents the choice set with $m$ competing products.

$$\Pr_n(i)\big|[C_m] = \frac{e^{\mu W_{in}}}{\sum_{l=1}^{m} e^{\mu W_{ln}}} \tag{3.5}$$

**Determination of the β-coefficients** As the result of the customer survey we know the response rate, i.e. how often each survey alternative is chosen. The response rate can be depicted as a probability density distribution, see Figure 3.

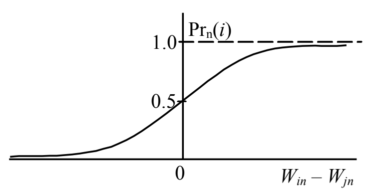

**Figure 2. Binary logit choice model**

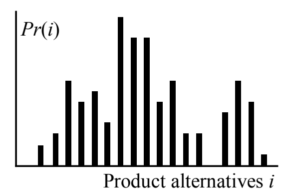

**Figure 3. Response rate probability distribution**

The goal then is to determine the β-coefficients and the utility function $W$ such that the multinomial demand model matches the probability distribution as closely as possible. The maximum log-likelihood method and the method of least squares can be utilized for this purpose. Model forming techniques such as Neural Networks and the Kriging method offer more flexibility and could be utilized under this circumstance to determine the form of the utility function $W$ when it is difficult to pre-specify the functional form of the utility function.

The total demand for a particular design is the summation of the choice probability, given by Equation 3.5, multiplied with the size of each market segment. Estimates of future demand can be facilitated by using pattern based or correlational forecasting of *existing* products. Forecasts of economic growth and the estimated change of the socioeconomic and demographic background of the market populations helps to refine these estimates.

## 4 EXAMPLE PROBLEM – UNIVERSAL MOTOR

The proposed DBD procedure is demonstrated through an academic problem - electric universal motor design (Simpson, 1998). The implementation of the proposed DBD framework consists of six major steps: Market Research, Alternative Generation and Engineering Analysis, Product Cost Modeling, Construction of the Demand Model, Determination of Selection Criterion and Risk Attitude, and finally, Optimization for Determining the Preferred Alternative.

**Step 1: Market Research** In this step an understanding of the market for universal motors market is gained, such as the market size, (potential) competing products are assessed, etc. A survey and focus group is used to identify the customer key attributes ***A*** and their desired range.

**Customer key attributes *A*** The motor often finds application in handheld power tools that are battery powered. It is therefore important to aim for low weight and maximum time the motor can operate on single battery charge. The customer key attributes ***A*** in this example are therefore identified as operating time B and mass M. The operating time of a motor powered by a particular battery is prolonged if the motor is more energy efficient. Hence energy efficiency $\eta$ is an engineering attribute. The power and the torque are also important to the customer and could be part of the customer key attributes. However, it is assumed that the company produces a family of universal motors (Nayak et al. 2000). This product family will be supplemented with a motor with a power P of 300 Watt and a torque T of 0.25 Nm. The power and the torque requirements are listed as *prescribed design requirements* as part of the customer key attributes.

**Step 2: Alternative Generation and Engineering Analysis**

**Alternative Generation** The variables controllable by a design engineer are called the design options ***X***, listed in Table 1. Note that the ranges are chosen wide as to ensure that possibly preferred design options are not excluded. All variables are treated as continuous in this study, including the turns of wire to facilitate the optimization process. To simplify the problem, the motor has two stator poles $p_{st}$, the laminate thickness is set to 0.63 mm, and the air gap $l_{gap}$ is set to 0.7 mm. Varying the design options ***X*** generates a continuum of alternatives. The problem now reduces to selecting the best possible alternative from this continuum.

