CONCURRENT ENGINEERING: Research and Applications

Decision Support in Concurrent Engineering – The Utility-Based Selection Decision Support Problem

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Abstract: Decisions are an important part of Concurrent Engineering and engineering design in general. Accordingly, more attention should be paid to the means and methods for making these decisions. In this article, a utility-based decision support method for the selection of an engineering design is presented. The utility-based selection decision support problem (u-sDSP) is a synthesized construct that facilitates selection decisions involving trade-offs among multiple, conflicting attributes and mitigation of risk associated with uncertain performance with respect to the attributes considered. The negative impact of unnecessary iterations on the product development cycle is reduced via the assurance of preference-consistent outcomes. Specifically, utility theory provides a mathematically rigorous means of clarifying and capturing designer preferences as well as identifying a preferred alternative in the context of stochastic uncertainty, while the selection decision support problem (DSP) – the construct within which utility theory is employed – facilitates the effective use of engineering judgment for (1) formulating and bounding decisions and (2) establishing a proper context. Application of the u-sDSP is illustrated with an example from rapid prototyping (RP), in which the goal is to select the appropriate technology and material combinations for testing the snap-fit design of a light switch cover plate assembly.

Key Words: selection, risk, uncertainty, utility theory, decision support problem, concurrent engineering, distributed collaborative design and manufacture, rapid prototyping.

1. Introduction

Engineers often face decisions involving conflicting objectives. The difficulty in decision making increases significantly as products and production processes become more complex. There are several factors that preclude ad hoc evaluation of and selection from a set of design alternatives. These include (1) numerous choices, (2) design alternative complexity, due to the number of attributes required to adequately characterize them, (3) measurement of attributes on different scales, (4) uncertainty with respect to attribute values, and (5) attribute trade-offs, which may or may not remain constant as attribute levels change. Therefore, decision support is warranted. Although multi-criteria decision making (MCDM) approaches can facilitate the resolution of trade-offs, the results are often misleading and inconsistent with decision maker preferences because all of these 'methods' have fundamental shortcomings that render them inappropriate for a *carte blanche* application, as effectively noted by Hazelrigg [1]. We assert that the term MCDM 'method' is a misnomer in a majority of cases, since it implies an axiomatic foundation and inherent mathematical rigor. Consequently, it is more appropriate to refer to these MCDM approaches as attention-directing tools that should be treated with caution. Awareness of this fact is crucial because practitioners consistently rely on these attention-directing tools and are likely to continue using them [2].

We recognize that many MCDM approaches can be valuable when used appropriately and in a proper context – a value that is lacking in the application of decision theory alone, as espoused by Hazelrigg and others (see, e.g., [3–10]). Although conformance of a selection method to the axioms of von Neumann and Morgenstern [11] and Arrow [12] does ensure mathematical correctness, prerequisite complete information is not available during the design process, but only during a retrospective analysis. Additionally, reliance on a single objective (i.e., cost) calls into question the entire domain of MCDM and precludes effective decision support for engineering design, a multiobjective effort by nature. In contrast to advocates of this perspective,

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who view utility theory as a stand-alone decision making method, we implement utility theory as part of a broader, comprehensive framework for decision support in engineering design [13–15]. In fact, we assert that despite its mathematical rigor, utility theory alone is not a design or a decision support methodology. It is most appropriate for clarifying decision maker preferences and for indicating the preferred alternative from among a set of feasible alternatives, but there are other important aspects of decision support for engineering design. For example, utility theory is not suitable for formulating and bounding decisions, including the specification of requisite constraints and bounds, documentation of design intent, and other means of employing a designer's judgment, and it is not appropriate for synthesizing an original design alternative or refining an existing one. Thus, the effective use of utility theory for decision support in engineering design is contingent upon its application within a proper context – a context that provides for the effective use of engineering judgment for formulating decisions. The selection DSP [16,17] provides such a context.

In this article, we assert that although mathematical rigor is fundamentally important, utility for practical applications is crucial as well. We advocate support for human judgment throughout the design process and introduce the utility-based selection decision support problem (u-sDSP) as a method that is both practical and anchored in mathematical rigor. The desired balance is achieved via incorporation of the strengths of both utility theory and the selection DSP, as indicated in Figure 1. The u-sDSP offers a sound means for representing designer preferences and identifying preferred alternatives, especially when uncertainty must be considered with respect to alternative performance (i.e., variability). In addition, the role of the designer and his/her judgment is preserved for providing context, structure, justification, and critical evaluation during the decision making process. We have adjusted the word formulation of the selection DSP, as illustrated in Figure 2. Details of the u-sDSP are provided in the next section, followed by an illustrative example of RP resource selection in Section 3.

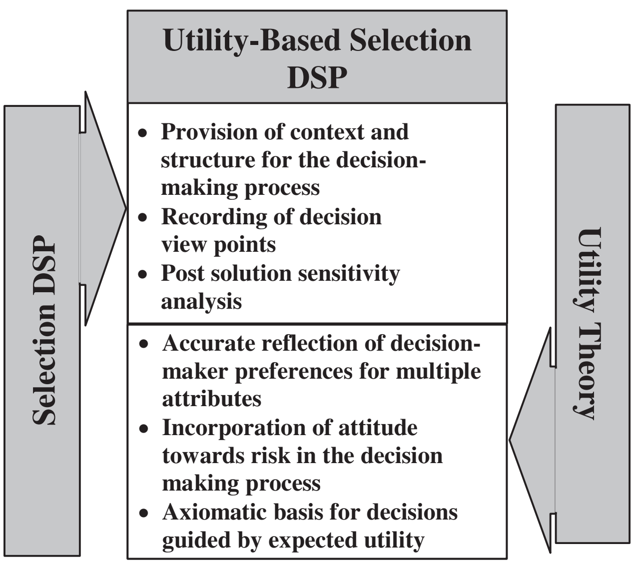


Figure 1. Origins of the utility-based selection DSP.

2. The Utility-Based Selection Decision Support Problem

The steps required for properly implementing the u-sDSP are summarized in Figure 3, and detailed subsequently. Whereas the underlying structure and sequence of steps are based on the selection DSP, utility theory is integrated to guide the quantification of designer preferences and the evaluation of alternatives via expected utility in Steps 4–6, based on the suggestions of Keeney and Raiffa [18].

