An Approach to Decision-Based Design With Discrete Choice Analysis for Demand Modeling

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In this paper, we present the importance of using a single criterion approach to Decision-Based Design (DBD) by examining the 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 evaluation 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.
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1 Introduction

In the engineering research community, there is a growing recognition that decisions are the fundamental construct in engineering design [1]. The Decision-Based Design (DBD) perspective [2] 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 [3–16], 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 [2] 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 [17] 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 are also provided in Section 2. Our proposed approach to single criterion DBD is presented in Section 3. An academic example problem on motor design is provided in Section 4. In Section 5, we discuss the advantages of our proposed approach and some of the open research issues related to its implementation.

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[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.

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 [2]. 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 [18], Pugh Matrix [19], Weighted Sum, Taguchi signal-to-noise ratio function [20], and Suh's design axioms [21]. However, these methods produce different results when applied to the same problem as they elicit and handle the decision-maker's preferences 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 procedure that involves multiattribute ranking, normalization, weighting, 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 [22], the selected alternative may result from the underlying voting method rather than the quality of the alternative itself. According to Coombs's condition [23], the chance of paradox is over 97% when six alternatives are ranked using multiple attributes. Along the same line, Arrow's impossibility theorem [23] 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 employed to facilitate alternative comparison when attributes have different dimensions. 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) through assigning weights to attributes. However, WS may lead to subjective choice, i.e. the attribute weights are based upon a 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 that attribute is correlated to a product's success [23]. WS assumes linear attribute tradeoff, which is only true for limited variation of attribute values.

The **multiattribute utility function** [24] 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 a decision-maker's risk attitude. Utility independence then seems questionable. Intuitively, high uncertainty (i.e. risk) of one attribute would have to be compensated by a reduced uncertainty of another 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. Finally, forming the multiattribute utility function involves normalization and weighting, their 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. Therefore, existing multicriteria approaches possess such limitations in one way or another. In fact, the selection of attributes themselves may be biased and incomplete. Multiattribute approaches are sometimes used incorrectly, i.e. the decision-maker's preference considered is not always relevant, e.g. a product's performance affects the end-user's product value, not the design engineer's. 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 [25]. 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 should be capable of capturing all quantifiable uncertainties in the life cycle development of a product*. Most, if not all, product design options can be either linked to cost or, via market demand, to revenue. Thus, it appears that the producer's economic benefit satisfies both aforementioned conditions when designing a commercial product; and it may well be the only criterion. The economic benefit does not only reflect the producer interest in making profit, it also captures customers interest as well since 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. [4] develop a computational approach to collaborative design, 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 [5] present an iterative two-stage approach, multiobjective optimization, followed by evaluation of selected alternatives. As an intermediate variable, the market demand of an alternative is determined by comparing the multiattribute utility values, which are obtained through conjoint analysis (CA), among a set of alternatives. 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 within the DBD framework.

2.4 Discrete Choice Analysis. In this section we provide the literature background of DCA, an approach extended in this work for product demand modeling. A more detailed description of DCA is given in Section 3.2 and an illustrative example for product demanding is provided in Section 4. 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 [17]. 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 methods such as logit or probit to predict the probability that any alternative is selected from a set of alternatives. 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), which deduces the respondent's choice from the rank order of alternatives as specified by the respondent [26,27], is that survey alternatives need neither to be characterized by the same attributes, nor at the same attribute 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 and enabling consideration of more attributes and more alternatives.

