DECISION THEORY FOR DESIGN ECONOMICS

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ABSTRACT

The traditional engineering design process ends too abruptly when economic or "nontechnical"factors must be considered. Leaving decisions about tradeoffs between cost and quality to marketing, accounting and management personnel has resulted in products that do not compete well in the international marketplace. Marketing personnel can determine customer preferences, but are poorly equipped to translate those preferences into product and manufacturing process specifications. Within a manufacturing company, engineers are the ones who possess the analytic capabilities required for true concurrent design decision making. This paper reviews our work on integrating decision analysis into the design process. We describe a method which will help engineers broaden the realm of their analysis to treat economic factors with the same respect they traditionally accord only to "technical" factors. Our approach is to integrate formal, mathematically rigorous methods for multiattribute utility decision-making with conventional design analysis. We present a two-phased approach for preliminary design evaluation followed by fine-tuning for design optimization. An example of turnbuckle material selection and design illustrates the methodology.

INTRODUCTION

This paper describes and reviews our research on integrating decision theory into design analysis. We view the recent surge of interest in engineering design theory as evidence that engineers — and the businesses that employ them — are seeking to improve their products to meet world-class competition, but understand that the traditional design process must first be improved before improved products can be realized. Sullivan [29] noted that a paradigm shift is occurring in engineering economy as a result of the "engineer's role in strategic and design-related decision processes." Indeed new approaches to addressing economic concerns in the design process are needed.

We see the weak link in the traditional design-evaluate-redesign process as the reliance on unstructured, ad hoc methods for two critical steps: multiattribute problem formulation which includes economics, and the decision making that is necessary after a set of Pareto-optimal design solutions is achieved. Our aim is to bring as much mathematical rigor to design decision making as has been brought to bear on conventional design analysis.

The typical product design process is shown in Figure 1. Minimum requirements or specifications are first defined, then an initial basic design is configured. Economic factors are typically not considered in these early design stages. Design analysis is then performed to specify physical design parameters, such as component geometry, required to satisfy the minimum specifications. The design is then evaluated to determine if its performance in other areas such as cost and ease of manufacture are acceptable. If so, the design process ends. If not,

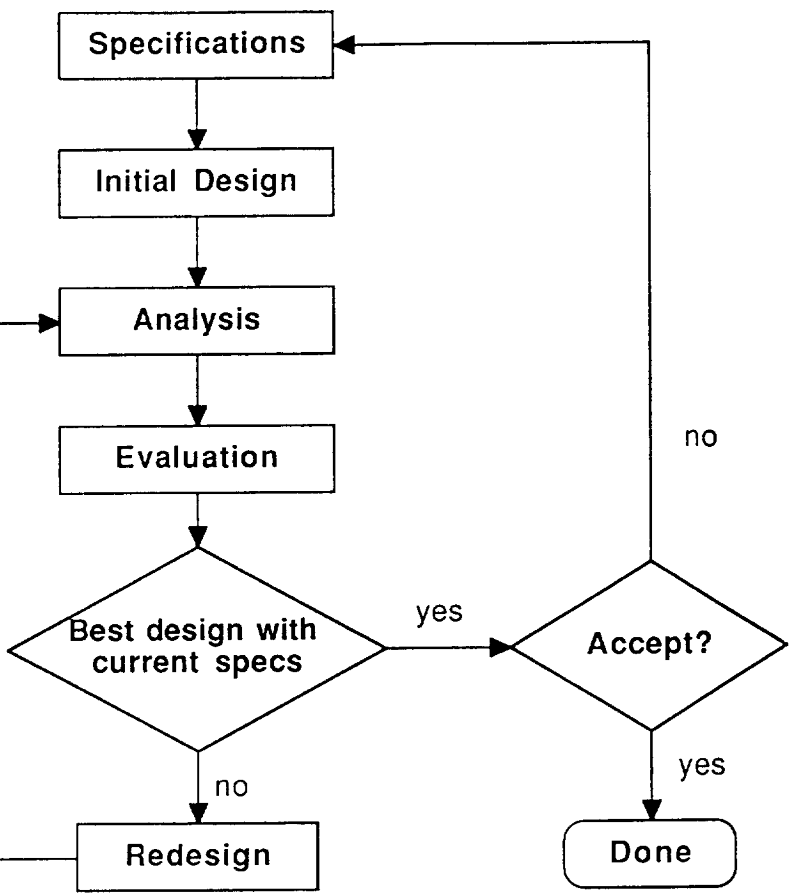

FIGURE 1. Iterative Design Process.

the design is modified, redesigned, and evaluated again in an iterative fashion until a satisfactory design is achieved. If the designer is unable to develop a satisfactory design, "revise specifications" is sometimes viewed as the next logical step. For example, a constraint such as minimum stiffness might be specified, and the minimum-cost design determined through iterative redesign. Then, if the design is still judged to be "too expensive", the stiffness constraint is relaxed if possible so that a less costly design can be achieved. We view this as a very inefficient and potentially error-prone process. Concurrent design should include all measures against which a design will be evaluated, including economic ones, from the start. In this way, more cost-efficient designs will result, and the design process itself will be more efficient.

This paper describes how the engineering design process can benefit from integration of decision theory and design analysis. One key benefit is that economic factors are easily integrated into design analysis. We have developed a theory of prescriptive decision analysis to remedy limitations of current approaches to decision making in design. The method is *descriptive* in that it emulates current procedures by allowing designers to provide input which reflects their preferences. At the same time, the method is *normative* in that is seeks to improve upon current decision-making procedures. It does this by decomposing an intractable decision problem into separately solvable sub-problems, providing structure to a previously unstructured or even *ad hoc* decision making process. The descriptive and normative approaches interface when the designer is allowed to provide his or her own input to a mathematically rigorous design analysis. The result is a methodology which permits the development of normative computer aids to design which progress beyond the automation of inadequate design procedures of the past.

The next section reviews and describes related work in integrating economics into design evaluation. The section following presents an example of traditional multiattribute design evaluation, and illustrates its limitations. Subsequently we describe our method for multiattribute design utility analysis which overcomes these limitations. We then compare the results of the traditional approach and the utility analysis approach for multiattribute preliminary design evaluation. Our approach to succedent design analysis, as opposed to preliminary design evaluation, which uses the utility function to direct the design process to the optimal combination of cost and performance is then presented. Finally, we extend the turnbuckle example to demonstrate this method.

RELATED RESEARCH ON ECONOMICS AND DESIGN ANALYSIS

Finger and Dixon [10, 11] review previous research efforts in mechanical design and identified "analysis and evaluation of designs at the early and intermediate stages" as a major research issue. In an effort to incorporate economic factors and customer preferences early in the design process, Cook [6] and Cook and DeVor [7] propose a model of a competitive manufacturing enterprise. One result is the development of *value theory* which, like multiattribute utility theory, easily handles multiple design and manufacturing concerns simultaneously. Value theory can be used to estimate product value in dollars by making use of current market demand information and customer preferences. This theory parallels that of Vasseur, Kurfess and Cagan [36], who propose a decision-analytic method for product design that can "reason about product quality, manufacturing processes, statistical tolerances and corporate profit." Suh [27] considers multiple design attributes through an axiomatic approach that "is a systematic method for guiding the design process and analyzing the results" (Gebala and Suh [12]). Pugh [24] presents a matrix-based approach to multiattribute design that permits design evaluation by comparing alternatives to a selected datum. Otto and Antonsson [20] propose several *trade-off* strategies for design decisions. The *conservative* design strategy makes trade-offs to improve goals with the lowest performance; the *aggressive* design strategy makes trade-offs cooperatively to improve the overall design; hybrid strategies are also possible.