Selection Decision Support Problem		*Utility-Based Selection Decision Support Problem*	
Given	A set of feasible alternatives	***Given***	Finite set of feasible alternatives.
Identify	The principal attributes influencing selection The relative importance of each attribute.	***Identify***	The principal attributes influencing selection. The uncertainties associated with each attribute.
Rate	The alternatives with respect to each attribute.	***Assess***	Decision-maker's utility with respect to each attribute and with respect to combinations of attributes.
Rank	The feasible alternatives in order of preference based on the attributes and their relative importance.	***Evaluate***	Each alternative using the decision-maker's utility functions.
		Rank	Most promising alternative(s) based on expected utility.

Figure 2. Comparison of selection DSP and u-sDSP word formulations.

Steps for a Utility-Based Selection Decision Support Problem

1. ***Describe the alternatives and provide acronyms.***
2. ***Describe each relevant attribute.***
   a. Provide scales for each attribute (i.e., indicate how each attribute is quantified).
   b. Provide ranges for each attribute (i.e., indicate an ideal value of each attribute and an unacceptable value for each attribute).
3. ***Specify levels and/or probability distributions for each attribute for each alternative.***
4. ***Assess utility functions for each attribute.***
   a. Identify the decision-maker's qualitative preference characteristics for each attribute (i.e., monotonic or target matching and risk averse/prone/neutral).
   b. Identify the decision-maker's quantitative preference characteristics for each attribute (i.e., five levels of each attribute with specific lottery-based definitions for each level; see accompanying text).
   c. Fit a utility function to the decision-maker's preferences for each attribute.
   d. Check the utility functions for consistency.
5. ***Combine individual utility functions into a multi-attribute utility function.***
   a. Identify relevant independence assumptions and corresponding functional form of the multi-attribute utility function.
   b. Assess scaling constants for the multi-attribute utility function.
   c. Check the multi-attribute utility function for consistency.
6. ***Evaluate the expected utility of each alternative.***
7. ***Select the most promising alternative based on expected utility.***
8. ***Post solution analysis and verification.***

Figure 3. Summary of the steps of the utility-based selection decision support problem.

2.1 Preparation

Before beginning Step 1, it is important to establish a context for the selection decision. What are the important goals, objectives, and functions of the design? How can these factors be measured? Is there enough information available for each of the alternatives? Should there be further analyses and refinement of some alternatives? Significantly, selection may be performed at different stages along a design timeline, and the information requirements differ at each stage. Therefore, it is important to characterize all the alternatives at a similar level of detail (if possible). It is also important to record the context of the selection decision and the viewpoints of the decision maker, both prior to and during the selection process.

2.2 Steps for Instantiation

Step 1: *Describe the alternatives and provide acronyms.* A designer should identify each feasible alternative under consideration and provide an acronym, if desired.

Step 2: *Describe each relevant attribute*. The independent attributes to be considered during selection must be identified. The set of attributes should be complete, reflecting all decision-critical characteristics of the alternatives being considered. In fact, each attribute should correspond to a clearly distinct characteristic. A description of the attribute and some indication of its manner of measurement and quantification are also required. Thus, scales must be determined for each attribute, based either on ratios, as defined by natural physical quantities, or on intervals defined by the decision maker. In the context of utility theory, relative importance is not assigned arbitrarily; instead, it is derived from a careful assessment of the decision maker's preferences for combinations of attributes, as discussed in Step 5. The final component of Step 2 consists of specifying a preferential range for each attribute by indicating values for the attribute in question that are 'ideal' and 'unacceptable' to the decision maker. The ideal level can be thought of as a target value, to which the decision maker aspires but does not expect to achieve. The unacceptable value is the least desirable level of the attribute that the decision maker is willing to accept. Thus, any attribute level beyond that which is deemed unacceptable should be of no value to the decision maker.

Step 3: *Specify levels and/or probability distributions for each attribute for each alternative*. Instead of simply rating each alternative with respect to each attribute, as is the case with the selection DSP, the u-sDSP allows for the characterization of each alternative with respect to performance variability, manifested as ranges or probability distributions of performance. Typically, such measures of variability can be determined from analysis, experimentation, and historical data. For example, instead of specifying a deterministic point value for the tensile strength of prototypes, a probability distribution or a uniformly distributed range of likely tensile strengths could be specified.

Step 4: *Assess utility functions for each attribute*. In this step, utility theory is infused into the conventional selection DSP procedure and used to comprehensively assess and quantitatively capture the decision maker's preferences.

(a) *Identify the decision maker's qualitative preference characteristics for each attribute*. Decision maker preferences can be characterized as either monotonic or nonmonotonic. Monotonic preferences describe instances in which a designer consistently prefers either strictly more (i.e., monotonically increasing) or strictly less of an attribute (i.e., monotonically decreasing). Nonmonotonic preferences, on the other hand, describe a target-matching scenario, where the goal is proximity to an ideal. During the specification of the ideal and unacceptable attribute levels in Step 2, the monotonicity of a decision maker's preferences is established. Another qualitative characteristic of a designer's preference structure involves the curvature (i.e., either concave or convex) of his/her utility function with respect to a particular attribute. Concave utility functions imply risk aversion (i.e., preference to act conservatively by avoiding risks), while convex utility functions imply risk proneness (i.e., preference of risky options over the certain ones, even when the expected outcomes are equivalent). It seems reasonable to assert that most designers under most circumstances are risk averse, preferring alternatives that offer on-target outcomes to those that have a considerable chance of yielding undesirable results. Although the qualitative aspects of a decision maker's preference structure may not be needed to assess quantitative utility functions, we believe it is useful for a decision maker to clarify the general trends of his/her preferences. This information can be used to ensure that the final shape of the utility function is indeed consistent with a decision maker's preferences.

(b) *Identify the decision maker's quantitative preference characteristics for each attribute*. Once the general shape of the decision maker's utility function for each attribute has been determined, the next step is to specify points along each utility curve so that a utility function can be fitted to the data to represent the decision maker's preferences. Two points are specified in Step 2, corresponding to ideal and unacceptable values. In Figure 4, these points are labeled x_* and x_0 and assigned utilities of 1 and 0, respectively. The remaining points are usually obtained by asking the decision maker a series of questions. (For more information, please consult a standard reference on utility theory, e.g., [18].) Specifically, a decision maker is asked to identify his/her certainty equivalent for a few lotteries. A lottery is a hypothetical situation in which the outcome of a decision is uncertain; it is used to assess a decision maker's preferences. A certainty equivalent is the level of an attribute for which the decision maker would be indifferent between receiving that attribute level for certain and receiving the results of a specified lottery. For example, to obtain the value of $x_{0.5}$ in Figure 4, the decision maker is asked to identify his/her certainty equivalent to the lottery shown in Figure 5. Generally, at least five points are identified along the decision maker's utility curve. Here, we have chosen to identify x_0, $x_{0.25}$, $x_{0.5}$, $x_{0.75}$, and x_*, as indicated in Table 1. The preference assessment procedure described here must be repeated for each of the attributes of interest.