3 An Approach to Decision-Based Design

3.1 The DBD Framework. The flowchart of our proposed DBD product selection process is shown in Fig. 1. The discussion is limited to the enhancements with respect to the DBD framework proposed by Hazelrigg [2]. Two different types of attributes are differentiated in our approach, namely the engineering attributes **E** and the key customer attributes **A**. The engineering attributes **E** are product properties that are of interest to a design engineer, represented as functions of design variables **X**. The engineering attributes may impose restrictions on design options, e.g. 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 key customer attributes **A** are product features (next to brand, price, and war-

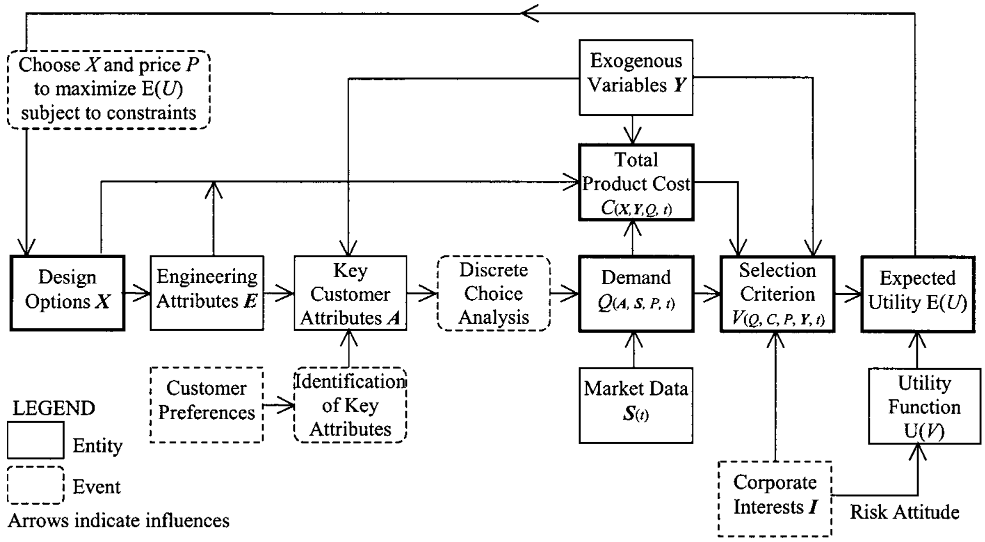

Fig. 1 Decision-based design flowchart

ranty) that a customer typically considers when purchasing the product. The arrows in the flowchart indicate the existence of relationships between the different entities (parameters) in DBD.

One major contribution of this paper lies in introducing DCA as a systematic approach to establish the relationship between the design options **X**, the socioeconomic and demographic background **S** of the market population, time t, and the demand Q. The selection criterion V is selected from the corporate interests **I**, that may encompass more than maximizing profit (i.e., net revenue). The corporate interests **I** may act as requirements (constraints), e.g., a specified minimum market share. In Section 2.3, we discussed that in developing commercial products, the economic benefit appears to be the only criterion that can reflect the interests of both the consumers and the producer, as well as capture all quantifiable uncertainties in the product life cycle development. In designing noncommercial products, for example spacecraft design, reliability could be the single criterion V, while a maximum expense or budget could be specified under **I**. The utility function U for the chosen single criterion V can be assessed using the Von Neumann-Morgenstern lottery method. The single selection criterion is associated with economic benefit in this paper and is expressed as a function of the demand Q, price P, total product cost C, encompassing the product's entire lifecycle. The time t is considered when discounting V to the net present value (NPV).

While Hazelrigg's framework is void of constraints, we recognize that constraints/requirements are fundamental in engineering decision-making and useful in reducing optimization burden by limiting the number of design options. However, constraints that limit a design engineer in generating design alternatives, or that exclude potentially valuable design alternatives should be avoided. *That is, rigorous decision-making only allows constraints that cannot be avoided*, such as constraints imposed by physical limitations (e.g. material stress limits, geometric constraints, see Step 2, Section 4), exogenous limitations (e.g. legislative requirements), etc.

Under the DBD framework, distributions of uncertain factors such as the exogenous variables **Y** and cost C are estimated. Thurston and Liu [28] 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 selection criterion, the net present value of profit in this paper. The optimal product design is determined by choosing both the design options **X** and the price P, such that the expected utility $E(U)$ 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 **X** and the price P in Hazelrigg's DBD framework.