Uncertainty in cost estimation has been a barrier to incorporating economics into the design process. Fabrycky [8] observed that improvements in product economic competitiveness can be achieved by "incorporating risk and uncertainty in design." Taguchi methods aim to increase product quality by reducing variability in manufactured parts (reducing the uncertainty in output). Wilde [38] demonstrated that, to achieve a higher quality product, an optimization formulation is preferred to Taguchi's method. Wilde showed an optimization model that illustrates the trade-off between quality, power consumption and cost. Otto and Antonsson [21] developed a way to model different uncertainty forms: probabilistic and possibilistic. Reddy and Mistree [24] used exact interval arithmetic to model uncertainty in a decision support design problem. Lavelle, Canada, and Wilson [17] suggested a design evaluation model based on a weighted sum of attributes, allowing uncertainty or inexactness in the weight assessment and alternative ratings. Bradley and Agogino [2] present a decision-analytic method for catalog selection problems in design. Thurston and Liu [33] present a method for incorporating uncertainty in the design process. They integrate manufacturing cost in the design evaluation process and demonstrate the effect of uncertainty on overall utility.

Wilhelm and Parsaei [39] suggest that the role of "non-quantifiables" in engineering economics needs more attention and note that promising approaches include the Analytic Hierarchy Process (AHP) and multiple criteria decision models. Application of these approaches include an AHP application in engineering economics (Boucher and MacStravic [1]) and a multiattribute utility analysis application in structural design (Locascio and Thurston [19]). By facilitating communication between diverse groups within a manufacturing industry and providing a mechanism for integrating subjective and objective factors from the initial product development stage, the House of Quality (Hauser and Clausing [14]) and Quality Function Deployment methods (e. g., Sullivan [28]) have gained acceptance in industry. Thurston and Locascio [34] describe how the House of Quality can be interpreted, using multiattribute utility analysis, as a design optimization problem. Other examples of economic analyses and decision analytic approaches include a case study of disk manufacture for airplane turbine engines (Park and Prueitt [23]) and an evaluation of local area networks that uses a decision support system to incorporate multiple attributes and nonlinear decision-maker preferences (Liggett and Sullivan [18]).

The decision-analytic approach to design advocated here seeks to integrate economics, "unquantifiables" and uncertainty into the design process. Thurston [30] describes a procedure for formulating a multiattribute utility design evaluation function, and using it to quantify beneficial tradeoffs between cost and performance. Thurston, Carnahan, and Liu [31] propose a new method for optimizing design utility. They use utility theory to construct a multiattribute objective function constrained by functional relationships between design decisions, cost and performance. This method was extended by Locascio and Thurston [19] to integrate subjective or "unquantifiable" attributes perceived by the customer. By integrating utility analysis with tools from artificial intelligence, new decision aids to design have been realized (Thurston and Sun, [35]). This paper builds on previous work by presenting a two-phased approach to integrating economics into design analysis; first multiattribute design *evaluation* in the preliminary design, then design *optimization* for the succeeding analysis.

Other common approaches to decision-making under multiple attributes include the *lexicographic ordering* method and the *dominance elimination* technique. The lexicographic ordering method simply ranks alternatives according to the most important attribute; the "best" alternative has the highest rank. Ties are broken by rank-ordering on the second most important attribute. The dominance elimination technique attempts to narrow the total number of alternatives by making pairwise comparisons, discarding alternatives whose attribute levels do not exceed the others. This reduced set is often called the Pareto optimal set or the efficient frontier. These methods are discussed in more detail later. The decision-analytic approach to design presented here, based on multiattribute utility theory, is superior these approaches because it considers all attributes concurrently and, not only narrows the number of possible alternatives, but identifies the best one with respect to all attributes.

CASE STUDY: TRADITIONAL MULTIATTRIBUTE EVALUATION FOR JOURNAL BEARINGS

This section presents an illustration of the traditional approach to multiple attribute (including economic) design evaluation, and exemplifies its deficiencies.

PROBLEM DESCRIPTION

The design problem is to select the best material for a journal bearing. A journal bearing is a mechanical element that acts as a sleeve around a rotating or oscillating shaft. Lubrication between the shaft and bearing facilitates relative sliding motion. The bearing element is designed to transmit loads from the shaft to the bearing support. Journal bearings are used in many applications including steam turbines, power-generating stations, and automotive engines (Shigley and Mitchell [26]).

TRADITIONAL MULTIATTRIBUTE DESIGN APPROACH

The conventional design process described next is adapted from an engineering design text, Farag ([9], chapter 23). Eight properties, shown in Table 1, are identified as "important" specifications in material selection and design for the bearing.

TABLE 1. Material Properties.

Property
Yield Strength
Fatigue Strength
Hardness
Corrosion Resistance
Wear Resistance
Thermal Conductivity
Young's Modulus
Cost

For each material property, an upper limit, lower limit, or target value is defined, indicating that each candidate material property must satisfy the limit or fall near a certain target value. For example, the attribute of material yield strength has a lower limit of 20 MPa indicating that any feasible material choice must have a yield strength above 20 MPa. The next step is to identify the candidate bearing materials which satisfy the specifications, or constraints on property limits. For this example, five types of metals satisfy the specifications: two types of whitemetals (tin-based and lead-based), two types of copper-based alloys, and an aluminum-based alloy. Their relevant properties are shown in Table 2. Cost is defined relative to a base material cost. One candidate material is assigned a relative cost of unity, and the other materials are scaled from that value.

Now these alternatives are compared on the basis of their overall performance. For each candidate material type/grade, a *merit function* was calculated to determine its overall rank. The merit function is typically some type of weighted sum, where each term represents the contribution of a single attribute. Since each attribute may have different units, the value of the attribute is often scaled to make a fair contribution to the overall merit function. Each scaled attribute is then multiplied by a weighting factor that reflects the attribute's relative importance. Each weighted, scaled attribute is then summed into the overall merit function. One form of the merit function is given by (Farag [9])

$$m = \left[\sum_{i=1}^{n_l} \alpha_i \frac{y_i}{x_i}\right]_l + \left[\sum_{j=1}^{n_u} \alpha_j \frac{x_j}{y_j}\right]_u + \left[\sum_{k=1}^{n_t} \alpha_k \left|\frac{x_k}{y_k}\right| - 1\right]_l$$

where

l, u, and t indicate the lower limit, upper limit, and target value properties
n_l is the number of lower limit properties
n_u is the number of upper limit properties
n_t is the number of target value properties
a_i is the weighting factor for lower limit property i
a_j is the weighting factor for upper limit property j
a_k is the weighting factor for target value property k
x_i is the candidate material property for lower limit property i
x_j is the candidate material property for upper limit property j
x_k is the candidate material property for target value property k
y_i is the specified limit for lower limit property i
y_j is the specified limit for upper limit property j
y_k is the specified limit for target value property k.