(c) *Fit a utility function to the decision maker's preferences for each attribute*. A utility function must be fit to the five points assessed in Step 4(b). Different functional forms are appropriate for different preference relationships. For example, a utility function of the form $u(x) = mx \pm b$ may be appropriate for risk-neutral preferences, while risk-averse preferences may require a utility function of the form $u(x) = a \pm e^{bx}$.

(d) *Check the utility functions for consistency*. It is a good practice to ask the decision maker a few additional lottery questions to check the consistency of the single-attribute utility functions.

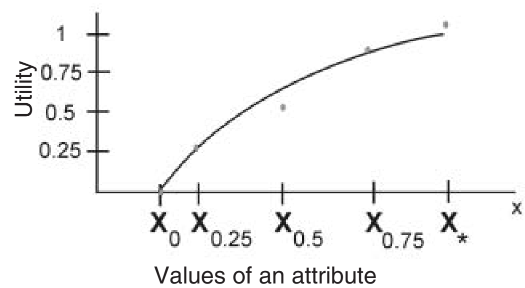
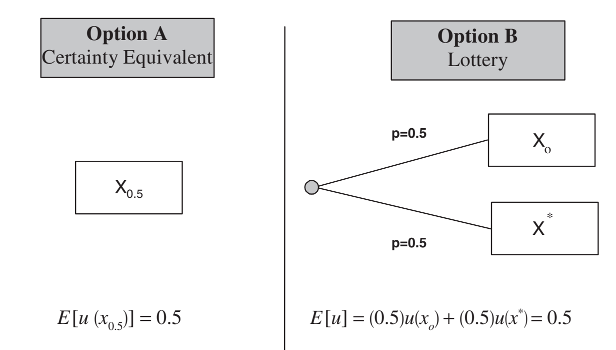


Figure 4. Utility curve based on five data points.



Instructions: Suppose design alternatives are characterized by one attribute, x. Choose a level of $x_{0.5}$ for attribute x such that you are indifferent between **Option A**, a design alternative with attribute $x_{0.5}$ for certain and **Option B** a design alternative with a 50% chance of having attribute x at level x_o and a 50% chance of having attribute x at level x*.

Figure 5. Utility assessment using lottery questions and certainty equivalents.

Table 1. Definitions for single-attribute utility function assessment.

Utility Value	Definition
1	The decision maker's ideal attribute level – beyond which the decision maker is indifferent to further improvements in the attribute.
0.75	The decision maker is indifferent between obtaining a design alternative with a 'desirable' attribute value for certain and a design alternative with a 50–50 chance of yielding either a tolerable or an ideal attribute level.
0.5	The decision maker is indifferent between obtaining a design alternative with a 'tolerable' attribute value for certain and a design alternative with a 50–50 chance of yielding either an unacceptable attribute value or an ideal attribute value.
0.25	The decision maker is indifferent between obtaining a design alternative with an 'undesirable' attribute value for certain and a design alternative with a 50–50 chance of yielding either a tolerable or an unacceptable attribute value.
0	The decision maker's unacceptable attribute level – beyond which he/she is unwilling to accept an alternative.

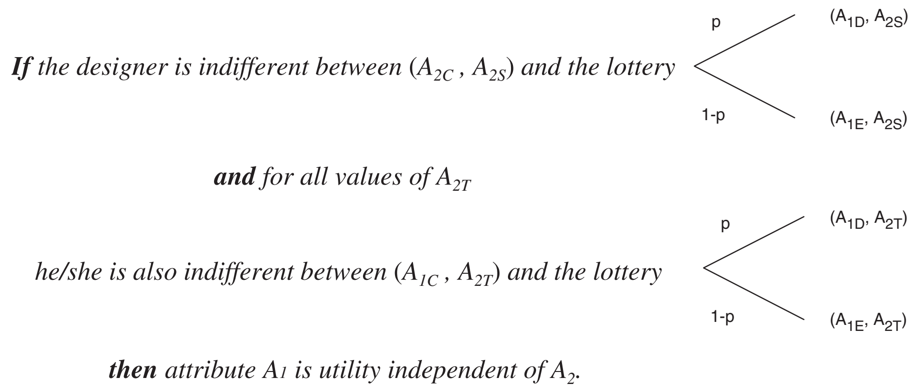


Figure 6. Utility independence.

Step 5: *Combine individual utility functions into a multiattribute utility function*. The preceding characteristics of utility functions have been described in the context of single-attribute utility functions. These are mathematical expressions of a designer's utility as a function of only a single attribute or characteristic of a design. Obviously, designs are evaluated on the basis of multiple attributes. Ideally, we need a utility function that accurately accounts for a designer's preferences, with regard to trade-off among multiple attributes. In other words, if n attributes $(A_1, A_2, \ldots, A_n)$ characterize a design, we wish to obtain a utility function that is a function of all these attributes, $u(A_1, A_2, \ldots, A_n)$. Ideally, we would like to obtain a utility function, such that

$$u(A_1, A_2, \ldots, A_n) = f[f_1(A_1), f_2(A_2), \ldots, f_n(A_n)] \tag{1}$$

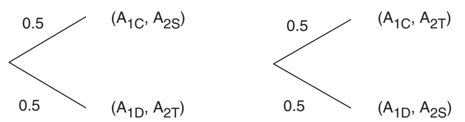
where, f_i is a function of attribute A_i only, for all i and where f has a simplified form, such as additive or multiplicative. If this can be achieved, then we can assess single-attribute utility functions independently for each attribute and then combine them (with some further constants dependent upon a designer's preferences for trade-offs among attributes) into a multiattribute utility function. Thus, the assessment of $u(A_1, A_2, \ldots, A_n)$ will be simplified greatly. In order to employ these simplified forms of the multiattribute utility function, however, a designer's preferences must be consistent with certain independence assumptions.

(a) *Identify relevant independence assumptions and the corresponding functional form of the multiattribute utility function*. There are two independence conditions of primary interest in determining the functional form of the multiattribute utility function [18,19]. These conditions are utility independence and additive independence. They may be defined and tested as follows:

Utility Independence – Again, suppose A_1 and A_2 are two separate attributes characterizing a design. Subscripts C, D, and E denote particular levels of attribute A_1, and subscripts S and T denote particular levels of attribute A_2. The utility independence condition is as indicated in Figure 6. In general, utility independence implies that a designer's preference for levels of an attribute is constant, regardless of the levels of other attributes. Like preferential independence, utility independence is not a symmetric property. If A_1 is utility independent of A_2, it is not necessarily true that A_2 is utility independent of A_1; the condition must be tested in a similar manner.