**Table 1. Specification of design options *X***

| | | |
|---|---|---|
| 1. Current | $0.1 < I < 6.0$ [A] | Continuous |
| 2. Motor Radius | $10 < r_o < 150$ [mm] | Continuous |
| 3. Stator Thickness | $0.5 < t_s < 15.0$ [mm] | Continuous |
| 4. Number of Turns of Rotor Wire | $100 < N_r < 1500$ [turns] | Continuous |
| 5. Number of Turns of Stator Wire | $1 < N_s < 500$ [turns] | Continuous |
| 6. Cross-Sectional Area Rotor Wire | $0.01 < A_{rw} < 2.0$ [mm$^2$] | Continuous |
| 7. Cross-Sectional Area Stator Wire | $0.01 < A_{sw} < 2.0$ [mm$^2$] | Continuous |
| 8. Stack Length | $10.0 < L < 200.0$ [mm] | Continuous |

**Engineering Analysis** The engineering analysis establishes the analytical relationship between the customer key attributes ***A*** and the design options ***X***, while considering the engineering attributes ***E***. Performance parameters associated with design constraints are part of the engineering attributes. The magnetizing intensity in the motor is not allowed to exceed the physical flux carrying capacity of steel $\varphi_{st}$ (Simpson, 1998). A feasible geometry constraint ensures that the thickness $t_s$ of the stator does not exceed the radius $r_o$ of the stator. The contributions to the motor mass, (i.e. the mass of the rotor, stator, and windings) and power losses (i.e. the losses occurring in the copper and brushes) are intermediary engineering attributes. The maximum allowable motor temperature depends on the insulation quality of the wire material. The wire insulation quality, which is assumed to vary slightly (uncertainty), affects the reliability of the motor. The motor temperature $T_m$ is determined as a function of ambient temperature $T_a$, electrical losses (heat source), radiant surface $A_{motor}$ and surface emissivity Em (dimensionless). All customer and engineering attributes, along with the important relationships, are listed in Table 2.

**Step 3: Product Cost Modeling** The product cost analysis establishes the relationship between the design options ***X*** and the total product cost *C* of the universal motor's life cycle. The cost strongly depends on the motor's intended use. The automation level of the manufacturing process (manufacturer specific) heavily influences the capital-labor ratio. Cost easily doubles when dimensions outside the standard range are needed.

**Table 2. Customer and Engineering attributes**

| **Customer Key Attributes *A*** | |
|---|---|
| Mass M [kg] | $M = M_w + M_s + M_r$ |
| Operating time B [hr] | $B = 1\ \eta$ |
| Power P [W] | $P = P_{in} - P_{loss} = 300$ |
| Torque T [Nm] | $T = K\ \varphi\ I = 0.25$ |
| **Engineering Attributes *E*** | |
| Efficiency $\eta$ (dimensionless) | $\eta = (P_{in} - P_{loss}) / P_{in}$ |
| Rotor wire length $l_{rw}$ [m] | $l_{rw} = 2L + 4(r_o - t_s - l_{gap})\ N_r$ |
| Stator wire length $l_{sw}$ [m] | $l_{sw} = p_{st}\ (2L + 4(r_o - t_s)\ N_s$ |
| Rotor wire resistance $R_r$ [Ohm] | $R_r = \rho\ l_{rw} / A_{rw}$ |
| Stator wire resistance $R_s$ [Ohm] | $R_s = \rho\ l_{sw} / A_{sw}$ |
| Power loss $P_{loss}$ [W] | $P_{loss} = I^2\ (R_r + R_s) + 2\ I$ |
| Mass windings $M_w$ [kg] | $M_w = (l_{rw}\ A_{rw} + l_{sw}\ A_{sw})\ \rho_{copper}$ |
| Mass stator $M_s$ [kg] | $M_s = \pi\ L\ (r_o^2 - (r_o - t_s)^2)\ \rho_{steel}$ |
| Mass rotor $M_r$ [kg] | $M_r = \pi\ L\ (r_o - t_s - l_{gap})^2\ \rho_{steel}$ |
| Flux carrying cap. of steel $\varphi_{st}$ [A turns /m] | $\varphi_{st} \leq 5000$ |
| Motor constant K (dimensionless) | $K = N_c\ \pi$ |
| Magnetizing intensity H [A turns /m] | $H = N_c\ I / (\ l_c + l_r + 2l_{gap})$ |
| Magneto magnetic force $\Im$ [A turns] | $\Im = N_s\ I$ |
| Magnetic flux [Wb] | $\varphi = \Im / \Re$ |
| Motor surface area $A_{motor}$ [m$^3$] | $A_{motor} = 2\ \pi\ r_o\ L + \pi\ r_o\ ^2$ |
| Motor temperature $T_m$ [$^o$C] | $T_m = T_a + I^2\ R / A_{motor}\ Em$ |