For this case study, it was determined that aluminum-based alloys achieved the highest merit parameter.

TABLE 2: Properties of Alternative Bearing Alloys (from Farag [9])

Material	Grade	Yield Strength (MPa)	Fatigue Strength (MPa)	Hardness (BHN)	Corrosion Resistance	Wear Resistance	Thermal Conduction (W/m k)	Young's Modulus (GPa)	Relative Cost
Whitemetals (tin-base)	1	30	27	17	5	2	50.2	51	7.3
Whitemetals (lead-base)	6	26.6	22	21	4	3	23.8	29.4	1.3
Copper-base alloy SAE	48	40	45	28	3	5	41.8	75	1.5
Copper-base ASTM	A	168	120	100	2	5	41.8	95	1.8
Aluminum-base alloy	770	173	150	70	3	2	167	73	1.5

LIMITATIONS OF TRADITIONAL APPROACH

This traditional "weighted average" approach does have some merit. First, it recognizes that multiple attributes contribute to the overall worth of each design alternative, and aims to compare them by aggregating their performance in multiple attributes into a single number. Second, the approach recognizes that all attributes might not contribute equally to overall merit, and utilizes weighting factors to express their relative importance. Finally, the approach recognizes that the attributes and ranges over which they are considered might be vastly different. For example, Table 2 shows that yield strength ranges from 26.6 to 173 MPa. while corrosion resistance ranges only from 2 to 5. Unless each attribute is converted to a common scale, differences in yield strength (which are large) will dominate the outcome, while differences in corrosion resistance (even if assigned a high weighting factor) will contribute so little to the total merit value that the attribute is essentially rendered inconsequential. The merit function addresses this through the ratios between candidate property values and property limits.

This traditional design example demonstrates that designers recognize the need to consider multiple design attributes in a mathematical fashion. Designers want a sound, analytical framework to evaluate design alternatives. The approach presented here shows one way to address these needs. Further discussion of this traditional approach, however, uncovers some deficiencies that suggest a better approach.

First, since the design decision is material selection, the attributes were identified by simply listing the properties that typically characterize different materials. A better approach would be to determine what characteristics of the finished artifact are relevant to design function or performance. For instance, Young's modulus was identified as an attribute. It was noted in the attribute selection discussion (Farag [9], p. 470) that a lower Young's modulus results in a larger deflection and greater material conformability, which are both more desirable. We assert that, rather than defining Young's modulus as an attribute, deflection and conformability should instead be the relevant design attributes. Young's modulus itself is not valued, but its effect on design function in the areas of deflection and conformability are.

The second deficiency with the attribute identification procedure is that the relationships between the attributes are ignored, allowing redundancy and overlapping in the overall evaluation of material alternatives. Again, this could lead to an unintended over-representation of one attribute in the overall merit function. If the attributes are instead defined to satisfy the preferential and utility independence conditions of classical utility analysis (von Neumann and Morgenstern [37]), a more accurate merit function can be determined.

Third, the merit function assumes that the increase in overall merit is directly proportional to an increase in each attribute level. Situations of marginal returns with improvement in an attribute level are not accounted for.

Finally, the weighting factors are typically assigned in an ad hoc manner. They are intended to reflect the relative importance of each attribute, with arbitrarily high numbers assigned to "more important" attributes and low numbers to "less important" ones. Yet, in design they play the critical role of measuring the willingness to trade a specific amount of one attribute for another. Some methods do exist to determine the weights analytically, rather than assign them arbitrarily. One approach is the pairwise comparison method, implemented in conjoint analysis (Green and Wind [13]) or Saaty's [25] analytic hierarchy process. These methods ensure that the weights are assigned in an internally consistent manner, but for design analysis, this approach still has limitations. Thurston [30] demonstrated that weighted average methods can lead to suboptimal results if used to calculate a merit function for a wide range of design alternatives. The reason is that the assignment of the weighting factors is made with certain attribute levels in mind, and can be heavily biased by the current design configuration's perceived weaknesses and strengths. An attribute may be deemed unimportant at the beginning of the design process, and very important later. As the current best design is improved during the iterative design process, the perceived "relative importance" of attributes can change. For example, in the case study presented here, a low weighting factor for hardness is justified because it is "expected that rotor shaft will be adequately hardened" (Farag [9], p. 474). In other words, the hardness attribute is expected to be high and therefore merits a low importance rating. But what if a new alternative is developed whose hardness is low? If this attribute is now "more important", then the weighting factor must be revised to reflect this change. In summary, the conventional weighting assignment might not accurately reflect the decision maker's actual preferences and willingness to trade one attribute off against another throughout the range of feasible alternatives.

More fundamentally, once the designer acknowledges that multiple attributes are considered in evaluating the relative worth of design alternatives, we assert that the notion that one attribute is "more important" than another loses its meaning and becomes inappropriate. A better method is needed which accurately reflects the fact that willingness to make tradeoffs depends on the current attribute levels. In essence, we need to assess the designers willingness to effect improvements in one attribute concurrent with the resulting changes in competing attributes.

DECISION-ANALYTIC APPROACH TO MULTIATTRIBUTE DESIGN EVALUATION

The approach we advocate is to construct a more rigorously defined merit function based on the strong theoretical foundations of classical multiattribute utility analysis as developed by von Neumann and Morgenstern [37] and Keeney and Raiffa [15].

MULTIATTRIBUTE UTILITY FUNCTION

Like the simple weighted average method, overall worth is determined as a function of the levels of performance in each attribute that the design alternative exhibits. Given conditions of preferential and utility independence of attributes, the overall multiattribute utility of an alternative is calculated from the multiplicative form given by equation 1,

$$U(x) = \frac{1}{K}\left[\prod_{i=1}^{n}(Kk_iU_i(x_i)+1)-1\right] \tag{1}$$

where $U(x)$ = the total utility of a design alternative
x_i = the performance level of attribute i
$U_i(x_i)$ = the single attribute utility function for attribute i
i = 1, 2, ..., n attributes
k_i = the single attribute scaling parameter for attribute i
K = the normalizing constant, derived from

$$1+K = \prod_{i=1}^{n}(1+Kk_i)$$

Unlike the simple weighted average method, the single attribute utility functions $U_i(x_i)$ are formally assessed through a well-defined procedure from the design decision maker, and may be nonlinear over the attribute range. Similarly, the single attribute scaling parameters k_i are formally assessed from the designer and represent the relative tradeoff he or she is willing to make between attributes. It is important to note that the parameters k_i do not represent the relative importance of attributes. If the problem is formulated such that a set of "axioms of rationality" are obeyed, and the appropriate independence conditions are satisfied, the recommended course of action will consistently reflect the actual preferences of the decision maker. Thurston [30] describes how to define attributes and their ranges for design problems. The effect of manufacturing cost uncertainty can be included by using probabilistic methods presented in (Thurston and Liu [33]).