Additive Independence – Again, suppose A_1 and A_2 (Figure 7) are two separate attributes characterizing a design. Subscripts C and D denote particular levels of attribute A_1, and subscripts S and T denote

If *a designer is indifferent between the following lotteries:*



For all values of A_1 and A_2, ***then*** *A_1 and A_2 are additive independent*

Figure 7. Additive independence.

particular levels of attribute A_2. In general, an additive independence implies that there are no interactions between a designer's preferences for different attributes.

Multilinear Multiattribute Utility Function – Suppose a design is characterized by n attributes – $A_1, A_2, \ldots, A_n$. A set of attributes is defined as any subset of the n attributes and could include any number of them, e.g. $\{A_2, A_5\}$. The complement of a set of attributes includes all of the attributes not included in the set. For example, if the entire set of attributes needed to characterize a design is $\{A_1, A_2, A_3, A_4\}$, the complement of the set $Y = \{A_1, A_4\}$ is $\bar{Y} = \{A_2, A_3\}$, where $\bar{Y}$ denotes the complement of Y.

Given the set of attributes $\{A_1, A_2, \ldots, A_n\}$ with $n \geq 2$, if $Y_i = A_i$ is utility independent of its complement $\bar{Y}_i$ for $i = 1, 2, \ldots, n$ then the multiattribute utility function may take a multilinear utility form:

$$U = \sum_{i=1}^{n} k_i u_i(A_i) + \sum_{i=1}^{n} \sum_{j>i} k_{ij} u_i(A_i) u_j(A_j) + \sum_{i=1}^{n} \sum_{j>i} \sum_{l>j} k_{ijl} u_i(A_i) u_j(A_j) u_l(A_l) + k_{123\ldots n} u_1(A_1) u_2(A_2) \ldots u_n(A_n) \quad (2)$$

Multiplicative Multiattribute Utility Function – Attributes $A_1, A_2, \ldots, A_n$ are mutually utility independent, if every subset of $\{A_1, A_2, \ldots, A_n\}$ is utility independent of its complement. If attributes A_1, $A_2, \ldots, A_n$ are mutually utility independent then the multiattribute utility function takes a multiplicative form:

$$U = \sum_{i=1}^{n} k_i u_i(A_i) + K \sum_{\substack{i=1 \\ j>i}}^{n} k_i k_j u_i(A_i) u_j(A_j) + K^2 \sum_{\substack{i=1 \\ j>i \\ l>j}}^{n} k_i k_j k_l u_i(A_i) u_j(A_j) u_l(A_l) + K^{n-1} k_1 k_2 \ldots k_n u_1(A_1) u_2(A_2) \ldots u_n(A_n) \quad (3)$$

K is a scaling factor that may be determined as

$$1 + K = \prod_{i=1}^{n} (1 + K k_i) \quad (4)$$

Thus, provided the independence assumptions apply to a designer's preferences, we may construct a multiattribute utility function using only n single-attribute utility functions (one for each of the n attributes) and $n+1$ scaling constants.

Additive Multiattribute Utility Function – If $\sum_{i=1}^{n} k_i = 1$, then $K = 0$ and the multiplicative form of the multiattribute utility function reduces to the additive form:

$$U = \sum_{i=1}^{n} k_i u_i(A_i) \quad (5)$$

This is true if both the multiutility independence and the additive independence properties hold.

An important point to remember with respect to these independence conditions is that the conditions apply to preferences for attributes rather than to the attributes themselves. Some engineers object to the use of utility functions in engineering design by noting that attributes of a design are rarely independent. For example, the weight and stiffness of a structure are usually interdependent. Both decrease or increase together. However, the utility independence conditions are still applicable, if attributes themselves are interdependent. The utility independence conditions apply only to a designer's preferences for these attributes. Even if these preference conditions are not satisfied, this does not imply that a multiattribute utility function cannot be constructed. It simply means that assessment of utility functions will be much more difficult. Single-attribute utility functions may not be feasible, and many more preference assessment questions must be asked and answered. It is also important to note that for multiple attributes, it is often a reasonable approximation to assume that the independence conditions hold [18]. In the example considered in Section 3, it is assumed, with justification, that the additive form of the multiattribute utility function is appropriate.

(b) *Assess scaling constants for the multiattribute utility function.* The scaling constants for the multiattribute utility functions are obtained by identifying as many independent equations as there are unknown scaling constants. These equations can be generated by using either lottery questions and certainty equivalents, as discussed earlier or by using certainty considerations. For example, one independent equation could be generated by asking the designer to specify a level of attribute A_3, denoted by A_{3-q}, for which he/she would be indifferent between alternatives $(A_{1-0}, A_{2-0}, A_{3-0})$ and $(A_{1-1}, A_{2-1}, A_{3-q})$, where A_{i-0} is the unacceptable level of attribute i and A_{i-1} is the ideal value of attribute i. Then, if the multiattribute utility function is additive,

$$k_1u(A_{1-0}) + k_2u(A_{2-0}) + k_3u(A_{3-0}) \\ = k_1u(A_{1-1}) + k_2u(A_{2-1}) + k_3u(A_{3-q}). \quad (6)$$

(c) *Check the multiattribute utility function for consistency*. Several consistency checks can be planned and implemented. For example, the decision maker could be presented with a pair of alternatives, and the preferred alternative should have the larger utility value.

Step 6: *Evaluate the expected utility of each alternative*. The expected utility of each alternative as a function of multiple attributes and their associated probability distributions is calculated using the single-attribute utility functions and scaling constants. For example, if the multiattribute utility function is additive, the expected utility of an alternative can be calculated as:

$$E[u(A_1, A_2, \ldots, A_n)] = \sum_{i=1}^{n} k_i E\,[u_i(A_i)] \quad (7)$$

where

$$E[u(A)] = \int u(a)f(a)\,dx \quad (8)$$

and $u_i(X_i)$ is calculated as in Equations (2), (3), or (5). Note that calculating expected utility, as in Equation (8) assumes that the probability distributions characterizing the performance of each alternative are independent.

Step 7: *Select the most promising alternative(s) based on expected utility*. The most promising alternatives are those with the highest overall expected utility.