The total product cost *C* is based on design, material, labor, capital, and repair / warranty costs. The material cost $M_c$ is determined as a function of the demand *Q* and the cost for the steel of the rotor and stator, and the copper wires. The cost of the wire depends on the wire diameter. Standard ranges are 0.52

– 0.65 mm for the rotor wire and 0.9 – 1.1 mm for the stator wire. Labor cost $L_c$ is determined from the cost split labor/material, which is about 30/70 (rule of thumb). This cost split depends on the automation level of finishing processes (manufacturer specific). It is assumed that the cost increases quadratically when the production quantity deviates from the optimal production capacity due to inefficiencies. The repair / warranty cost depends among others on the reliability of the motor. It is assumed that the reliability depends solely on the motor temperature $T_m$. $G(T_m)$ is the computed fraction of motors that need repair during the warranty period. The warranty period itself and the impact of marketing vs. marketing cost are not considered in this example.

It is assumed that all cost remain constant except the labor cost, which is expected to rise 3% annually. Additionally the total cost depends on the demand, which is expected to grow 5% annually. The total cost is summarized in Table 3.

**Table 3. Total product cost**

| **Total Cost** [USD] | |
|---|---|
| Design cost $D_c$ | $D_c = 500{,}000$ |
| Material cost $M_c$ | $M_c = Q\,(M_w\,P_{copper} + (M_s + M_r)\,P_{steel})$ |
| Labor cost $L_c$ | $L_c = 30\,L_g\,M_c / 70$ |
| Capital cost $C_c$ | $C_c = A_c\,Q / (4.5\ 10^6 + Q)$ |
| Capacity cost $C_{cap}$ | $C_{cap} = 50\,[\,(Q - 5\ 10^5) / 1000\,]^2$ |
| Repair, warranty $R_c$ | $R_c = 1.5\,P\,Q\,G(T_m)$ |

**Exogenous variables *Y* and Uncertainty handling** The exogenous variables considered are, stack length variation, labor cost growth factor $L_g$, demand uncertainty as a result of the demand analysis, the demand growth, and the wire insulation quality. The variation of the stack length L affects the mass M, efficiency $\eta$, operating time B, total product cost *C*, and demand *Q*. The labor cost growth factor $L_g$ affects the uncertainty of the predicted demand. The demand growth factor, and varying wire insulation quality affects the total product cost *C*. All exogenous variables ultimately impact the selection criterion *V*. The effect of uncertainty on the selection criterion is assessed by Monte Carlo simulation. An overview of the exogenous variables is presented in Table 4.

**Table 4. Exogenous variables (normal distribution)**

| **Exogenous variable *Y*** | Mean | St. Deviation |
|---|---|---|
| Stack length L [mm] | Variable | 0.0005 + 0.02 Mean |
| Labor cost growth factor $L_g$ | 1.03 | 0.02 |
| Demand *Q* [motors / year] | Variable | 0.01 Mean |
| Demand growth factor | 1.05 | 0.04 |
| Wire insulation quality [$^o$C] | 90 | 2 |

**Step 4: Construction of the Demand Model** The demand *Q* is determined as a function of the customer key attributes *A*, price *P*, and the socioeconomic and demographic background of the market population ***S***. The demand is estimated with DCA. The choice set of this example contains three alternatives. The alternatives are: the "survey alternative" (i.e. the new motor design), "any other motor", by which is meant any other motor brand the respondent knows, and the third choice alternative is "none of these", i.e. the respondent chooses not to buy any of the motors listed in the choice set. The customer key attributes and price are considered at three levels each. The choice alternative "any other motor" is considered at one level of mass, operating time, and price, listed in Table 5.