CAPITAL VS. VARIABLE COSTS

Traditional engineering economic analysis falls short in fully capturing how economic factors can effect design decisions. If our method were purely normative, we would perform a traditional engineering economic analysis to convert the required capital investment and cash flow for each alternative to a common metric using equivalent annual cost or net present value analyses at the appropriate interest rate. However, we have found that the "time value of money" alone fails to fully reflect the way in which manufacturing concerns view the tradeoff between capital investment requirements and variable costs. This is especially true for industries where investment in tooling and machinery requires a substantial, long term commitment, such as the automotive industry. For this reason, it is sometimes necessary to define "capital cost" and "variable cost" as separate and distinct attributes. Thurston [30] compares steel and polymer composite materials for automotive frame and skin systems. Steel generally has significantly larger capital cost requirements than composites, but lower variable cost. Capital and variable costs are thus defined as separate attributes, along with weight, corrosion resistance and design flexibility. This enables the designer to fine-tune the tradeoff analysis, to calculate beneficial capital cost vs. performance tradeoffs and also variable cost vs. performance tradeoffs. The willingness to pay an increase in variable costs in order to gain a 1% decrease in capital costs were calculated, and the results varied significantly for different automotive companies. This information can be used in concurrent engineering to determine what levels of effort are appropriate for process design improvement vs. product design improvement for a particular manufacturing interest.

OTHER APPROACHES:

LEXICOGRAPHIC ORDERING AND DOMINANCE ELIMINATION

Analogous to word alphabetizing, the lexicographic ordering method identifies one attribute as the "most important" and alternatives are ranked according to an evaluation of that one criterion (as in the first letter of the word). If there is a tie for the best alternative, a second attribute is assigned secondary importance and the "current best" are re-ordered. This ordering process continues until one alternative is selected as the optimum. This method is easy to understand and crudely simple. In most cases, however, this method is inappropriate for making decisions under multiple attributes, since the method virtually ignores all but one attribute.

The *dominance elimination* technique attempts to reduce the number of candidate alternatives in an effort to make easier the selection of the best alternative. In this method, each alternative is compared with the others on the basis of attribute levels. If alternative A is superior to alternative B in every attribute, then the alternative B may be eliminated from consideration. (To be more precise, A must be equal or superior to B in every attribute, and superior to B in at least one.) The process continues for every alternative, making pairwise comparisons to eliminate the dominated alternatives, until one alternative remains. More commonly however, several undominated alternatives remain in the selection set, where each alternative is better in some attributes and worse in others. The decision-maker must then decide among this reduced set of alternatives. Other schemes may be employed to further eliminate alternatives (e. g., assigning minimum tolerable levels for each attribute). In problems of two or three attributes, a plot of the efficient frontier may aid in selecting the best alternative, allowing the decision-maker to visually make trade-offs between attributes. In most cases, however, a graphical solution is not possible due to problem size, or the graphical representation may not help identify the best alternative - leaving several alternatives as candidates. Again, decisions between the remaining alternatives are left to the decision-maker. Although dominance elimination may help reduce the decision space, a single alternative seldom dominates, and we are usually faced with the original fundamental problem: finding the optimum alternative with multiple competing attributes.

Dominance elimination is analogous to the idea of Pareto optimality. A Pareto optimum solution is achieved if no single attribute (or objective) can be improved without causing at least one other attribute to worsen. Unfortunately, the conflicting nature of attributes usually makes it impossible to optimize more than a single objective at a time. Most often, the Pareto optimum solution is actually a set of solutions, each representing the optimal solution for one of the objectives. The decision maker is faced with deciding among them, or developing a compromise solution which partially achieves each objective. Several methods have been used, such as the "min-max" approach described by Osyczka [22] which seeks to minimize the relative deviations from each optima. This approach considers all the attributes simultaneously but assumes they are of equal importance. When the attributes are not of equal importance, weighted sum methods are used. The limitations of this weighted sum approach are as described earlier: *ad hoc* assessment of weights, biases resulting from the current design configuration's perceived weaknesses and strengths, inability to reflect nonlinear preferences over each attribute range, and unintended dominance of one attribute due to lack of normalizing or scaling.

Formulation of an objective function based on utility theory differs fundamentally from the Pareto optimal formulation. Utility analysis provides a mathematically-based procedure for finding the optimal balance between multiple competing objectives. Multiattribute utility analysis takes dominance elimination and Pareto optimality to a new level - analytically leading the decision-maker to the best *combination* of the dominant alternatives/Pareto optimal solutions.

It should be noted that several researchers have used the phrase "utility function" (Osyczka [22]), (Jendo [16]), in describing approaches to multiobjective optimization, but it is clear they are referring to the general concept of overall worth or value, rather than to an explicitly defined utility function constructed on the basis of the axiomatic foundations established by von Neumann and Morgenstern [37].

Osyczka [22] also remarks that since the evaluation of utility functions is difficult, the applications are rather limited. Nevertheless, we believe that if attribute levels are to be traded off in a manner which reflects the intentions of decision-makers, the additional effort to assess and use the utility function should be put forth. The time required to assess and use a utility function is no longer prohibitive due to the increased availability of advanced computational capabilities. This in itself represents a desirable tradeoff; i.e., the benefits of concurrent design (design for cost *and* design for performance) now outweigh the cost of assessing utility functions in design optimization.

CASE STUDY: PRELIMINARY DESIGN OF A TURNBUCKLE

This section presents an example comparison between the conventional and decision analytic methods to demonstrate the benefits of the latter approach.

PROBLEM DESCRIPTION

The preliminary design problem is material selection for components of a turnbuckle. A turnbuckle is a mechanical element composed of two ringbolts and a loop, shown in Figure 2. The ringbolts are used to form a coupling that, when turned, are used to tighten or loosen the tension in the loop member. Typical applications for a turnbuckle include guy wires for telegraph poles and sports equipment (Farag [9]). We wish to determine the optimum material combination for specified static and fatigue loads. Steel, aluminum and copper alloys are considered for the ringbolt and loop. It is assumed that the ringbolt material is manufactured from bar stock, first threaded by rolling, and then bent to form the ring. The loop material is manufactured by shell molding, then thread cutting.

TRADITIONAL DESIGN FORMULATION

The conventional design process described next is adapted from Farag [9], chapter 21. Both tensile and fatigue loads act on the turnbuckle. Due to these loads, the turnbuckle may fail if the loop or one of the ringbolts fails by yielding, shearing of the threads, fatigue fracture, creep strain, or corrosion. Since we assume that the turnbuckle will not be subjected to high-temperature service conditions, creep strain failure will not be a concern. Typical design analysis calculations that must be performed for each candidate material are described next.

Since the turnbuckle is subjected to both static and fatigue loads, the Soderberg failure criterion (e. g., Shigley and Mitchell [26], or Budynas [5]) is used to determine the ringbolt tensile area

$$A_r = \frac{n_m K_t L_m}{UTS_r} + \frac{n_a K_{f_r} L_a}{S_{e_r}} \tag{2}$$

where n_m = factor of safety for static strength

n_a = factor of safety for fatigue strength

L_m = static load

L_a = fatigue load

K_t = static stress-concentration factor

K_{fr} = fatigue stress-concentration factor of the ringbolt material

UTS_r = tensile strength of the ringbolt material

S_{er} = modified endurance limit of the ringbolt material.