Step 8: *Postsolution sensitivity analysis and verification*. It is important to review the results of Step 7. First, do the results seem logical, given the alternatives and their attribute values? If the results are unexpected, perhaps the decision maker's preferences, the characterization of alternatives, and/or the application of preferences to design alternatives have been clarified during the selection process. Otherwise, it may be necessary to revisit Steps 2–5. In particular, it should be verified that (1) the set of attributes includes all significant characteristics of the alternatives and that (2) the attributes measure distinct characteristics of the alternatives. In addition, it should be verified that appropriate levels and/or probability distributions have been assigned for each attribute for each alternative and that utility functions consistently reflect designer preferences. Second, is there a clearly preferred alternative? If expected utilities for two or more alternatives are similar in value, indicating that there is no clearly preferred alternative, a sensitivity analysis is recommended to investigate the sensitivity of the expected utility of the alternatives to small variations in attribute values. If a sensitivity analysis does not distinguish clearly among the alternatives, further characterization of the alternatives in terms of additional or alternate attributes may be required. Third, is there a need for more analysis and refinement of alternatives? Upon inspection of the results and the performance of each alternative, it may become clear that (1) none of the alternatives performs acceptably with respect to the evaluation criteria, (2) sufficient information is not available for one or more alternatives, or (3) one or more important attributes were absent in the selection decision. In any of these cases, further refinement of the alternatives may be required, followed by repeated application of the u-sDSP.

A practical application of the u-sDSP to resource selection in the rapid prototyping (RP) domain is demonstrated in the following section. In the example, application of the u-sDSP is illustrated for supporting a selection decision that is characterized by several attributes, varying degrees of uncertainty, and important trade-offs, among other attributes. Particular attention is given to structuring and bounding the problem as well as clarifying and assessing designer preferences.

3. Example: Selection of Rapid Prototyping Materials and Processes for Testing Snap-fits on a Light Switch Cover Plate Assembly

In this example, the u-sDSP is employed to support a designer who must select an appropriate RP material and technology for producing functional prototypes of alternative designs. Rapid prototyping offers significant potential for reducing cost and time to market for the development of new, redesigned, and customized products. Since its introduction, the RP technology has moved far beyond visualization and marketing purposes and is now being employed as a means of product validation, rapid tooling of injection molded parts, and low-volume manufacture. Given the increasing impact of Solid Freeform Fabrication (SFF) on the product development process, we have been exploring related issues in the Rapid Tooling Test Bed (RTTB) within the Systems Realization Laboratory (SRL) and the Rapid Prototyping and Manufacturing Institute (RPMI) at Georgia Tech. The RTTB supports distributed engineering activities related to the design of parts and injection molds (Figure 8) and their fabrication and the selection of prototyping technologies, Given a product design problem and a candidate design, the RTTB is intended

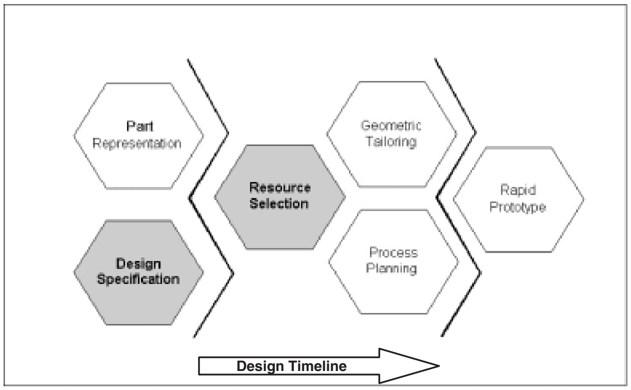


Figure 8. Distributed engineering activities of the RTTB.

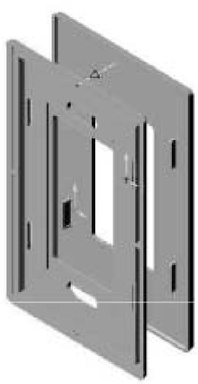


Figure 9. Light switch cover plate assembly.

to provide a framework for facilitating the passage of information along a design timeline and to assist a designer in obtaining useful prototypes, where 'useful' means that the prototype mimics some desired production characteristics [20]. As illustrated in Figure 8, tailoring SFF processes and materials to function similarly to production parts consists of at least three main activities: SFF material and process selection, geometric tailoring (i.e., design modification for SFF manufacturing), and SFF process planning. Our focus in this example is on resource selection, the first key constituent.

The manufacturer of a two-piece light switch cover plate assembly (see Figure 9) requires a flexible support system, such as the one in Figure 8, for facilitating rapid introduction of new products into global markets. As indicated in the figure, an important aspect of rapid prototyping involves selecting a proper resource combination (i.e., material and process). RP resource selection is a selection problem involving a large and often disparate number of complex alternatives, which are characterized by attributes measured on widely differing scales, with different degrees of uncertainty. In this example, our focus is on selecting RP resources for producing functional rapid prototypes for testing and validating different snap-fit designs for the light switch cover plate assembly. Thus, the primary objectives of the resulting prototype, in decreasing order of importance, are (1) functional product validation, particularly with respect to the snap-fitting of components, (2) determining closeness of fit or tolerance of the two interfacing components, (3) obtaining a feel for the product, and (4) visual and physical confirmation of 3D interface integrity. These objectives are closely related to several of the rapid prototyping attributes listed in Table 2, where we have indicated (Y or N) whether each attribute is included in the u-sDSP in this example. Our reasoning is summarized in the third column of the table and based generally on the objectives listed here. A functional prototype should allow us to closely approximate the snap-fit characteristics – specifically functional robustness for assembly and disassembly – of a final production part. The relevant material characteristics of the prototype should emulate the polycarbonate production material. Since testing fit and tolerance is a secondary objective, we are also concerned with the overall accuracy of the parts.

Why is this example – selecting an RP material and process for functional prototyping of a snap-fit light switch cover plate – challenging for a decision maker? First, there are several RP materials and processes to choose from; the appropriate choice is not obvious in most cases. In this example, many attributes (as indicated in Table 2) are required to evaluate the suitability of an RP material–process combination for functional prototyping. Most of these attributes are measured on different scales. In addition, data associated with each RP alternative for each of the attributes in Table 2 is uncertain in most cases; the performance of the RP alternatives vary with the application; and the form and completeness of the available data vary from manufacturer to manufacturer. Finally, the suitability of an RP material–process combination for this application depends heavily on multiple attributes, and a decision maker must properly evaluate trade-offs among the attributes, when making a selection.