**Table 5. Attributes and levels used in the survey**

| Attribute name | Survey alternative | Any other motor |
|---|---|---|
| Mass M [kg] | 0.2 | 1.0 |
| | 0.6 | |
| | 1.0 | |
| Operating time B [hr] | 0.40 | 0.80 |
| | 0.65 | |
| | 0.90 | |
| Price *P* [USD] | 5.00 | 5.75 |
| | 6.50 | |
| | 8.00 | |

A total of 27 alternative combinations are generated (full factorial design). Hence, 27 different choice sets are possible with the attributes listed in Table 5. An example of a choice set is shown in Table 6.

**Table 6. Example of a choice set**

| **Choice Set # 17** | Survey alternative | Any other motor | None of these |
|---|---|---|---|
| Power [Watt] | 300 | 300 | |
| Torque [Nm] | 0.25 | 0.25 | |
| Mass [kg] | 0.6 | 1.0 | |
| Operating time [hr] | 0.90 | 0.80 | |
| Price [USD] | $ 6.50 | $ 5.75 | |
| Indicate whether this is the product you are want to buy and how many | | | |

**Multinomial logit choice model** The choice behavior of the respondents is modeled by an additive utility function (Equation 3.1). It should be noted that the utility function can assume any form that best fits the data set. The attributes $\boldsymbol{Z_i}$ describe each choice alternative ***A***, price *P*, and socioeconomic background of the market population ***S***.

**Table 7. Multinomial choice model**

| | Choice set alternative attributes ($\boldsymbol{Z_i}$ ($\boldsymbol{A}$, $P$, $\boldsymbol{S}$)) | | | |
|---|---|---|---|---|
| β Coefficient | Survey alternative | Any other motor | None of these | β-coefficient Estimate |
| β 1 | 1 | 0 | 0 | -2.22 |
| β 2 | 0 | 1 | 0 | -1.63 |
| β 3 | mass | mass | 0 | -103.40 |
| β 4 | operating time | operating time | 0 | -206.94 |
| β 5 | 0 | 0 | operating time | 52.36 |
| β 6 | price / income | price / income | 0 | -13.83 |
| β 7 | 0 | 0 | price / income | 5.03 |
| β 8 | age ≤ 35 years | age ≤ 35 years | 0 | 0.21 |
| β 9 | 0 | 0 | age ≤ 35 years | 0.11 |
| β 10 | age > 35 years | age > 35 years | 0 | -0.09 |
| β 11 | 0 | 0 | age > 35 years | -0.12 |

Two classes of consumers are discerned, a class of consumers older than 35 years and a class with an age less than 35 years. Table 7 shows the multinomial choice model and coefficient estimates of the universal motor demand. The utility of "None of these" is used as base, β1 and β2 provide the offset of the other two utility functions. Coefficient 3, 4, and 5 correspond to the customer key attributes ***A***. The socioeconomic attribute "income" and price *P* is considered in the combined price/income attribute, corresponding to β6 and β7. β8 through β11 are coefficients for the two age categories.

The probable choice can be predicted with the multinomial choice model and Equation 4.1, given the consumer class, income level, the product attributes and price.

$$\Pr_n(1)\big|[1,3] = \frac{e^{U_{1n}}}{e^{U_{1n}} + e^{U_{2n}} + e^{U_{3n}}} \tag{4.1}$$

$U_{1n}$ denotes the *n*-th consumer class' utility of the "survey alternative", $U_{2n}$ the utility of the "any other motor" alternative, and $U_{3n}$ the utility of the "none of these" alternative. $Pr_n(1)$ is the predicted probability that alternative 1 is chosen from the three choice alternatives. The aggregated predicted choice probabilities and the market size data are used to estimate the demand.