3.2 Constructing the Demand Model. Discrete Choice Analysis (DCA) [17,29,30] is introduced to model demand Q as the function of key customer attributes **A**, price P, and socioeconomic and demographic attributes **S**. A DCA is carried out in the following major phases:

I Identify key customer attributes **A** and the range of price P;

II Collect quantitative choice data of proposed designs versus alternative choice options;

III Record customers' socioeconomic and demographic background **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 key customer attributes and price as factors. Each survey alternative together with alternative choice options (e.g., competing products or services) form a set of discrete choices, from which a respondent chooses one or more alternatives he or she most probably will purchase and indicates the quantity (how many). Each respondent usually completes a (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, modeling techniques such as logit [17,30] or probit [17,29,30] could be used to create a model to forecast the demand for a new design. Interpretation of logit coefficients is straightforward through the assumption of attribute independence, and logit is considered as a special case of the more general probit. Phase IV is detailed next.

Multinomial Analysis. It is assumed that the survey respondents select the alternatives among those available that maximize their utility. The respondent's utility can be parameterized as a function of observable *independent* explanatory variables (key customer attributes **A**, socioeconomic and demographic attributes **S**, and price P) and unknown coefficients β, which represent the respondent's taste, see Eq. (1). The β-coefficients are estimated from the choice data of the market survey. The customer utility functions W_{in} are indicated with the subscript n, representing the

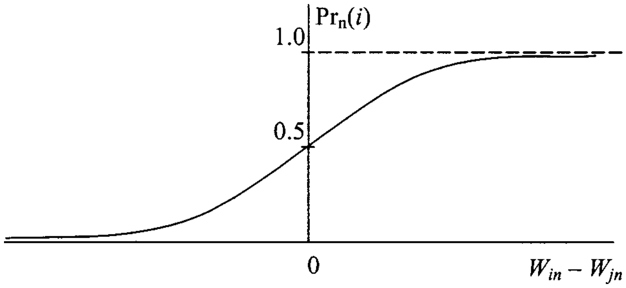

Fig. 2 Binary Logit Choice model

n^{th} respondent, the index i refers to the i-th alternative in Eq. (1). There is no functional form imposed on the form of the utility function W, i.e. W can be additive, multiplicative, quadratic, etc.

$$W_{in}=f(\beta,\mathbf{Z}_i), \quad \mathbf{Z}_i=(A_1,\ldots,A_j,S_1,\ldots,S_k,P) \tag{1}$$

An individual's choice may correspond to an infinite number of attributes [31]. Therefore, due to unobserved attributes, but also unobserved taste variations 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 customer's true utility U consists of a deterministic part W and a random disturbance ε (called the disturbance), see Eq. (2). The disturbance may be assumed normal according to the central limit theorem.

$$U_{in}=W_{in}+\varepsilon_{in} \tag{2}$$

The probability that a given alternative is chosen is then defined as the probability that it has the greatest customer utility among the available alternatives [17]. Considering a choice set that contains two alternatives (binary choice), the probability that alternative 1 is chosen depends on the probability that the customer 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 customer utility*, i.e.

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

Logit approximates the normal distribution with a logistical distribution, which can be evaluated in a closed format. Equation (4) shows the choice probability as modeled by binary logit.

$$\begin{aligned}\Pr_n(1)|[1,2]=\Pr_n(U_{1n}\geqslant U_{2n})&=\frac{1}{1+e^{-\mu(W_{1n}-W_{2n})}}\\&=\frac{e^{\mu W_{1n}}}{e^{\mu W_{1n}}+e^{\mu W_{2n}}}\end{aligned} \tag{4}$$

$\Pr_n(1)$ 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 Eq. (4) and the IID assumption can be found in [17]. The binary logistical cumulative distribution function of the difference of the (deterministic) customer utilities $W_{1n}-W_{2n}$ is depicted in Fig. 2. Note that the predicted choice probability does not reach unity, nor zero. The binomial logit choice model is extended to multinomial logit (MNL) in Eq. (5). C_m represents the choice set with m competing products.