Why is this example of interest to industry? Typical product development processes often entail phases that are common to the realization of all products in a particular sector. For example, resource selection plays a significant role in the production of virtually all rapid prototypes. Whereas the parameters defining a particular prototype are case specific, the attributes factoring into the resource selection decision are commonly considered. A decision template can be formulated for resource selection attributes and instantiated in a software application (facilitating preference assessment) that is coupled to a database (ensuring up-to-date information content). Once such a decision template has been formulated for a phase, the effort inherent

Table 2. Selection criteria and mindset for rapid prototypes.

Attributes	Interest	Reason
Tensile strength	Y	Important for validation of strength requirements of snap-fit design.
Young's modulus	Y	Important for validation of stiffness requirements of snap-fit design.
Flexural strength	Y	Important for validation of strength requirements of snap-fit design.
Flexural modulus	Y	Important for validation of stiffness requirements of snap-fit design.
Detail capability	Y	The ability to reproduce the part in sufficient detail is important due to the small size of key features.
Accuracy	Y	The ability to reproduce the part with sufficient accuracy is important due to the small tolerances.
Elongation at break	N	No continuous, prolonged tensile stresses are expected.
Hardness (Shore D)	N	The hardness of this material is of no direct consequence for this application.
Notched izod impact	N	No impact forces are expected for this application.
Density	N	This factor is not really important since the densities of most of the polymers under consideration are close to that of polycarbonate and the part itself is relatively thin. The overall feel of the product should thus not be effected significantly.
Heat deflection temperature	N	We are not concerned with thermal stability of the product at this time.
Resistance	N	Although insulation of the circuitry is important, it is accomplished in the internal casing of the switch.
Durability	N	All validation efforts are short term based.
Functionality	N	The relevant aspects of this property are already covered in the mechanical properties chosen.
Build time	N	There is no particular rush and all production times are relatively fast.
Cost	N	This attribute matters only for considering material and processes separately.
Total cost	N	Although cost is always important, in this particular case there is no point in saving money by producing a prototype not capable of meeting the requirements associated with its intent.

in customizing this template for a particular product is greatly simplified. In essence, the task is reduced to choosing a subset of pertinent attributes, assessing the corresponding decision maker preferences, plugging in the latest version of a database characterizing alternative performance with regard to the attributes considered, and computing the results, all at the push of a (few) button(s). It is important to note that the underlying mathematics is fairly easy to encode and the payoff in efficiency is significant. Additionally, software implementation allows a decision maker to effectively negotiate even the largest of alternative spaces, making the method extremely scalable.

There are three primary advantages of implementing such an approach. The first lies in the ability to reevaluate a given decision using updated information (e.g., additional alternatives, updated uncertainty levels, etc.) with minimal effort (i.e., updating the corresponding database and 'rerunning' the selection). The second is that the effort involved in formulating a new selection decision is reduced to answering a series of questions. The third advantage is that the design intent is captured and the corresponding scenario can be recalled at a later point in time, aiding the transfer of responsibility from one designer to another. Each of these implications is especially significant when derivative, adaptive, and variant products are considered.

What is illustrated in the following example? In Steps 1–3, the decision maker first bounds the problem by identifying potential RP material–process alternatives, describing them, and providing acronyms. Then relevant attributes are described, providing scales and ranges for each and specifying probability distributions for any associated variability. These steps are preserved from the selection DSP. Once the problem is bounded and formulated, the decision maker applies utility theory in Steps 4–6 to assess the utility functions that represent his/her absolute preferences for each attribute, combines the utility functions into a multiattribute utility function, and utilizes it to evaluate each alternative RP material–process combination. When implementing these steps, the decision maker will not implement utility theory as a 'black box'; instead, emphasis is placed on identifying the qualitative (as well as the quantitative) characteristics of the decision maker's preferences and checking the utility functions for consistency. Finally, the results of Steps 6 and 7 are critically reviewed and verified; guidelines for a post-solution sensitivity analysis are provided in Section 2.

Step 1 – *Describe the alternatives and provide acronyms.* The RP materials considered are SOMOS 7110 and SOMOS 8120 by DSM Somos®, SL 7510 by Vantico AG, P400 by Stratasys Inc., and TJ 65 by 3D Systems.

The choice of the RP process consists of the SLA 250, SLA 3500, and ACTUA machines by 3D Systems and the FDM 1650 machine by Stratasys Inc. It is important to note that the materials and processes considered in this case study are based on resources available within the RPMI in 2001. The reader is referred to the manufacturer for descriptions of the resources.

Step 2 – *Describe each relevant attribute.*

(a) *Provide scales for each attribute* (*i.e.*, *indicate how each attribute is quantified*. Relevant attributes are presented in Table 3, along with their assigned acronyms, descriptions, units, and scales.

(b) *Provide ranges for each attribute* (*i.e.*, *indicate an ideal value and an unacceptable value* of *each attribute*. Ranges for each of the attributes are given in Table 3. A target value is desired for each of the first four attributes; thus, ideal and both upper and lower unacceptable values must be specified. Since lower numerical values of detailed capability and accuracy are always preferred, only ideal and upper unacceptable value are provided.

Step 3 – *Specify levels and/or probability distributions for each attribute for each alternative*. Alternatives and their respective variability in terms of probability distributions are shown in Table 4. Although uniform distributions have been used here, other distributions could be used as well. Probability distributions should be chosen based on available data and engineering judgment.

Table 3. Attributes considered and their corresponding units, descriptions, scales, and values.

Attribute	Acronym	Description	Units	Scale	Lower Unacceptable	Ideal	Upper Unacceptable
Tensile strength	(TS)	The strength of the material under tension	MPa	Ratio	50	65	75
Young's modulus	(YM)	The modulus of elasticity of the material	MPa	Ratio	1500	2137	2600
Flexural strength	(FS)	The strength of the material under bending	MPa	Ratio	70	95	120
Flexural modulus	(FM)	The modulus of flexural stiffness tof the material	MPa	Ratio	1800	2344	2800
Detail capability	(DC)	A measure of a process's resolution (i.e., what level of detail a machine is capable of reproducing – smallest possible feature size).	mm	Ratio		0.4	0.9
Accuracy	(A)	The capability of a machine to maintain the dimensional requirements posed when using a specified material.	Qualitative	Interval		0.02	0.1

Table 4. Probability distributions of alternatives.