**Step 5: Determination of the Selection Criterion and Risk Attitude** The selection criterion *V* is the net present value of the net cash flow. There are no other corporate interests ***I*** considered. The utility function that accounts for the risk attitude is listed in Figure 4. The discount rate $D_r$ is chosen as 15%. The problem description is summarized in Figure 4.

**Step 6: Optimization for Determining the Preferred Alternative** The preferred design alternative with the highest expected utility of the net present value of profit, while considering the engineering constraints is determined with optimization techniques. The results of the preferred alternative are presented in Table 8. Figures 5, and 6 show the probability distributions of the demand, and net present value of the profit of the preferred design alternative.

It is observed that although the distributions of input uncertainty are normal as shown in Table 5, the output distribution of the accumulated NPV of the profit shown in Figure 6 is non-symmetric. This is mainly because of the assumption that the manufacturing cost rise significantly when the demand deviates from the optimum production capacity. It is also noted that there is a probability of financial loss, which again brings out the importance of considering the designer's risk attitude. A maximum allowable risk (i.e. a quantifiable financial loss with known probability) could be part of the corporate interests, i.e. the maximum risk one is willing to take.

**GIVEN**

| | |
|---|---|
| Terminal voltage $V_t$ | 115 [Volt] |
| Stator poles $p_{st}$ | 2 |
| Production quantity | 500.000 [motors/year] (estimate) |
| Product life cycle | 5 [year] |
| Discount rate $D_r$ | 15 % |

**Customer key attributes *A*** (Table 3)
**Engineering attributes *E*** (Table 3)
Determines the analytical relationship between ***X*** and ***A***
**Demand model** *Q*
The demand model is obtained using the multinomial logit technique to fit the discrete choice survey data (Equation 4.3)
**Cost model** *C* (Table 4)
Determines the analytical relationship between ***X*** and *C*
**Corporate interests *I***
None other than the single selection criterion *V*
**Single criterion** *V*
Net revenue $V = Q\,(P - C)$
**Utility function** $U_{vNM}(V)$
$U_{vNM}(V) = -274 + 20 \log(V + 5.9\ 10^6)$
**Market Data *S*** (Socioeconomic and demographic attributes)

**FIND**
Design options ***X*** (Table 2) and price *P*

**SUBJECT TO**

| | |
|---|---|
| Power requirement | P = 300 [Watt] |
| Torque requirement | T = 0.25 [Nm] |
| Maximum motor radius | $r_{o,max}$ = 150 [mm] |
| Feasible geometry | $t < r_o$ |
| Magnetizing intensity | $H_{max} \leq 5000$ [Wb] |

**MAXIMIZE**
Expected utility of the net present value of profit *V*

**Figure 4. Problem description**

**Table 8. Results of the DBD simulation**

| | | |
|---|---|---|
| Power | 299.7 [Watts] | |
| Torque | 0.249 [Nm] | |
| Preferred design options | Current | 3.63 [Amp.] |
| | Motor Radius | 31.9 [mm] |
| | Stator Thickness | 5.8 [mm] |
| | Number of Turns of Rotor Wire | 989 [turns] |
| | Number of Turns of Stator Wire | 55 [turns] |
| | Cross-Sectional Area Rotor Wire | 0.26 [mm$^2$] |
| | Cross-Sectional Area Stator Wire | 0.46 [mm$^2$] |
| | Stack Length | 22.5 [mm] |
| Engineering Attributes | Efficiency | 0.66 |
| | Magnetizing Intensity | 2193 [Amp. Turns/m] |
| Customer Key Attributes | Mass | 0.97 [kg] |
| | Operating time | 0.66 [hr] |
| | Price | 6.58 [USD] |
| Results | Expected Demand (year 5) | 510,000 [motors] |
| | Expected NPV Profit (accumulated) | 4,100,000 [USD] |