$$\Pr_n(i)|[C_m]=\frac{e^{\mu W_{\text{in}}}}{\sum_{l=1}^{m} e^{\mu W_{\text{ln}}}} \tag{5}$$

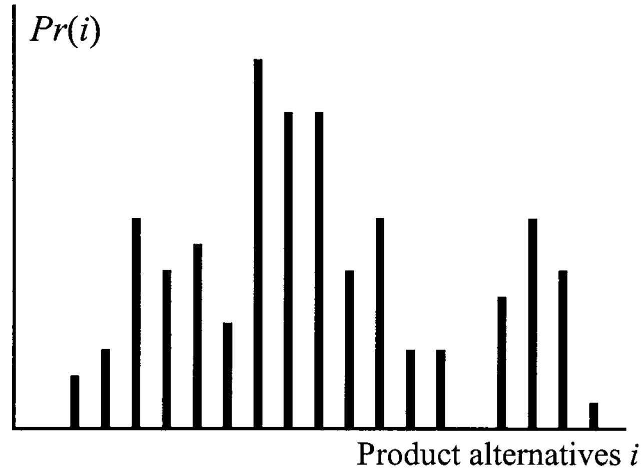

Fig. 3 Response rate probability distribution

Determination of the β-coefficients. As 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 as illustrated in Fig. 3.

The goal then is to determine the β-coefficients and therefore the customer utility function W such that the multinomial demand model predictions match the observed probability density distribution as closely as possible. The maximum log-likelihood method and the method of least squares can be utilized for this purpose.

The demand for a particular design is the summation of the choice probability of each respondent n, given by Eq. (5), adjusted for the ratio of respondent sample size versus the size of the market population. The accuracy of the demand estimates can be increased by identifying unique β-coefficients and customer utility functions 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 [17]. Estimates of future demand can also 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 [32]. 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 key customer attributes **A** and their desired range.

Key customer attributes A. The motor often finds applications 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 key customer 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

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 sire	$1<N_s<500$ [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

Table 3 Total product cost

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

efficiency η is classified as an engineering attribute. The key customer attributes and engineering attributes are listed in Table 2. The power and the torque are also important to the customer and could be part of the key customer attributes. However, it is assumed that the company produces a family of universal motors [33]. 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 key customer 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 prevent that these constraints accidentally exclude the preferred design alternative. All variables are treated as continuous in this study, including the turns of wire to facilitate the optimization process. 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 to simplify the problem. Varying the design options **X** generates a continuum of alternatives. The problem now reduces to selecting the best possible alternative from this continuum.

Engineering Analysis. The engineering analysis establishes the analytical relationship between the key customer 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 φ_{st} [32]. A geometric constraint ensures that the thickness t_s of the stator doesn't exceed the radius r_o of the stator. 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.

Table 2 Customer and engineering attributes

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

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; cost easily doubles when dimensions outside the standard range are needed. The level of manufacturing process automation (manufacturer specific) heavily influences the capital-labor ratio.

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 assumed to be 30/70. 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 costs remain constant except 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.

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 η, 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 net present value. 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.

Step 4: Construction of the Demand Model. The demand Q is determined as a function of the key customer attributes **A**, price P, and the socioeconomic and demographic background of the market population **S**. The demand is estimated using DCA. The

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 [°C]	90	2

Table 5 Attributes and levels used in the survey

Key customer attribute	Survey alternative	Your usual brand of choice
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	