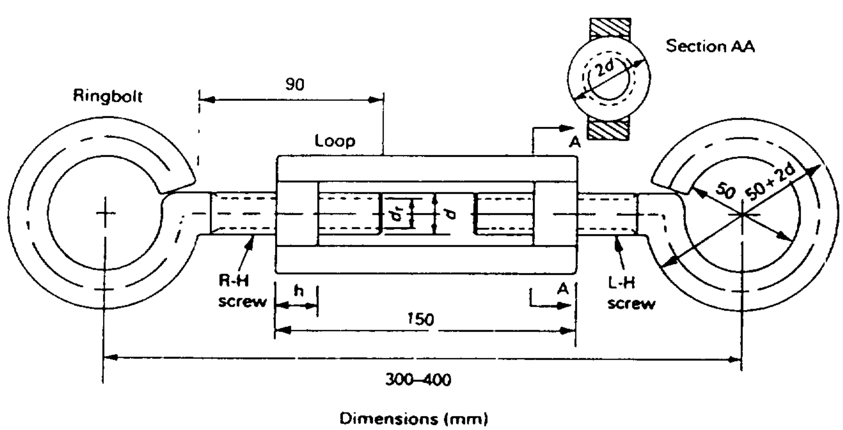

FIGURE 2. Turnbuckle assembly (from Farag, [9]).

For this example, $n_m = 1.5$ and $n_a = 3.0$ (Shigley and Mitchell [26]), $K_t = 1$ for ductile materials, $L_m = 20\ kN$ and $L_a = 5\ kN$. The other variables in equation 2 are material dependent.

The required ringbolt tensile area is first calculated from equation 2, then a ringbolt with the next smaller tensile area is selected from a catalog of standard metric threads. With this standard ringbolt, the major diameter of the ringbolt, d, is prescribed and the mass of the ringbolt may be calculated, using the geometry of the turnbuckle, from

$$w_r = \frac{\rho_r}{1000}\left[\frac{\pi d^2}{4} l_r + \frac{\pi^2 d^2}{4}(D+d)\right] \tag{3}$$

where ρr is the ringbolt material density, l_r is the length of the ringbolt leg, and D is the inner diameter of the ringbolt.

Next, the length of engagement h between the loop and ringbolt, constrained by shear failure of the threads of either component, is calculated from

$$h = \max\left[\frac{n_m K_t L_m}{\tau_{s_r} A_{S_r}} + \frac{n_a K_{f_r} L_a}{\tau_{a_r} A_{S_r}}, \frac{n_m K_t L_m}{\tau_{s_l} A_{S_l}} + \frac{n_a K_{f_l} L_a}{\tau_{a_l} A_{S_l}}\right]$$

where τ_{sr} = the static shear strength of the ringbolt material
τ_{sl} = the static shear strength of the loop material
τ_{ar} = the fatigue shear strength of the ringbolt material
τ_{al} = the fatigue shear strength of the loop material
A_{Sr} = the shear stress area per unit length of the ringbolt
A_{Sl} = the shear stress area per unit length of the loop thread.

Like the ringbolts, the webs that connect the threads of the loop are subjected to both static and fatigue loading. The required cross-sectional area of the webs is found (again, using the Soderberg criterion) from

$$A_w = \frac{n_m K_t L_m}{UTS_l} + \frac{n_a K_{f_l} L_a}{S_{e_l}}$$

where K_{fl} = fatigue stress-concentration factor of the loop material
UTS_l = tensile strength of the loop material
S_{el} = modified endurance limit of the loop material.

The mass of the loop is found using the web area and the geometry of the turnbuckle to be

$$w_l = \frac{\rho l}{1000}\left[\frac{3\pi d^2}{2}h + l_l A_w\right] \tag{4}$$

where ρl is the density of the loop material and l_l is the length of the loop. The total mass of the turnbuckle is the sum of the ringbolt and loop masses.

$$w_{total} = w_r + w_l$$

TYPICAL MULTIATTRIBUTE DESIGN EVALUATION

The relevant attributes for the multiattribute design evaluation stage are identified as weight, corrosion resistance, and cost (both fixed manufacturing cost and material cost). Weight can be calculated from equations 3 and 4. The candidate materials (steel, copper alloys, and aluminum alloys) all meet the specified limits on weight, corrosion resistance and cost. To narrow the number of possible material combinations, Farag [9] notes that the component combinations must be of the same material type to prevent galvanic corrosion. In other words, a copper alloy ringbolt may be paired only with a copper alloy loop. For purposes of illustration, only ferrous alloy combinations are considered here. For the ringbolt material, four grades of steel are considered; for the loop material, three grades of Gray CI steel and three grades of Nodular CI steel cast alloys are considered. Each candidate material is assigned a corrosion resistance rating, where 1=poor, 2=fair, 3=good, and 4=very good. When different grades of the same material are used for the ringbolt and the loop, the lower corrosion resistance rating is used to rate the entire system. Cost is rated on a relative scale as in the previous example. A representative material is assigned a relative cost of unity for manufacturing cost and material cost. Then all other materials are assigned cost ratings relative to this material. The cost scale of a material, part, component, or system is often given on a per unit basis. The relative cost per unit mass for a given ringbolt and loop pair is calculated from

$$cost = 2w_r c_r + w_l c_l$$

where c_r and c_l are the relative cost of the ringbolt and loop materials, respectively.

For each loop and ringbolt material pair, weight, corrosion resistance, and cost are estimated. To determine the optimum combination of materials, an expression for evaluating the performance index of candidate material combinations is given by the weighted sum

$$\gamma = \alpha_{cost}(\text{scaled relative cost}) + \alpha_{cr}(\text{scaled corrosion resistance}) \\ + \alpha_{weight}(\text{scaled total weight})$$

The weighting factors for each of the three attributes "are taken as" (Farag [9]) 0.5 for scaled relative cost, 0.3 for scaled corrosion resistance, and 0.2 for scaled total weight. The resulting ten best material combinations ranked according to their performance indices are shown in Table 3. For each scaled attribute and the total performance index, lower is preferred to higher.

DECISION ANALYTIC APPROACH TO DESIGN EVALUATION

To formulate this design problem in a decision-analytic framework, we first identify our decision maker as the design engineer. We wish to define our attributes such that they are mutually utility independent. By asking the designer the appropriate lottery questions, it was determined that corrosion resistance, cost and weight are mutually utility independent. In the traditional approach dscribed above, relative cost was an attribute. Since we wish to determine a more accurate assessment of willingness to pay, and since our designer might have difficulty expressing preferences for relative costs, we instead use actual cost per part in dollars as our cost attribute. Our designer can express preferences for cost when presented in these terms. Since our design attributes are utility independent, we can use the multiplicative form of the multiattribute utility function given in equation 1 to evaluate any design alternative.