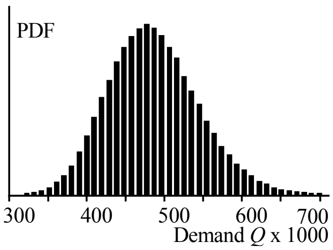


**Figure 5. Demand (year 5) distribution**

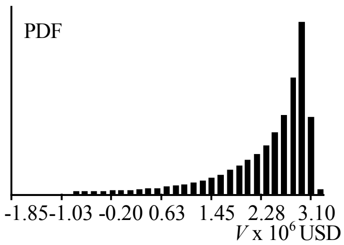


**Figure 6. Net Present Value distribution**

## 5 CLOSURE

We propose in this paper a DBD approach that enhances Hazelrigg's DBD framework and that utilizes a single criterion in alternative selection. By examining the limitations associated with the multicriteria approaches, we illustrate that a single-criterion approach is more appropriate to unambiguously select the preferred alternative in a rigorous manner. We develop a systematic procedure for implementing the DBD approach. The technique of discrete choice analysis has been introduced for constructing a product demand model, which is crucial for the evaluations of both the profit made from the product and the cost associated with producing the product. The advantages of the proposed procedure for constructing the demand function can be summarized as follows:

– Our method does not involve any ranking, weighting, and normalization, thus avoiding paradox associated with multicriteria approaches.
– Probabilistic choice addresses the uncertainties associated with unobserved taste variations, unobserved attributes, and model deficiencies.
– Competing products are considered, enabling analysis of market impact and competitive actions through "*what if*" scenarios.
– 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.
– Customer survey embedded in DCA resembles as close as possible the real purchase behavior of consumers, reducing respondent errors and enabling the analysis of more attributes.

The limitations of the proposed DBD approach are associated with the assumptions for using DCA. The Independence from Irrelevant Alternatives Property (IIA), may lead to paradox if the choice set is not chosen appropriately (Ben-Akiva and Lerman, 1985). It should be noted that the IIA property applies to an *individual*, not the population as a whole. This implies that the predictive quality of MNL models will improve when more socioeconomic and demographic attributes are included. It should also be noted that the MNL analysis detailed in Section 3.2 assumes a normal distribution of the random part of the utility function. This distribution can be normal, Weibull or another distribution function. Additionally it is assumed in this paper that the scale parameters $\mu$ are assumed equal, indicating that the shape of the disturbance of every attribute is the same, which is a simplistic treatment.

Under the proposed DBD framework, the role of engineers is to conduct analyses and provide the information of performance attributes. Many practical issues and open research questions need to be answered before the DBD approach can be truly implemented in an industrial setting. For example, how should we develop flexible design representations so that potential design options are not left out? How should we enhance the analytical capabilities in those areas that are currently very weak? What are the limitations of the single criterion approach, should we assess the technical versus economical feasibility to decide whether we should apply the DBD approach? The all-in-one strategy requires huge computational resource to effectively search the design space, evaluate the design performance under uncertainty, and to identify the optimal solution for a problem that has a high dimensionality and is highly nonlinear. How should we develop computational techniques that can facilitate this optimization? Will engineers and managers trust the decision-making to a computer simulation, especially when the state of the art optimization techniques cannot always guarantee to determine the global optimum? How will DBD affect the information flow related to product design within companies?

To further the research on the implementation of DBD and the method for constructing the demand function, we will continue to validate the proposed approach by comparing the method with the favorable properties of design alternative selection methods proposed by Hazelrigg (http://dbd.eng.buffalo.edu/speakers/hazelrigg.pdf and Hazelrigg 1999). The method for constructing the demand function could be evaluated by applying it to an existing product and comparing the theoretical result with the actual data. An axiomatic framework is desired for rigorous validation. It could be a long journey to develop a complete theory of DBD. We wish this work has helped us to move one step forward.

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