Table 7 Multinomial choice model

β coefficient	Choice set alternative attributes ($\mathbf{Z}_i(\mathbf{A},P,\mathbf{S})$) Survey alternative	Your usual brand of choice	None of these	β-coefficient estimate
$\beta 1$	1	0	0	−2.22
$\beta 2$	0	1	0	−1.63
$\beta 3$	mass	mass	0	−103.40
$\beta 4$	operating time	operating time	0	−206.94
$\beta 5$	0	0	operating time	52.36
$\beta 6$	price/income	price/income	0	−13.83
$\beta 7$	0	0	price/income	5.03
$\beta 8$	age≤35 yrs	age≤35 yrs	0	0.21
$\beta 9$	0	0	age≤35 yrs	0.11
$\beta 10$	age>35 yrs	age>35 yrs	0	−0.09
$\beta 11$	0	0	age>35 yrs	−0.12

choice set of this example contains three alternatives: "survey alternative" (i.e. the new motor design), "your usual brand of choice," by which is meant the motor brand the respondent usually purchases, 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 choice option "your usual brand of choice" is used in place of listing each competing product to reduce the number of possible choice sets and to simplify respondents' task. Competing motors could be more explicitly included in the choice set when one is interested in the individual market shares of these motors. The key customer attributes and price are considered at three levels each, while power and torque are considered as prescribed design requirements and fixed at 300 Watt and 0.25 Nm respectively as explained in Step 1. The level of the attributes for "your usual brand of choice" depends on the definition obtained from each individual respondent, an example of a particular respondent is given in Table 5. An example of a choice set is shown in Table 6.

Multinomial logit choice model. The choice behavior of the respondents is modeled using an additive customer utility function (Eq. (1)). It should be noted that the utility function can assume any form that best fits the data set, subject to econometric reasoning. That is, demand forecasting accuracy increases if the utility function form better captures the true customer's choice behavior. The choice alternatives are described by explanatory variables $\mathbf{Z}_i$, which encompasses the key customer attributes $\mathbf{A}$, price P, and socioeconomic background of the market population $\mathbf{S}$.

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 fitted multinomial choice model and customer utility coefficient estimates. The coefficient estimates are obtained by fitting the multinomial choice model to the survey data using maximum likelihood estimation. The utility of "none of these" is used as base, $\beta 1$ and $\beta 2$ provide the offset (intersect or constant) of the utility of the "survey alternative" and "your usual brand of choice," respectively. The "survey alternative" and "your usual brand of choice" share the same coefficients (see $\beta 3$, $\beta 4$, $\beta 6$, $\beta 8$, and $\beta 10$) for attributes mass, operating time, price/income, age ≤35 yrs, and age>35 yrs, respectively while "none of these" has very different coefficients (see $\beta 5$, $\beta 7$, $\beta 9$, and $\beta 11$). This is because the sensitivity of the respondent's choice for the option "none of these" differs from those for the first two motor options. For instance, the demand for the first two motor options decreases when operating time increases, that is, more respondents choose not to buy and select the option "none of these." Similar econometric reasoning applies to the other explanatory variables. Coefficient 3, 4, and 5 correspond to the key customer attributes $\mathbf{A}$. The socioeconomic attribute "income" and price P is considered in the combined price/income attribute, corresponding to $\beta 6$ and $\beta 7$. $\beta 8$ through $\beta 11$ are coefficients for the two age categories. The choice probability can be predicted using the multinomial choice model Eq. (6) with the key customer attributes, age, income, and price as inputs.

Table 6 Example of a choice set

Choice Set # 17	Survey alternative	Your usual brand of choice	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 want to buy and how many			

$$\Pr_n(1)|[1,3]=\frac{e^{U_{1n}}}{e^{U_{1n}}+e^{U_{2n}}+e^{U_{3n}}} \quad (6)$$

U_{1n} denotes the n-th consumer class' utility of the "survey alternative," U_{2n} the utility of the "your usual brand of choice" 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 profit (i.e., net revenue). The utility function that accounts for the risk attitude is listed in Fig. 4. The discount rate D_r is 15%, based on the manufacturer's option to invest in another project with an expected annual return of 15% (opportunity cost). The problem description is summarized in Fig. 4.

Step 6: Optimization for Determining the Preferred Alternative. Optimization techniques are employed to determine the preferred design alternative with the highest expected utility of the net present value, while considering the engineering constraints. The results of the preferred alternative are presented in Table 8. Figure 5 and Fig. 6 show the preferred design alternative's probability distributions of the demand, and the net present value respectively.