We next need to assess the designer's preferences over each attribute range, represented by the single-attribute utility function. Using the certainty equivalent lottery assessment method, the single attribute utility functions for weight, cost and corrosion resistance are given respectively by

$$U_1(x_1) = -0.05448 + 333.13e^{-0.005x_1}$$

$$U_2(x_2) = 1.10408 - 0.016009e^{0.72x_2}$$

$$U_3(x_3) = \frac{1}{2}(x_3 - 1)$$

where x_1 is the turnbuckle weight in grams, x_2 is the per part cost in dollars, and x_3 is the corrosion resistance rating. Note that our designer expressed a nonlinear relation between attribute level and utility for weight and cost. In contrast with the typical design approach, the decision-analytic design approach

TABLE 3. Ten best turnbuckle material combinations: Traditional design approach (from Farag [9]).

Material		Weight	Relative	Corrosion	Performance	Rank
Ringbolt	Loop	(g)	Cost	Resist	Index	
AISI 1340	Nod. CI 120-90-02	1151.1	7.11	3	1.748	1
AISI 1340	Gray CI Grade 60	1327.4	6.69	3	1.896	2
AISI 1015	Gray CI Grade 60	1620.7	3.37	1	1.944	3
AISI 1340	Gray CI Grade 40	1445.8	6.94	3	1.952	4
AISI 1340	Nod. CI 80-55-06	1197.3	7.37	3	1.982	5
AISI 1015	Nod. CI 120-90-02	1449.0	3.90	1	1.997	6
AISI 1015	Gray CI Grade 40	1743.7	3.62	1	2.001	7
AISI 1340	Nod. CI 60-40-18	1243.5	7.62	3	2.025	8
AISI 1015	Nod. CI 80-55-06	1495.2	4.15	1	2.041	9
AISI 1015	Nod. CI 60-40-18	1541.4	4.39	1	2.085	10

permits a nonlinear preference structure that more accurately represents preferences over the range of acceptability for each attribute. For this example, the design engineer is risk prone with respect to cost, risk averse with respect to weight, and risk neutral with respect to corrosion resistance.

The scaling parameters that represent our designer's willingness to make tradeoffs between attributes are assessed as $k_1 = 0.2$, $k_2 = 0.7$, $k_3 = 0.2$ and the normalizing constant is calculated as $K = -0.321547$.

Equation 1 can now be used to evaluate the utility of any combination of loop and ringbolt materials. Table 4 shows the single attribute utilities and overall utility from equation 1 for each of the ten combinations identified earlier in Table 3. The highest ranking material combination selected is AISI 1015 steel for the ringbolts and Gray CI grade 60 cast alloy for the loop. This combination has the lowest cost ($2.60/part) and a somewhat heavy weight (1.62 kg) with a poor corrosion resistance rating. This combination of cost, weight and corrosion resistance yields the greatest design utility. Note also that this optimum differs from the optimum selected from the traditional design analysis, which placed sixth in the decision-analytic rankings.

It should be noted that a dominance elimination technique could have been used to help narrow the set of candidate solutions. By comparing the attribute levels for weight, relative cost, and corrosion resistance in Table 3, we could eliminate several of the alternative material combinations from consideration. For example, the alternative material combination AISI 1015/Nod. CI 80-55-06 has a lower weight, lower relative cost, and the same corrosion resistance rating as the alternative material combination AISI 1015/Nod. CI 60-40-18. We could, therefore, eliminate the latter alternative from consideration, since it is dominated in every attribute. We can proceed in a similar fashion to eliminate several more alternatives, leaving four alternatives in a reduced selection set. At this point in the dominance elimination method, we still face the original problem: selecting the optimum material combination, subject to several competing attributes. We must make a decision about the trade-offs between weight, cost and corrosion resistance to identify the best solution. Although the dominance elimination technique is successful in reducing the set of alternatives it fails to provide a sound, analytically-based procedure to finding the one best alternative. Multiattribute utility analysis, therefore, is the preferred method for the general problem of decision-making in design.

SENSITIVITY ANALYSIS

If market conditions were to change after conducting this analysis, and now the designer is more willing to make tradeoffs between certain attributes, the optimum combination of materials might change. For example, if the designer is now more willing to tradeoff cost for corrosion resistance, the scaling

TABLE 4. Ten best turnbuckle material combinations: Decision-based design approaches.

Material		Single Attribute Utilities			Total	Rank
Ringbolt	Loop	Weight	Cost	Corrosion Resist	Utility	
AISI 1340	Nod. CI 120-90-02	1.000	0.27	1	0.553	6
AISI 1340	Gray CI Grade 60	0.382	0.45	1	0.556	7
AISI 1015	Gray CI Grade 60	0.046	1.00	0	0.707	1
AISI 1340	Gray CI Grade 40	0.187	0.35	1	0.460	9
AISI 1340	Nod. CI 80-55-06	0.783	0.14	1	0.435	8
AISI 1015	Nod. CI 120-90-02	0.183	0.96	0	0.704	2
AISI 1015	Gray CI Grade 40	0.000	0.98	0	0.689	3
AISI 1340	Nod. CI 60-40-18	0.610	0.00	1	0.315	10
AISI 1015	Nod. CI 80-55-06	0.134	0.94	0	0.682	4
AISI 1015	Nod. CI 60-40-18	0.095	0.92	0	0.659	5

parameters could be assessed to be $k_1 = 0.2$, $k_2 = 0.4$, $k_3 = 0.4$. The same ten material combinations are evaluated with the modified design evaluation utility function (now of the additive utility form). The results are presented in the Table 5 under the heading Decision-Based Design #2. We find that the optimum material combination changes when the scaling parameters change. This analysis shows that for this case study, the optimum design is sensitive to changes in the scaling parameters.

DECISION ANALYTIC APPROACH TO DESIGN OPTIMIZATION

We now take a more critical look at the traditional design process, especially the "specifications" stage. As we have shown, only after *non-economic* specifications are satisfied do designers begin to examine the resulting costs. This might be adequate during preliminary design, but not later. If we view preliminary design as *evaluation* and comparison of alternatives, then we may interpret the final, or fine-tuning phase of design as *optimization*. During these later stages, it becomes increasingly inefficient to define, relax, and redefine specifications in order to decrease unacceptably high costs.

The multiattribute evaluation function of equation 1 provides a way to identify the best combination of attributes represented in a discrete number of preliminary alternatives. However, during later design stages where a continuous range of design decision variables is considered, equation 1 alone does not specify which decisions the designer should make in order to achieve the optimal combination of attributes. The designer cannot simply decide to achieve high performance in each attribute, since he or she is constrained by the conflicting nature of the attributes.

In (Thurston, Carnahan, Liu [31]) we developed a methodology for complete formulation of multiattribute design optimization problems. Since the designer makes direct decisions only on parameters such as component geometry, and not on attribute levels, the decision problem is to maximize the multiattribute utility function $U(\mathbf{x})$ by choice of the elements of the design vector, $\mathbf{y}$. If we determine the relationship between the design decision variable vector $(\mathbf{y})$ that the designer directly controls and the design attribute vector $(\boldsymbol{x})$, we can define constraints $\mathbf{x} = \mathbf{g}(\mathbf{y})$ on the feasible region. For example, the designer can control component geometry y to effect improvements in weight x. This is also where manufacturing cost estimation models such as those developed by Boothroyd and Dewhurst [4] and Boothroyd, Dewhurst, and Knight [3] should be integrated into design analysis. Models such as theirs can be used to write constraints that relate manufacturing and assembly cost to design decision variables.