Alternatives										
Process	Material	Type of Distribution	Lower Bound/ Mean	Upper Bound/ Variance	Type of Distribution	Lower Bound/ Mean	Upper Bound/ Variance	Type of Distribution	Lower Bound/ Mean	Upper Bound/ Variance
						Attributes				
		Tensile Strength			Young's Modulus			Flexural Strength		
SLA250	DSM7110	Uniform	44	69	Uniform	1758	2413	Uniform	59	110
SLA3500	SL7510	Uniform	42.3	55.46	Uniform	1877	2869	Uniform	78	96
SLA3500	DSM8120	Uniform	23	29	Uniform	633	773	Uniform	23	29
FDM1650	P400	Uniform	31	37	Uniform	2234	2730	Uniform	58	72
MJM2100	TJ75	Uniform	9	11	Uniform	90	110	Uniform	9	11
						Attributes				
		Flexural Modulus			Detail Capability			Accuracy		
SLA250	DSM7110	Uniform	1710	2668	Uniform	0.45	0.55	Uniform	0.04	0.05
SLA3500	SL7510	Uniform	2374	2902	Uniform	0.45	0.55	Uniform	0.04	0.05
SLA3500	DSM8120	Uniform	621	759	Uniform	0.45	0.55	Uniform	0.04	0.05
FDM1650	P400	Uniform	2358	2882	Uniform	0.45	0.55	Uniform	0.121	0.135
MJM2100	TJ75	Uniform	90	110	Uniform	0.67	0.83	Uniform	0.121	0.135

Step 4 – *Assess utility functions for each attribute.*

(a) *Identify the decision maker's qualitative preference characteristics for each attribute*. The monotonicity of the decision maker's preferences and the corresponding attitude towards risk for each of the attributes are presented in Table 5.

(b) *Identify the decision maker's quantitative preference characteristics for each attribute*. The certainty equivalents for each of the five chosen utility levels for each attribute are shown in Table 5. These values are obtained by employing lottery questions like those described in Section 2. For target-matching attributes, certainty equivalents, both above and below the ideal value, must be identified through questioning.

(c) *Fit a utility function to the decision maker's preferences for each attribute*. Coefficients for the utility functions corresponding to the decision maker's preferences for each attribute are provided in Table 6. The utility functions have been fit to normalized data. Sample normalized utility functions for detail capability and tensile strength are presented in Figure 10. The term normalized, here, refers to the scaling of each attribute from 0 to 1, within its respective range of interest.

(d) *Check the utility functions for consistency*. The consistency of the utility functions can be validated by presenting the decision maker with lottery questions, using utility levels not explicitly assessed previously. An example of such a check is provided in Figure 11.

Step 5 – *Combine individual utility functions into a multiattribute utility function.*

(a) *Identify relevant independence assumptions and corresponding functional form of the multiattribute utility function*. It has been verified that utility and additive independence conditions are valid for the decision maker of this example. For brevity, we do not provide the details here.

(b) *Assess scaling constants for the multiattribute utility function*. The scaling constants for combining single-attribute utility functions into one multiattribute

Normalized Utility Function for Monotonic Attributes (i.e., Detail Capability)

$$U(x) = 2.018 - \exp(0.6934x)$$

Normalized Functions for Non-Monotonic Attributes (i.e., Tensile Strength)

Left Hand Side

$$U(x) = 1.022 - \exp(-2.402x)$$

Right Hand Side

$$U(x) = 2.018 - \exp(0.6934x)$$

Figure 10. Sample normalized utility functions.

Table 5. Monotonicity, attitude toward risk, and preference levels of attributes.

		Attitude Towards	Left-Hand Side Utility					Right-Hand Side Utility			
Attribute	**Monotonicity**	**Risk**	**0**	**0.25**	**0.5**	**0.75**	**1**	**0.75**	**0.5**	**0.25**	**0**
Tensile strength	Target	Averse	50.00	51.75	54.43	58.88	65.00	68.86	71.32	73.40	75.00
Young's modulus	Target	Averse	1500.00	1571.83	1682.02	1864.75	2137.00	2300.94	2420.63	2522.13	2600.00
Flexural strength	Target	Averse	70.00	72.82	77.14	84.32	95.00	103.85	110.31	115.80	120.00
Flexural modulus	Target	Averse	1800.00	1861.34	1955.45	2111.50	2344.00	2505.46	2623.34	2723.31	2800.00
Detail capability	Decreasing	Averse	0.90	0.82	0.71	0.58	0.40	–	–	–	–
Accuracy	Decreasing	Averse	0.10	0.34	0.25	0.15	0.02	–	–	–	–

Note: Although it may seem counterintuitive to assign decreasing monotonicities to the final two attributes, higher Detail Capability and higher Accuracy are both characterized by smaller values.

Table 6. Coefficients for normalized single-attribute utility functions of the general form $y = a + bx + ce^{dx}$.

	Attribute Utility Function Coefficients							
	Left-hand Side				Right-hand Side			
Attribute	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
Tensile strength	1.0219	0	−2319.2006	−0.1550	2.0177	0	−0.0084	0.0730
Young's modulus	1.0219	0	−286.1830	−0.0038	2.0177	0	−0.0407	0.0015
Flexural strength	1.0219	0	−833.8994	−0.0961	2.0177	0	−0.0717	0.0277
Flexural modulus	1.0219	0	−2831.0420	−0.0044	2.0177	0	−0.0283	0.0015
Detail capability	2.0177	0	−0.5742	1.3868	0	0	0	0
Accuracy	2.0177	0	−0.9615	1.8247	0	0	0	0

utility function are assessed with indifference questions, as described in Section 2 for Step 5(b). For this particular case, we have asked the decision maker to specify the value of an attribute, denoted by $TS_?$, for which he/she is indifferent between the following two options:

Option A – (TS_0, $YM_{0.55}$, $FS_{0.55}$, $FM_{0.55}$, $DC_{0.55}$, $A_{0.55}$). – The attribute in question is at its worst level and all remaining attributes are at a particular level (here, utility = 0.55).

Option B – ($TS_?$, $YM_{0.45}$, $FS_{0.45}$, $FM_{0.45}$, $DC_{0.45}$, $A_{0.45}$). – The attribute in question is at a level specified by the decision maker, denoted here by $TS_?$, and all remaining attributes are at a less preferred utility level (here, utility = 0.45).

All of the values used in these comparisons are listed in Table 7. As mentioned earlier, these trade-off comparisons are conducted for $n-1$ attributes. The k-value for the remaining attribute is obtained from the condition that the k-values must sum to 1. The resulting set of scaling factors is presented in Table 8. The multiattribute utility function characterizing the decision maker's preferences is represented by $U = \sum k_i u_i$.

(c) *Check the multiattribute utility function for consistency*. The method for checking the consistency of a multiattribute utility function is similar to that for a single-attribute utility function. If the results of all utility checks are acceptable to the decision maker, the multiattribute utility function may be accepted, and the expected utility of the available alternatives may be assessed accordingly. If this is not the case, one should iterate until the utility checks are satisfied. For brevity, the checking procedure is not presented in detail.