It is observed that, although the distributions of input uncertainty are normal as listed in Table 5, the output distribution of the accumulated NPV of the profit shown in Fig. 6 is non-symmetric. In this example this is mainly caused by 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 decision maker's risk attitude. A maxi-

GIVEN

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

Key customer attributes $\boldsymbol{A}$ (Table 3)

Engineering attributes $\boldsymbol{E}$ (Table 3)

Determines the analytical relationship between $\boldsymbol{X}$ and $\boldsymbol{A}$

Demand model Q

The demand model is obtained using the multinomial logit technique to fit the discrete choice survey data, see Eq. (4)

Cost model C (Table 4)

Determines the analytical relationship between $\boldsymbol{X}$ and C

Corporate interests $\boldsymbol{I}$

None other than the single selection criterion V

Single criterion V

Net revenue — $V = Q\,(P - C)$

Utility function $U_{vNM}(V)$

$U(V) = -274 + 20\log(V + 5.9\ 10^6)$ (fictitious)

Market Data $\boldsymbol{S}$ (Socioeconomic and demographic attributes)

55% younger than 30 years

FIND

Design options $\boldsymbol{X}$ (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]

Fig. 4 Problem description

mum 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 *able* to take.

5 Closure

We propose in this paper a DBD approach that enhances Hazelrigg's DBD framework and that utilizes a single criterion for 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 evaluation 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 can be considered, enabling analysis of market impact and competitive actions through "*what if*" scenarios.
— Choices need not share the same set of attributes or attribute levels, expanding market testing possibilities and leaving more freedom to the marketing engineer.
— The customer survey embedded in DCA resembles closely 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. Unlike probit, the Independence from Irrelevant Alternatives property may lead to paradox when using a logit choice model if the choice set is not chosen appropriately [17]. It should be noted that the IIA property applies

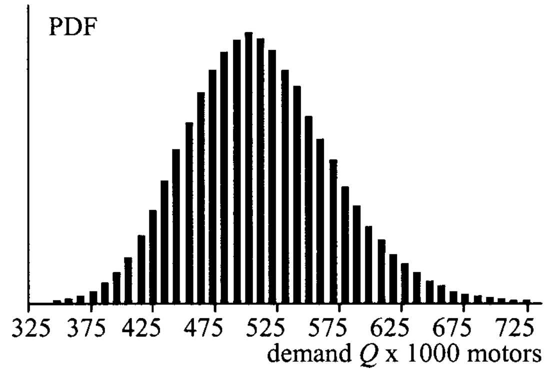

Fig. 5 Demand (year 5) distribution

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]
Key customer 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]

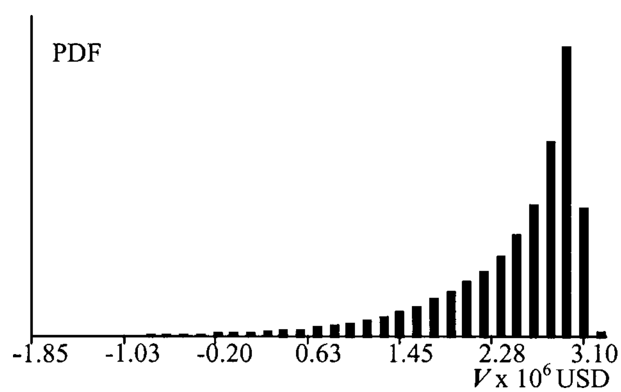

Fig. 6 Net present value distribution

to an *individual*, not the population as a whole. This implies that the predictive quality of logit models will improve when more socioeconomic and demographic attributes are included. It should also be noted that, although DCA assumes a normal distribution of the random part of the utility function, this distribution can be normal, Weibull or another distribution function. An additional assumption of logit is that the scale parameters μ are considered 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 engineering 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 [34,35]. The method for constructing the demand function could be evaluated by applying it to an existing product. However, 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 move one step forward.

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