TABLE 5. Ten best turnbuckle material combinations: Traditional design and two decision-based designs.

Material		Traditional Design Results		Decision-Based Design			
				#1		#2	
Ringbolt	Loop	Performance Index	Rank	Total Utility	Rank	Total Utility	Rank
AISI 1340	Nod. CI 120-90-02	1.748	1	0.553	6	0.708	1
AISI 1340	Gray CI Grade 60	1.896	2	0.556	7	0.654	2
AISI 1015	Gray CI Grade 60	1.944	3	0.707	1	0.409	7
AISI 1340	Gray CI Grade 40	1.952	4	0.460	9	0.577	4
AISI 1340	Nod. CI 80-55-06	1.982	5	0.435	8	0.614	3
AISI 1015	Nod. CI 120-90-02	1.997	6	0.704	2	0.422	6
AISI 1015	Gray CI Grade 40	2.001	7	0.689	3	0.394	9
AISI 1340	Nod. CI 60-40-18	2.025	8	0.315	10	0.523	5
AISI 1015	Nod. CI 80-55-06	2.041	9	0.682	4	0.404	8
AISI 1015	Nod. CI 60-40-18	2.085	10	0.659	5	0.387	10

At this stage, the specifications are analyzed. If a specification such as "minimum strength" must be satisfied at a certain level, but there is no benefit to exceeding the specification, it is left intact. However, if there is potential benefit to exceeding the specification, or if the original specification may be relaxed, it is treated as a negotiable attribute x in the utility function. The absolute "minimum strength" specification is now used to define the "worst tolerable" end of the range for that attribute. The opposite end of the range can be limited by the "best expected" level. We can formulate our optimization problem as a nonlinear program given by

$$\underset{\mathbf{y}}{\text{maximize}}\ U(\mathbf{x}) \tag{5}$$

$$\begin{aligned} \text{subject to} \quad & \mathbf{x} = \mathbf{g}(\mathbf{y}) \\ \text{and} \quad & g_i(\mathbf{y}) \geq x_{il} \\ & g_i(\mathbf{y}) \leq x_{iu} \qquad \text{for } i = 1, \ldots, n \end{aligned}$$

where x_{il} and x_{iu} are lower and upper bounds, respectively, on attribute i.

After the relationships between the attributes and the design variables are determined, substitution of this representation $g(\mathbf{y})$ into the objective function yields a new objective function, $V(\mathbf{y}) = U[\mathbf{g}(\mathbf{y})]$ and the maximization problem becomes

$$\underset{\mathbf{y}}{\text{maximize}}\ V(\mathbf{y})$$

$$\begin{aligned} \text{subject to} \quad & g_i(\mathbf{y}) \geq x_{il} \\ & g_i(\mathbf{y}) \leq x_{iu} \qquad \text{for } i = 1, \ldots, n. \end{aligned}$$

By formulating the design problem as a nonlinear program, formal optimization algorithms may be applied to obtain the best design. This objective function differs from the evaluation function presented in equation 1 in that the design attributes are further written in terms of the design decision variables. Optimization of this nonlinear program yields the optimal values of the decision variables that represent the best combination of the design attribute levels, as defined by the maximum multiattribute utility. The methodology stresses a design process which is "value driven"; the value imparted by performance attributes guides design decisions and drives the design process. This technique has been used to determine the optimal gauge for automotive body panels (Thurston and Essington [32]), and a bumper beam (Thurston, Carnahan, Liu [31]). In both cases, the optimal design was not the minimum weight configuration, but rather the configuration that resulted in the best combination of weight, manufacturing cost and stiffness. For automotive body panels, we demonstrated that the optimal material and design was dependent on manufacturing production volume.

DECISION-ANALYTIC APPROACH TO DESIGN OPTIMIZATION: TURNBUCKLE

This section illustrates an example of the decision-analytic formulation for design optimization. For the turnbuckle example, multiattribute utility was used in the preliminary phase to identify the best material combination. Now we wish to improve the design by determining the optimum turnbuckle diameter d. The static load specification of $20kN$ must be satisfied, and there is no benefit to be gained by exceeding the specification, but we are willing to consider performance tradeoffs over a range of fatigue strength.

At this stage, it is desirable to redefine attributes to reflect the current range of alternatives. In this way, a more precise measurement of preferences can be gained. Since we have selected a material and are now considering only variations in diameter d, corrosion resistance is no longer included, since it is constant over our decision space. The relevant attributes are now weight, cost and fatigue performance rating, which measures the turnbuckle performance under alternating load. Holding all other decision variables constant, we determine that the feasible range on diameter d that corresponds to a common acceptable range for weight, cost and fatigue strength is 12 mm to 24 mm.

We next determine the constraints $\mathbf{x} = g(y)$ that relate the decision variable (diameter d) to the attributes. These relationships are determined by examining the design equations described previously. For each ringbolt diameter, the variable A_r in equation 2 is fixed and the maximum allowable alternating load, L_a, may be determined. Weight and cost are found by using $L_a(d)$ and other known parameters that are now fixed for each diameter. The resulting relations between diameter and weight, cost, and fatigue performance were plotted and the following relationships determined

$$x_1(d) = 9.386d^2 - 99.003d + 490.85$$

$$x_2(d) = 0.01544d^2 - 0.16655d + 0.81743$$

$$x_3(d) = 35.75d^2 - 5.0612d - 4304.9$$

where x_1 is the turnbuckle weight in grams, x_2 is the per part cost in dollars, and x_3 is the fatigue performance rating in Newtons. These attributes are defined over the ranges

$$654.4g \leq x_1 \leq 3521.1\text{g},$$

$$\$1.04 \leq x_2 \leq \$2.60, \text{ and}$$

$$782.4\text{N} \leq x_3 \leq 16165.6N.$$

The single attribute utility functions assessed over this range were found to be

$$U_1(x_1) = 1.228 - \frac{x_1}{2866.72}$$

$$U_2(x_2) = 1.223 - 0.214x2$$

$$U_3(x_3) - 0.051 + \frac{x_3}{15383.3}$$

Since each attribute level x_i is a function of diameter d, we can plot single attribute utilities as a function of d as shown in Figure 3. As diameter increases, weight and cost worsen, while fatigue performance improves. We cannot determine the optimal diameter from this figure, only the combinations of weight, cost and fatigue performance corresponding to a specific diameter. We now determine the optimal combination of competing attributes and its corresponding diameter. The scaling parameters that represent desirable tradeoffs are assessed to be $k_1 = 0.2$, $k_2 = 0.3$, $k_3 = 0.5$ for weight, cost, and fatigue performance, respectively.