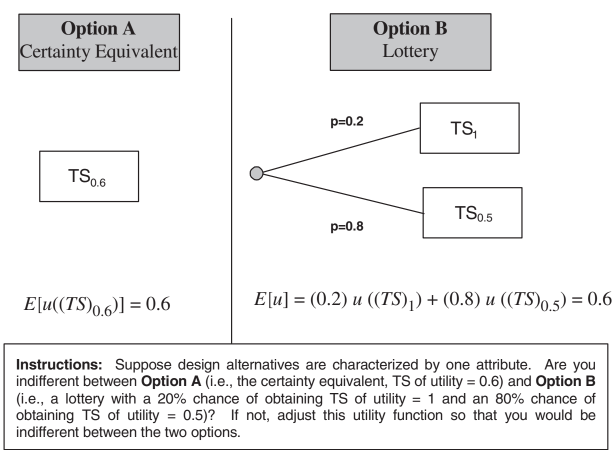


Figure 11. Utility function consistency check.

Step 6 – *Evaluate the expected utility of each alternative*. Since the decision maker's overall preference structure is represented by the multiattribute utility function, the next step is to calculate the decision maker's expected utility for each alternative. These expected utilities take into consideration not only the relative importance of certain attributes within the overall preference structure but also the values and the uncertainty associated with each attribute for each alternative. The results of these calculations are provided in Table 9. It is important to note that three alternatives had negligible expected utilities; this is due to their poor (i.e., out of range) performance with respect to the decision maker's preferences for each attribute. Most likely, the decision

Table 8. Results of scaling factor assessment.

Attribute	*k*-Values
Tensile strength	0.193741
Young's modulus	0.1864461
Flexural strength	0.189041
Flexural modulus	0.1922651
Detail capability	0.1563661
Accuracy	0.0821421

Table 9. Selection run results.

Alternatives		Expected Utility
Process Material	Process Material	
SLA250	DSM7110	0.62214
SLA3500	SL7510	0.44195
SLA3500	DSM8120	0
FDM1650	P400	0
MJM2100	TJ75	0

Table 7. Comparative trade-off values for determining k-scaling constants for attributes.

	Comparison 1		Comparison 2		Comparison 3		Comparison 4		Comparison 5	
Attribute	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
Tensile strength	53.61	62	54.85	53.61	54.85	53.61	54.85	53.61	54.85	53.61
Young's modulus	1699.16	1648.19	1648.2	2030	1699.16	1648.19	1699.16	1648.19	1699.16	1648.19
Flexural strength	77.82	75.82	77.82	75.82	75.82	90	77.82	75.82	77.82	75.82
Flexural modulus	1970.09	1926.56	1970.09	1926.56	1970.09	1926.56	1926.56	2227	1970.09	1926.56
Detail capability accuracy	0.68	0.72	0.68	0.72	0.68	0.72	0.68	0.72	0.72	0.42

maker could have rejected these alternatives at the beginning of the selection process; they have been retained here for completeness.

Step 7 – *Select the most promising alternative based on expected utility*. The most preferred alternative is the one with the highest expected utility. As evidenced by the results, the final material–process combination most suited to meet the needs of our decision maker is using DSM 7110 resin on the SLA250 machine. Considering the alternatives, this result seems reasonable. It is supported by expert opinion and by results previously achieved using the Archimedean formulation of the selection DSP. In this former case, however, the weighting scheme was chosen through the use of pairwise comparison techniques. As might be expected, the weighted merit function had to be tweaked and a number of selection runs conducted until a result representative of designer preferences was obtained.

Step 8 – *Postsolution sensitivity analysis and verification*. Among the material choices, DSM 7110 resin has material properties closest to those of the intended production material (i.e., polycarbonate). The SLA 250 machine is capable of producing the desired prototype in adequate detail and with sufficient accuracy to meet the proposed requirements. Thus, since the results of Step 7 seem logical and indicate a clearly preferred alternative, a post solution sensitivity analysis is not required in this case. However, in many selection decisions, the selection process may lead to unexpected results and/or alternatives with similar expected utilities. In these cases, a post solution sensitivity analysis and verification procedure is recommended, as discussed in the previous section.

4. Conclusion

The effort to increase concurrency in engineering design has been impeded by a steady increase in the scope, distribution, and complexity of engineering projects, accompanied by an analogous transition in the number and scope of decisions involved in their realization. Many of these decisions entail evaluating a set of feasible alternatives, based on complex, nondeterministic information and selecting a preferred alternative(s). In this article, we present the utility-based selection decision support problem (u-sDSP), a rigorous, step-by-step construct for supporting human judgment in making critical selection decisions, throughout the design process. The u-sDSP is a synthesized construct, based on the selection DSP and augmented with utility theory. Primarily, it facilitates selection decisions involving both trade-offs among multiple, conflicting attributes and mitigation of risk associated with variability in the performance of alternatives. Whereas utility theory provides a mathematically rigorous means for clarifying and capturing designer preferences and identifying a preferred alternative in the context of risk and uncertainty, the selection DSP – the construct within which utility theory is employed in this article – facilitates the effective use of engineering judgment for formulating and bounding decisions and establishing context. The result is a method with practical value. The usefulness of this method is demonstrated for rapid prototyping resource selection, a complex, multiattribute, nondeterministic type of selection decision, in which alternatives are characterized by attributes measured on widely differing scales and with different degrees of variability. It is argued that the example is representative of many complex selection decisions in engineering design.

Often, there is a fundamental chasm between pure mathematical rigor and practical tractability, but this rift is often ignored. We agree with Hazelrigg that many attention-directing tools are mathematically flawed and produce inherently inconsistent results. We also concur that there is a fundamental need for substantiating any method from a theoretical or mathematical standpoint (see, e.g., [1,21]). However, we assert that validation is not complete without considering the subjective or practical aspects of a method (see, e.g., [22]) and that effective use of a method is contingent upon a fundamental understanding of underlying assumptions and inherent limitations that is often missing. Hence, we advocate a careful reflection (with regard to the problem at hand, the underlying assumptions/limitations of the attention-directing tool or method considered, and interpretation of results) before implementing any selection method or tool (c.f., [2]).

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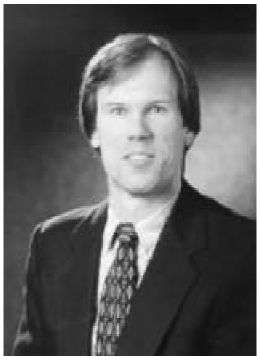

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