The design optimization formulation from equation 5 for the turnbuckle design is given by

maximize $U(x_1, x_2, x_3)$

$$= 0.2\left[1.228 - \frac{x_1}{2866.72}\right] + 0.3[1.223 - 0.214x_2] + 0.5\left[-0.051 + \frac{x_3}{15383.3}\right]$$

subject to

$$x_1(d) = 9.386d^2 - 99.003d + 490.85$$

$$x_2(d) = 0.01544d^2 - 0.16655d + 0.81743$$

$$x_3(d) = 35.75d^2 - 5.0612d - 4304.9.$$

and $$654.4 \le x_1 \le 3521.1$$

$$1.04 \le x_2 \le 2.60$$

$$782.4 \le x_3 \le 16165.6$$

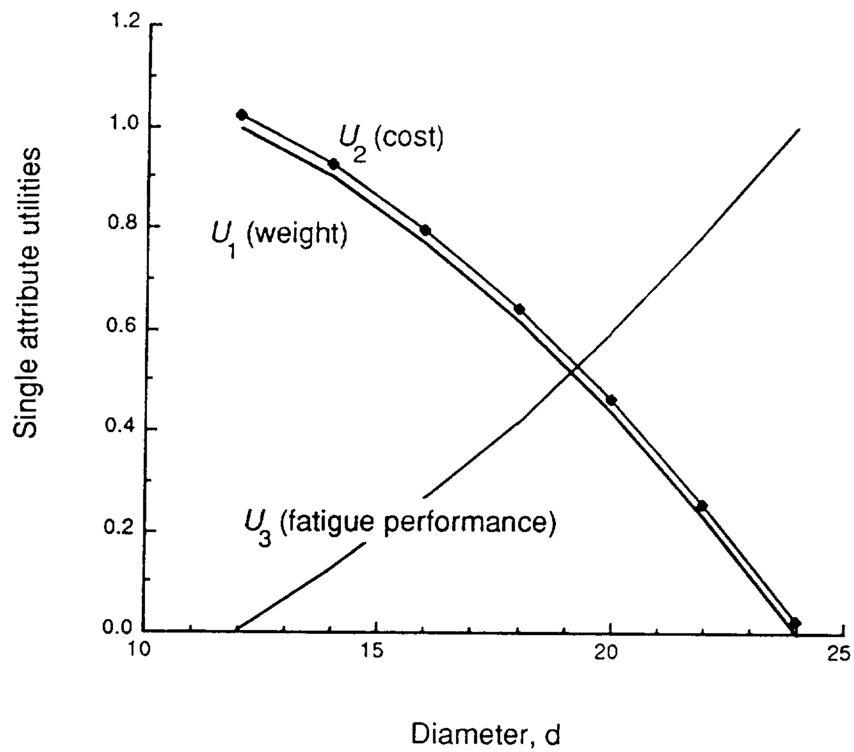

FIGURE 3. Single attribute utilities as a function of diameter.

Since the maximum utility is subject to equality constraints, we may substitute these equations into the objective function to obtain total design utility as a function of the design variable (subject to simple bounds). A plot of this function over the allowable range on diameter, shown in Figure 4, illustrates the location of the optimal diameter. The maximum utility is found at a diameter of $d = 18\ mm$, which corresponds to a weight of 1749.9 g and a cost of \$2.83 per part. This turnbuckle can resist a fatigue load of 7187 N. Note that this optimal design is neither minimum weight, nor minimum cost, nor rates the highest fatigue performance, but is the design with the best combination of weight, cost, and fatigue performance for the turnbuckle.

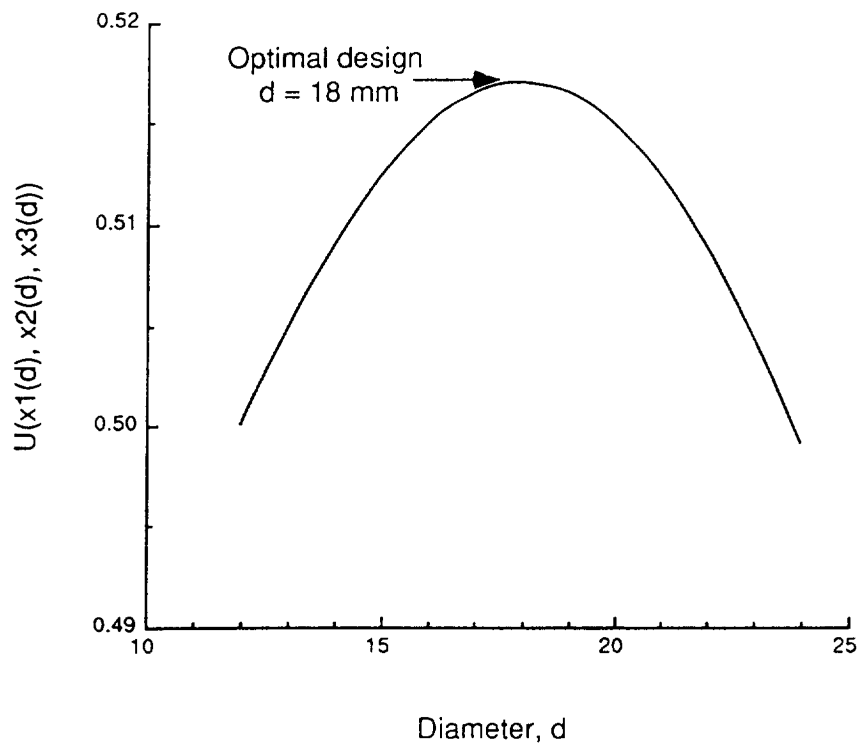

FIGURE 4. Total design utility as a function of diameter.

CONCLUSION

This paper has described the limitations of traditional methods to consider economics in the design process. During preliminary design, weighted sum methods do not inadequately reflect preferences nor the willingness to trade cost for performance. During later stages, design specifications artificially constrain the solution space. We have presented a method for accurately determining the appropriate trade-offs between the conflicting attributes of cost and performance, and determining the optimal design over the true range of feasibility. Our multiattribute decision model in a design framework permits simultaneous consideration of competing issues, and gives the designer guidance on how design decisions should be made.

Our approach streamlines the iterative design process, freeing the engineer from continual re-definition of the design problem, enabling him or her to focus instead on generating creative solutions. In addition, it enables customer preferences, which are often vague and viewed as "unquantifiable," to be integrated in meaningful way into numerical methods for design analysis. Concurrent design decision making results in fewer iterations, a more efficient design process, and better products.

This will help engineers take on greater responsibility and a larger role within the corporation. The traditional engineering design process cannot easily accommodate economic and "non-technical" factors. Decisions about tradeoffs between cost and quality should be incorporated into the design process, rather than left to marketing, accounting and management personnel. Marketing personnel can determine customer preferences, but are poorly equipped to translate those preferences into product and manufacturing process specifications.

Within a manufacturing company, engineers are the ones who possess the analytic capabilities required for true concurrent design decision making. The decision-analytic approach to concurrent design described in this paper will provide engineers with the analytic tools to treat "non-technical" factors with the same respect they traditionally accord only to "technical" factors.

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BIOGRAPHICAL SKETCHES

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